Power Outage Estimation and Resource Dimensioning for Solar Powered Cellular Base Stations

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Abstract—One of the major issues in the deployment of solar powered base stations (BSs) is to dimension the photovoltaic (PV) panel and battery size resources, while satisfying outage constraints with least cost. The fundamental step in this dimensioning is to evaluate the power outage probability associated with a particular configuration of PV panel and battery size. This paper addresses this issue by first proposing an analytic model to evaluate the power outage probability of a solar powered BS. The proposed model accounts for hourly as well as daily variation in the harvested solar energy as well as the load dependent BS power consumption. The model evaluates the steady state probability of the battery level which is then used to estimate the BS power outage probability. Next, given a tolerable power outage probability, we address the problem of obtaining the cost-optimal PV panel and battery dimensions for the BS. The proposed model and framework have been evaluated using empirical solar energy data for geographically diverse locations.

Index Terms—Green communications, outage estimation, resource dimensioning, solar energy, base stations, Cellular networks.

I. INTRODUCTION

Solar powered BSs use PV panels to harvest solar energy to power the base station during the day, and use battery banks to store the excess energy for nights and bad weather periods. Such BSs are becoming increasingly popular due to a number of reasons: (i) they are a green solution for reducing the carbon footprint of network operators, (ii) they can reduce the operating expenditure, and (iii) they provide a means for extending cellular coverage in regions without reliable grid power. As of 2014, there are around 43,000 solar powered BSs across the globe [1], and the bulk of the deployment is in regions of developing countries with poor or no grid connectivity. Further, currently there are 321,000 off-grid (i.e. without any grid connectivity) and 701,000 bad-grid (i.e. connected to a grid supply with frequent power outages, loss of phase, or fluctuating voltages) BSs in the world [1]. Presently, these base stations rely on diesel generators whose operating cost is around ten times greater than powering through the grid [2], and are thus all suitable candidates for solar powering.

One of the major challenges in the deployment of solar powered BSs is to dimension the PV panel and battery sizes. Both over and under-provisioning of these resources is undesirable. Under-provisioning of resources leads to more frequent outages thus leading to poor quality of service (QoS) and dissatisfied customers. On the other hand, over-provisioning leads to unnecessary increase in the capital expenditure (CAPEX).

The general methodology for addressing this problem is to find the configuration of PV panel and battery size (over a search space) that minimizes the overall cost, while satisfying the power outage constraint specified by the operator [2], [3]. In the context of this work, a power outage is defined as an event where the BS does not have enough power and is thus shut off. Solving this dimensioning problem requires the computation of the power outage associated with any given configuration of the PV panel and battery size.

In [4] we try to address this problem and to that end propose some simple models for the battery level, solar irradiation and traffic to move forward towards such an evaluation. We propose a discrete time Markov chain for capturing battery level at the BS and in the model we also accommodate the hourly variations of the harvested solar energy as well as the network traffic. For clarity, the model is presented again in this paper. Further, in this current work we study in detail the system performance in terms of the various system parameters and how they affect the power outage probability. Also, this work evaluates the closed form expression for the steady state probabilities of the various states in the model which is one of the key step in estimating the power outage probability. We validate the proposed model and methodology to estimate the power outage by comparing against results obtained using real solar irradiance trace from two geographically diverse locations and also show its superiority over a previously existing method for outage estimation [5].

The rest of the paper is organized as follows. In Section II we present the related work and in Section III we present the background material and system model. Section IV presents the model for evaluating the power outage probability. Section V presents the methodology for obtaining the steady state probabilities of the system states and the power outage probability. Section VI describes the problem of cost optimal dimensioning. Finally, Section VII presents simulation results to validate our methodology and Section VIII concludes the paper.
II. RELATED WORK

With the increasing focus on green energy, there have been a number of works that deal with the problem of dimensioning resources for reliable performance of solar powered systems. Guidelines for dimensioning resources for solar powered systems are presented in [6], [7] while [8] proposed the use of the probability of loss of power supply as a reliability index in dimensioning problems. In [9]-[13] the authors propose methodologies for dimensioning of battery size based on the number of days of autonomy (i.e. number of consecutive days for which the battery should be able to power the system even if there is no solar energy harvested). The size of the PV panels in such an approach is chosen such that with the average solar irradiation of the worst weather month, the PV panels are able to harvest energy equivalent to the daily average power consumption. The storage dimensions in this method is determined by the product of the days of autonomy and the average daily power consumption. While such methods are simple and provide a rough approximation, they have a number of disadvantages: the solution provided is not necessarily cost-optimal, the designer has to decide the days of autonomy which requires experience, and it does not provide any guarantees on the outage probability.

The problem of cost-optimal dimensioning of resources for solar powered systems specifically targeting cellular BSs is considered in [2], [14], [15]. The dimensioning in [2], [14], [15] is done through simulations by using long-term solar irradiation data (either real or synthetically generated). An overview of commercial software tools used for simulation based dimensioning solar powered systems is presented in [16]. Simulation based approaches are not only computationally intensive, but also does not provide any insights into the performance of the system. Literature on modeling of solar powered systems includes [17] and [18] that model solar energy using Beta and log-normal distributions, respectively, and use these models to dimension resources for a solar powered system. A Markov chain based model for energy storage is proposed in [19], but it considers solar irradiation with exponential distribution thus assuming the solar irradiation to be memoryless. Existing literature has shown that the solar energy is better modeled as a Markov process and these models have been used to dimension storage for solar powered systems in [20], [21], [22]. Further, [5] proposes a Markov model for solar energy which is used to dimension cost optimal PV panel and battery sizes. However, a greater accuracy than that offered by the model in [5] is required in cellular network planning [23] (and as also shown by the results in this paper).

While existing literature has addressed various individual aspects of dimensioning solar-powered systems, there is no work which integrates the modeling of solar energy, network traffic, and battery levels while being simple and accurate. Thus in this paper we present a framework which incorporates all these factors into the model in order to evaluate the system performance, and the framework is tailored specifically for dimensioning resources for solar powered cellular BSs.

III. SYSTEM DESCRIPTION

In this section we present the system model and some background details.

A. Base Station Power Consumption

The base station power consumption comprises of two parts: a fixed part which is due to air conditioners, losses in cable feeders etc. and a variable part, which depends on the instantaneous traffic load being handled by the base station. This paper considers a Long Term Evolution (LTE) macro BS, the power consumption for which is given by [24], [25]

\[ P_{BS} = \gamma_{TRX}(P_0 + \Delta K P_{max}), \quad 0 \leq K \leq 1 \]  

where \( \gamma_{TRX} \) denotes the number of transceivers, \( P_0 \) denotes power consumption at zero traffic, \( \Delta \) denotes slope of load dependent BS power consumption, \( K \) is the normalized traffic at the given time (i.e. the traffic normalized with respect to the maximum traffic that can be supported by the BS) and \( P_{max} \) is the power amplifier output at maximum traffic. Example values of \( P_0, \Delta \) and \( P_{max} \) for a macro BS are 118.7 W, 2.66 and 40 W respectively [24].

The traffic load at a cellular BS consists of a mix of voice and data. Both voice and data traffic show diurnal patterns where the traffic peaks are reached during certain hours of the day and lower levels at nights [26], [27], [28]. In addition, the traffic levels during weekends are generally different from that during weekdays [26], [27], [28], [29]. While the load is lower on weekends in business areas, the traffic on weekends may be higher than that on weekdays in residential areas. We assume that the telecom operator has the average traffic profile (or an estimate of the same) for weekdays and weekend for the given site. This average traffic profile can be used to evaluate the normalized traffic load which can be used in Eqn. (1) to calculate the power consumption of the BS. For illustrative purposes, in this paper we use traffic profile data from a large scale cellular network traffic study (from 1668 BSs in London, UK) which consists of both voice and data traffic [29].

Demand for cellular network services is a dynamic process that is expected to show continued growth in the future. Thus the network planning and dimensioning process has to account for the expected traffic growth over the lifetime of the BS. In this paper we consider a target BS lifetime of 10 years and assume that the traffic increases at 50% Compound Average Growth Rate (CAGR) per year based on Cisco’s Mobile traffic forecast [30].

B. Solar Energy Resource and Batteries

For modeling and evaluation, we use statistical solar irradiation data from the National Renewable Energy Laboratory (NREL), USA [31]. The weather data files are fed into the System Advisor Model (SAM), a tool developed by NREL which gives the hourly solar power generation for a PV panel with a given rating [32]. We use 10 years of solar data for two locations: San Diego (USA) and Jaipur (India). For PV panels, we assume default values for the DC-AC loss factor (assumed to be 0.77) and the tilt of the PV panels (assumed to be the latitude for the given location) [33].
We assume that the BS uses lead acid batteries for charge storage due to their popularity and cost advantages over other storage options. The operating conditions of a battery strongly influence the lifetime of a battery and discharging it to very low values can significantly reduce its lifetime. To calculate the battery lifetime, we use a model based on the number of charge cycles to failure for different values of the depth of discharge (DoD) \([34]\). DoD is defined as the lowest level a battery hits in a given discharging-charging cycle. For modeling the battery lifetime, the entire range of DoD (0-100) is split into \(M\) regions. Then, for the operating period (say \(T\) years), the number of cycles corresponding to each DoD region is counted. The battery lifetime, \(L_{\text{Bat}}\) is then

\[
L_{\text{Bat}} = T / \left( \sum_{i=1}^{M} \frac{Z_i}{CTF_i} \right),
\]

where \(Z_i\) is the number of cycles with DoD in region \(i\), and \(CTF_i\) is the cycles to failure corresponding to region \(i\) \([34]\). The relationship between the DoD and cycles to failure is generally provided by the battery manufacturer \([35]\).

To accommodate the miscellaneous losses during transfer of energy from the PV panel to batteries, and from the batteries to power the BS, we consider the charging and discharging efficiencies of the batteries which are denoted by \(\eta_c\) and \(\eta_d\), respectively in this paper.

IV. MODEL FOR EVALUATING BS POWER OUTAGE PROBABILITY

In this section, we present the framework to evaluate the power outage probability of a solar powered BS.

A. System Resources

We denote the number of PV panels installed at the BS by \(n_{PV}\), where each panel has a DC rating denoted by \(E_{\text{panel}}\). The overall DC rating, \(PV_w\), is then given by

\[
PV_w = n_{PV} E_{\text{panel}}.
\]

Also, let \(n_b\) denote the number of batteries used by the BS, each with a storage capacity denoted by \(E_{\text{bat}}\). Thus the overall battery storage capacity, \(B_{\text{cap}}\), is given by

\[
B_{\text{cap}} = n_b E_{\text{bat}}.
\]

To prevent deep discharges, the batteries are disconnected when the charge level drops below a predefined DoD. Such events correspond to power outages at the BS. To calculate the power outage probability, we use discrete time Markov chains to model the solar energy, load, and the battery level on a daily basis. Next we describe these models in detail.

B. Model for Harvested Solar Energy

Daily variations in the solar energy at a location have been shown to be well modeled as a Markov process \([36], [4]\). We classify any given day into one of three solar day types: \(S1\), \(S2\) and \(S3\). Among these, \(S1\) and \(S2\) represent very bad weather and bad weather days, respectively, while \(S3\) denotes a good weather day. We use two day types for bad weather days since they have a greater impact on the outage probability. A given day is classified as one of the three day types based on the solar energy harvested on that day using a standard PV panel size (taken as 1 kW in this paper). Days with daily harvested energy below \(\gamma_1\) are classified as \(S1\), between \(\gamma_1\) and \(\gamma_2\) are classified as \(S2\), and all other days are classified as \(S3\). The transition probabilities between the three day types for a given location is calculated using ten years’ statistical weather data. The Markov process for the state transitions is shown in Fig.1(a).

We also calculate the average hourly solar energy harvested for each of the day types using the statistical weather data (assuming a PV panel with DC rating 1 kW). The average energy values are denoted by a vector \(H\) that depends on the day type:

\[
H = (h_1, h_2, \cdots, h_{24}); \quad \mathcal{H} : \mathcal{H} \in \{H_1, H_2, H_3\}
\]

where \(H_1, H_2\) and \(H_3\) are the average harvested energy profiles for day type \(S1\), \(S2\) and \(S3\), respectively. The procedure for estimating the transition probabilities and the average solar profile has been presented in Section V-C. For a PV panel of size \(PV_w\), the profile of harvested solar energy, \(\mathcal{E}\) is given by

\[
\mathcal{E} = PV_w \mathcal{H}.
\]

C. Model for BS Load

Previous studies have shown the traffic load at a base station follows diurnal patterns, and the overall load levels are different during weekends when compared to weekdays \([26], [27], [28]\). Thus our model considers two load types: low (\(L1\)) and high (\(L2\)), that depend on the day of the week. The transitions between the load day types is approximated as a two-state Markov process, as shown in Figure 1(b). The transition probabilities for the Markov process are chosen such that on an average, five weekdays are followed by two weekend days.

Similar to the solar energy profile \(H\), we define the 24 hour load profile vector \(L\) as the average load during each hour of the day. \(L\) has two values depending on whether it is a high or low load day, and is expressed as

\[
L = (l_1, l_2, \ldots, l_{24}); \quad L : L \in \{L_1, L_2\}
\]

where \(l_1\) denotes the average base station load for the first hour and so on, while \(L_1\) and \(L_2\) are the average load profile
vectors for a low load and a high load day, respectively. We present the methodology for estimating $\mathcal{L}$ in Section V-C.

D. Model for Battery Level

For modeling the battery level at a BS, the overall battery bank capacity, $B_{cap}$, is rounded off to the closest integer value above it. For mathematical tractability, the possible battery levels are discretized into blocks of 1 kWh. Thus the number of levels in the battery model, $N$, is given by

$$N = \lceil B_{cap} \rceil$$

and the battery may be in any one of the $N$ possible levels at any given point in time.

E. BS Outage Probability

The state of the system is defined as a 3-tuple consisting of: the solar day type, the load type and the battery level. For notational simplicity, the state of the system is denoted by $\mathcal{U}$ which is defined as

$$\mathcal{U} = 2N(\alpha - 1) + \beta + 2(b - 1)$$

where $\alpha \in \{1, 2, 3\}$ is the solar day type ($\alpha = 1$ for $S1$, $\alpha = 2$ for $S2$ and $\alpha = 3$ for $S3$), $\beta \in \{1, 2\}$ is the load day type ($\beta = 1$ for low load and $\beta = 2$ for high load) and $b \in \{1, 2, ..., N\}$ is the battery level.

The state space is shown in Figure 2. There are $6N$ possible states since there are three, two and $N$ choices for the solar day type, load type and the battery level, respectively. Further, each column in the figure (separated by dashed lines) represents states with the a particular battery level (indicated on the top of the figure). As per our notation defined in Eqn. (9), the first, second and the third rows correspond to day type $S1$, $S2$ and $S3$ respectively. Also, the odd positions in each row (shown by empty circles) denote low load days while the even positions (shown by dark circles) denote high load days.

The transition in system state is modeled at the beginning of each day (i.e. every 24 hour period). The state on a given day only depends on the battery level, solar day type (i.e. energy harvested) and the load day type (i.e. power consumption) of the previous day. Thus the system state can be modeled as discrete time Markov chain, whose transition probability matrix is denoted as

$$T_B = \begin{bmatrix}
\sigma_{(1,1)} & \cdots & \sigma_{(1,N)} \\
\vdots & \ddots & \vdots \\
\sigma_{(N,1)} & \cdots & \sigma_{(N,N)}
\end{bmatrix}$$

where $\sigma_{(u,v)}$ is the probability of transition from state $\mathcal{U}$ to $\mathcal{V}$.

The batteries are disconnected from the load when the charge level goes below a specified state of charge, $\xi$, to prevent deep discharges and the consequent battery degradation. Thus the battery level never goes below $\xi B_{cap}$ and the states below this level are not visited in our model. This boundary battery level which we denote by $N'$ is shown in Figure 2, and is given by

$$N' = \lceil \xi B_{cap} \rceil.$$  

For a given state $\mathcal{U}$, the next battery level depends on the initial battery level $b$, the solar day type $\alpha$, and the load type $\beta$, and can be computed using function $BLC(\mathcal{U})$ shown in Algorithm 1 (adopted from our previous work [4]). This function accepts the state of the system $\mathcal{U}$ and uses it to extract the information regarding $b$, $\mathcal{H}$ and $\mathcal{L}$. Note that $b'$ is initialized to the battery level $b$ and then updated for each hour of the next 24 hour period. To prevent battery degradation, we avoid deep discharges by preventing $b'$ from going below a threshold $\xi B_{cap}$ by disconnecting the battery. Thus if in any hour $b'$ drops below $\xi B_{cap}$, we mark the state as an outage.

Algorithm 1 Battery Level Calculation (BLC) Algorithm

1: function $BLC(\mathcal{U})$
2: if $1 \leq \mathcal{U} \leq 2N$ then
3:  $\mathcal{H} = \mathcal{H}_1$;
4:  $b = \lceil \mathcal{U}/2 \rceil$;
5: else if $2N + 1 \leq \mathcal{U} \leq 4N$ then
6:  $\mathcal{H} = \mathcal{H}_2$;
7:  $b = \lceil (\mathcal{U} - 2N)/2 \rceil$;
8: else
9:  $\mathcal{H} = \mathcal{H}_3$;
10: $b = \lceil (\mathcal{U} - 4N)/2 \rceil$;
11: end if
12: if $\mathcal{U}/2 == 1$ then
13:  $\mathcal{L} = \mathcal{L}_1$;
14: else
15:  $\mathcal{L} = \mathcal{L}_2$;
16: end if
17: initialize: $b' = b$, $O(\mathcal{U}) = 0$
18: $\mathcal{E} = PV_w\mathcal{H}$;
19: for $t = 1 : 24$ do
20: if $\mathcal{E}(t) \geq \mathcal{L}(t)$ then
21:  $b' = b' + \eta_c (\mathcal{E}(t) - \mathcal{L}(t))$;
22: end if
23: if $b' > B_{cap}$ then
24:  $b' = B_{cap}$;
25: end if
26: if $b' < \xi B_{cap}$ then
27:  $b' = \xi B_{cap}$;
28:  $O(\mathcal{U}) = 1$;
29: end if
30: end for
31: return: round($b'$)
32: end function
state, and record it in a vector $O$. Also, the charge level does not exceed the battery capacity $B_{\text{cap}}$. The function $BLC(U)$ returns $b'$ rounded off to the closest integer, since our model only allows discrete battery levels. The next battery level can thus be obtained as

$$b' = BLC(U).$$

For any given battery level, there are six possible states (based on the solar day and load type). Thus the next state can be one of six states with that battery level. The next battery level is completely determined by the current state $U$. With $\alpha$ and $\beta$ denoting the solar day and load type, respectively, the transition probability from state $U$ to state $V$ is given by

$$\sigma(U, V) = \begin{cases} p_{01q1} & V = 2BLC(U) - 1 \\ p_{01q2} & V = 2BLC(U) \\ p_{02q1} & V = 2BLC(U) + 2N - 1 \\ p_{02q2} & V = 2BLC(U) + 2N \\ p_{03q1} & V = 2BLC(U) + 4N - 1 \\ p_{03q2} & V = 2BLC(U) + 4N \\ 0 & \text{otherwise} \end{cases}$$

(13)

For each state with battery level $n$, Eqn. (13) provides the probabilities for the transition matrix in Eqn. (10).

The steady state probability vector is denoted by $\pi$ and is computed in the next section. Recall that $BLC(U)$ computes and stores the power outage status (0 for no power outage and 1 for power outage) for each state in the vector $O$. The power outage probability, $\Omega$, is then given by

$$\Omega = O\pi.$$  

(14)

For any choice of $PV_w$ and $n_b$, the associated outage probability may be evaluated by using the methodology presented above. Then, for an operator specified tolerable outage probability $\lambda$, the feasible dimensioning solutions are all configurations of $PV_w$ and $n_b$ that satisfy

$$\Omega \leq \lambda.$$  

(15)

Section VI addresses the problem of obtaining the cost optimal configuration that selects the PV panel and battery sizes that satisfy the required outage constraint with minimum cost.

V. STEADY STATE PROBABILITY ESTIMATION

This section presents a methodology for obtaining closed form solutions for the outage probability. In the model presented in Section IV, there are different levels of change (i.e. “jumps”) in the battery levels when there is a transition from one state to another, depending on the solar day type ($S1, S2$ or $S3$), load day type ($L1, L2$), and PV panel and battery sizes. These transitions are shown in Figure 3 for states with battery level $n$. To avoid cluttering, we only show the state transitions for the low load states. For high load states, we only show the battery levels of the final states for each transition. The change in the battery levels when the load day type is low ($L1$) for solar day type $S1$ and $S2$ are denoted by $k_1$ and $k_2$, respectively, whereas the changes when BS traffic is high ($L2$) for solar day types $S1$ and $S2$ are denoted by $k'_1$ and $k'_2$, respectively. The magnitudes of these changes depend on the PV panel size and can be obtained using Algorithm 1 by considering a scenario where the change is not bound by the lower or upper limits. The change in the battery level on a $S1$ day type ($k_1, k'_1$) are negative for realistic PV panel sizes.

To simplify the model and reduce the state space, we first note that the battery level does not go below $N' = [\xi B_{\text{cap}}]$ or above $N = [B_{\text{cap}}]$. In addition, the impact of the day and load types on the operation of the BS results in additional simplifications on the state transitions. To visualize these simplifications, we consider practical deployment scenarios where the BSs are provided with sufficient battery capacity and PV panels to endure occasional periods of sustained bad weather. For realistic resource dimensions, on a $S3$ (i.e. good) day, the PV panels harvest enough energy to power the BS and fully charge the batteries (irrespective of the initial battery level on that day). Thus in the evenings of $S3$ days, the battery starts discharging after being charged to $N$ and at the end of the day, the final battery level depends on whether it is a high or low load day. We denote the final battery level at the end of 24 hours to be $N_{sh}$ and $N_{sl}$ for high and low load days, respectively. Since $S3$ days are the best in terms of energy generation, $N_{sh}$ and $N_{sl}$ act as the upper limits of the battery level at the end of a high/low load day for $S1$ and $S2$ days also, and states with higher energy levels can be eliminated from the state space. The states with battery level $N_{sh}$ and $N_{sl}$ play a critical role in determining the steady state probabilities of the other states. Therefore they are termed critical states in the rest of the paper, and all other states are non-critical states.

A. Steady State Probability of Critical States

To evaluate the steady state probabilities of the critical states, we consider the structure of the state transition diagram, as shown in Figure 3. While $k_1$ and $k'_1$ are always negative for realistic PV panel dimensions, $k_2$ and $k'_2$ may be positive or negative depending on the PV panel size. The various possibilities for the values of $k_2$ and $k'_2$ that lead to different structures of the state transition diagram are shown in Table I. This paper presents the analysis for Cases 1, 2 and 3 and the remaining cases may be modeled similarly.

Before considering each case, we present general results on the steady state probability of being in states with solar day type $S1, S2$ and $S3$, denoted by $P_1, P_2$ and $P_3$, respectively. From Figure 2 we have

$$P_1 = \pi_1 + \pi_2 + \pi_3 + \cdots + \pi_{2N-1} + \pi_{2N}$$

$$P_2 = \pi_{2N+1} + \pi_{2N+2} + \pi_{2N+3} + \cdots + \pi_{4N-1} + \pi_{4N}$$

$$P_3 = \pi_{4N+1} + \pi_{4N+2} + \pi_{4N+3} + \cdots + \pi_{6N-1} + \pi_{6N}.$$
Let $Q_1$ and $Q_2$ be the steady state probability of being in states with low and high load days, respectively. We then have

$$P_1Q_1 = \pi_1 + \pi_3 + \pi_5 + \cdots + \pi_{2N-1}$$
$$P_1Q_2 = \pi_2 + \pi_4 + \pi_6 + \cdots + \pi_{2N}$$
$$P_2Q_1 = \pi_{2N+1} + \pi_{2N+3} + \pi_{2N+5} + \cdots + \pi_{4N-1}$$
$$P_2Q_2 = \pi_{2N+2} + \pi_{2N+4} + \pi_{2N+6} + \cdots + \pi_{4N}$$
$$P_3Q_1 = \pi_{4N+1} + \pi_{4N+3} + \pi_{4N+5} + \cdots + \pi_{6N-1}$$
$$P_3Q_2 = \pi_{4N+2} + \pi_{4N+4} + \pi_{4N+6} + \cdots + \pi_{6N}.$$

Note that $P_1, P_2, P_3, Q_1$ and $Q_2$ are obtained from empirical solar irradiation and traffic load data (see Section V-C).

1) Case 1: $k_2 < -1, k_2' < -1$: The structure of the state transitions for this case is shown in Figure 4. The figure shows states with battery levels between $N'$ and $N_{dl}$, and their state transitions. To avoid cluttering the figure with a large number of states, we denote all non-critical states using a representative battery level $n$. The transition probabilities have been marked on the respective lines except for the cases where it is $1. Recall that all states with solar day type $S3$ transition to a state with battery level $N_{dl}$ or $N_{sh}$, depending on the load day type. We use this fact to simplify our analysis. The summations at the bottom of the figure show the addition of these probabilities which populate the various critical states. Recall that the probabilities of low and high loads for a solar day of type $S3$ are $P_3Q_1$ and $P_3Q_2$, respectively, and indicated at the summation symbols in Figure 4. To avoid clutter, the transitions from any state to a battery level, say $a$, which has non-critical states, have not been drawn completely and are marked by ($a$).

Considering the balance equations at various boundaries around the critical states (denoted by the dotted circles marked A-L in Figure 4), the steady state probability for the critical states can be shown to be:

$$\pi_{2N_{sh}} = p_{11}q_{12}P_3Q_1$$
$$\pi_{2N_{sh}} = p_{11}q_{12}P_3Q_1$$
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$$\pi_{2N_{sh}} = p_{11}q_{12}P_3Q_1$$
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$$\pi_{2N_{sh}} = p_{11}q_{12}P_3Q_1$$
$$\pi_{2N_{sh}} = p_{11}q_{12}P_3Q_1$$
$$\pi_{2N_{sh}} = p_{11}q_{12}P_3Q_1$$

2) Case 2: $k_2 > 0, k_2' > 0$ and Case 3: $k_2 > 0, k_2' = 0$: We consider Case 2 and Case 3 together because their state transition diagrams have the same structure. Since $k_2$ and $k_2'$ are non-negative in these two cases, the critical states with solar day type $S2$ can also result in transitions to critical states. More specifically, high load states with battery level $N_{sh}$ and $N_{sl}$ and solar day type $S2$ may result in transitions to any of
the critical states with battery level $N_{sh}$. Similarly, low load states with battery levels $N_{sh}$ and $N_{sl}$ and solar day type $S2$ may have transitions to critical states with battery level $N_{sl}$.

To obtain the steady state probabilities of the critical states for these cases, we consider the boundaries shown by dotted circles in Figure 5. The balance equations for boundaries $H$ and $K$ around states $2N + 2N_{sl} - 1$ and $2N + 2N_{sl}$ can be written as

$$\pi_{2N_{sl}+2N-1} = p_{32}q_{11}P_{3}Q_{1} + (p_{2N_{sh}+2N-1} + p_{2N_{sl}+2N-1})p_{22}q_{11}$$
$$\pi_{2N_{sl}+2N} = p_{32}q_{12}P_{3}Q_{1} + (p_{2N_{sh}+2N-1} + p_{2N_{sl}+2N-1})p_{22}q_{12}$$

From the previous two equations we can conclude that

$$\pi_{2N_{sl}+2N-1} / \pi_{2N_{sl}+2N} = q_{11} / q_{12}$$

Similarly, balance equations around boundaries $B$ and $E$ around states $2N + 2N_{sh} - 1$ and $2N + 2N_{sh}$ can be written as

$$\pi_{2N_{sh}+2N-1} = p_{32}q_{21}P_{3}Q_{2} + (p_{2N_{sh}+2N} + p_{2N_{sl}+2N})p_{22}q_{21}$$
$$\pi_{2N_{sh}+2N} = p_{32}q_{22}P_{3}Q_{2} + (p_{2N_{sh}+2N} + p_{2N_{sl}+2N})p_{22}q_{22}$$

which in turn imply

$$\pi_{2N_{sh}+2N-1} / \pi_{2N_{sh}+2N} = q_{21} / q_{22}$$

From Equations (28)-(33), we have

$$\pi_{2N_{sh}+2N-1} = \frac{p_{22}q_{21}p_{3}(Q_{2} - p_{22}q_{21}Q_{2} + p_{22}q_{22}Q_{2})}{(1 - p_{22}q_{22} - p_{22}q_{21} + p_{22}q_{22}Q_{2})}$$
$$\pi_{2N_{sh}+2N} = \frac{p_{32}q_{21}p_{3}(Q_{1} - p_{22}q_{21}Q_{1} + p_{22}q_{22}Q_{1})}{(1 - p_{22}q_{22} - p_{22}q_{21} + p_{22}q_{22}Q_{1})}$$

Using the steady state probabilities above, the steady state probabilities of the other critical states can be obtained as

$$\pi_{2N_{sh}+2N} = p_{31}q_{21}P_{3}Q_{2} + (\pi_{2N_{sh}+2N} + \pi_{2N_{sl}+2N})p_{21}q_{21}$$

In Cases 2 and 3, some of the non-critical states with day type $S2$ may also transition to critical states due to $k_2$ and $k'_2$ being non-negative. However, these transitions have been neglected due to the following reasons: (i) the number of non-critical states with solar day type $S2$ contributing to critical states is very small (due to $k_2$ and $k'_2$ being small even for large PV panels) and (ii) the overall probability, $P_2$, of states with solar day type $S2$ is typically much smaller than those with solar day type $S3$. Thus the contribution of the few non-critical states with solar day type $S2$ is negligible in comparison to those with solar day type $S3$ (where all states contribute to the steady state probability of critical states). Further, our simulation results show that this approximation does not have any appreciable effect on the accuracy of the model.

The steady state probabilities of the critical states for Cases 4-8 can similarly be obtained.

B. Calculating steady state probability of non-critical states

To obtain the probabilities of the non-critical states, we first define seed states as $[\pi_{2N_{sl}+2N}, \pi_{2N_{sh}+2N}, \pi_{2N_{sh}+2N}, \pi_{2N_{sh}+2N}, \pi_{2N_{sh}+2N}, \pi_{2N_{sh}+2N}, \pi_{2N_{sh}+2N}, \pi_{2N_{sh}+2N}]$ (i.e. critical states with day type $S1$ and $S2$). The seed states are the critical states whose steady state probabilities may be used to obtain the steady state probabilities of all non-critical states. Note that critical states with solar day type $S3$ are not seed states for they do not lead to transition into non-critical states. To present an intuitive idea of our methodology, consider a simple scenario with just six possible battery levels, as shown in Figure 6. For illustration, we assume $k_1 = -2, k'_1 = -4, k_2 = -1$ and $k'_2 = -3$. For simplicity, let
us assume that the states with battery level 6 are the critical states and states 11, 12, 23 and 24 are the seed states.

To obtain the steady state probability of a non-critical state, we consider the balance equations around its boundary. As an example, consider boundary A around state 5 in Figure 6. There may be transitions into state 5 from states 9 and 24. However, states 9 and 19 (non-critical states) are visited only as a result of transitions from states 11, 12, 23 and 24 (seed states). The probability of all transitions into state 5 (or any non-critical state) can be expressed in terms of the steady state probabilities of the seed states. For example, we have

\[
\begin{align*}
\pi_5 &= p_{11}q_1q_9 + p_{21}q_1q_{19} + p_{21}q_{21}q_{24} \\
\pi_9 &= p_{21}q_1q_{23} \\
\pi_{19} &= p_{12}q_1q_{11} + p_{22}q_1q_{21} \\
\pi_{21} &= p_{22}q_1q_{23}.
\end{align*}
\]

Using the equations above, \(\pi_5\) may be expressed in terms of the steady state probability of the seed states as

\[
\pi_5 = p_{21}p_{12}q_1^2\pi_{11} + p_{21}q_1((p_{22}q_1)^2 + p_{11}q_{21})\pi_{23} + p_{21}q_{21}\pi_{24}.
\]

Thus, in order to obtain the steady state probability of any non-critical state, we need to find all possible transition paths to that state, starting from any of the seed states. To achieve this, we propose a path tracking algorithm shown in Algorithm 2: \(PATR(N_s, n, k, \phi(.), f(.), g(.), N_{sl}, N_{sh})\). The inputs to the algorithm include \(N_s\) (the battery level of the seed states, typically \(N_{sl}\) or \(N_{sh}\)), \(n\) (the battery level of the target non-critical state), \(k = [k_1, k_1', k_2, k_2']\), and the functions \(\phi(.), f(.)\) and \(g(.)\) that track the battery level, solar energy state and BS load state, respectively, of the intermediate states in the paths from the seed states to state with battery level \(n\).

Recall that there are no transitions from states with solar day type \(S3\) to the non-critical states. Thus we have only four state transitions of interest from a given battery level (from states with solar day type \(S1\) and \(S2\)) and these transitions are to states whose battery levels are different by any of the values in \(k = [k_1, k_1', k_2, k_2']\). The algorithm uses the vectors \(\phi', f'\) and \(g'\) to track the battery level, solar day type and load day type of the intermediate states in a path from a seed state to states with battery level \(n\). The vectors \(\phi, f\) and \(g\) serve as inputs with the (incomplete) paths discovered so far, and \(\phi, f\) and \(g\) are null vectors when the function \(PATR\) is initially called. From the current state in the path, we consider all four possible transitions (based on \(k\)), and \(T\) denotes the battery level after the transition. Next we ensure that boundary conditions are not violated. If the resulting battery level after the transition is \(n\), we add the entire path as an entry in the global path indicator variables (i.e. \(\Phi, F\) and \(G\)). Note that we also evaluate the number of transitions that have been made in the current path (stored in variable \(t\)). Since the number of transitions becomes large (typically \(> 4\)), the likelihood of occurrence of that path (which equals the product of the state transition probabilities between all intermediate states) becomes very small and thus can be neglected. Thus while the path length is smaller than a threshold \(t_{\text{max}}\), the \(PATR\) algorithm is iteratively called with \(T\) as the current battery level.

We denote the number of possible paths by \(s\) and \(\Psi\) denotes all possible paths from the seed states to states with battery level \(n\). Each element of \(\Psi\) represents a path that is uniquely characterized by the values of \(\Phi, F\) and \(G\) as

\[
\Psi = \{\psi_1, \psi_2, \ldots, \psi_s\}; \quad \psi_l = (\Phi_l, F_l, G_l).
\]

The vectors \(\Phi_l, F_l\) and \(G_l\) are of the form

\[
\begin{align*}
\Phi_l &= \{\phi_{l1}, \phi_{l2}, \ldots, \phi_{lu}\} \\
F_l &= \{f_{l1}, f_{l2}, \ldots, f_{lu}\} \\
G_l &= \{g_{l1}, g_{l2}, \ldots, g_{lu}\}
\end{align*}
\]

where \(u\) is the number of intermediate stages in the \(l\)-th path and \(\phi_{lu}, f_{lu}\) and \(g_{lu}\) denote the battery level, solar day type, and load day type of the initial state, and so on. Let \(\Lambda_l\) denote the steady state probability of the seed state of the \(l\)-th path. Then the steady state probability of a state \(U\) with battery level \(n\), solar day type \(\alpha\) and load day type \(\beta\), can be written as

\[
\pi_{U} = \sum_{l=1}^{s} \Lambda_l p_{f_{l1}f_{l2}g_{l1}g_{l2}} p_{f_{l3}f_{l4}g_{l3}g_{l4}} \cdots p_{f_{lu} \alpha q_{fu} \beta}.
\]

Finally, the steady state probabilities of all the states may be used in Equation (14) to obtain the overall outage probability.

**Remarks:** Our model implicitly assumed that \(N_{sl}\) and \(N_{sh}\) are separated by a unit difference in the charge levels, which, to a large extent, is a result of the granularity in the battery levels being taken to be 1 kW. However, based on the base station type/size, this difference may not be around 1 kW (and can be, say 0.5 kW or 2 kW etc.). In that case, to use the proposed model, the granularity of the system would need to be adjusted so that \(N_{sl}\) and \(N_{sh}\) are still separated by a
unit charge. Also note that our model assumes that all states with solar day type S3 transition to a state with battery level \( N_{sh} \) or \( N_{sl} \). While this assumption is valid in most realistic scenarios, it does not hold for very small PV panels (e.g. 7 kW or smaller for macro base stations). However, such small PV panels are not used in practical scenarios, since the number of batteries required for such scenarios tends to be too large to be economically and spatially feasible [3]. This can also be observed from Figures 11 and 12 which show that as the PV panel size decreases, the number of batteries required for a given threshold on the outage probability increases sharply, thereby increasing the capital cost.

### C. Parameter Estimation

The state transition probabilities and solar energy profiles for the solar energy model described in Section IV-B are obtained using historical solar irradiation data. The solar irradiation data is fed to NREL’s SAM tool which gives the hourly harvested solar energy for a PV panel with DC rating 1 kW as an output. Due to seasonal variations, different months in the year have different values for the various parameters in the model. To find the parameters for a given month, we consider the series of data corresponding to the days of that particular month from all years in the historical solar energy data. This data is then fed to the SAM tool to generate the hourly harvested solar energy. Next we calculate the solar energy generated for each day considering PV panel efficiency for the last year of the BS’s targeted lifetime, and use it for categorizing the day into a given type (S1, S2 or S3). The values of \( \gamma_1 \) and \( \gamma_2 \) to categorize the days are estimated for a given PV panel size based on the energy harvested in a day compared to the average daily BS power consumption, \( \Gamma \). For a PV panel with rating \( PV_w \), \( \gamma_1 \) and \( \gamma_2 \) are given by

\[
\gamma_1 = \frac{0.5 \Gamma}{PV_w}, \quad \gamma_2 = \frac{\Gamma}{PV_w}.
\]

The intuition behind the choice of thresholds \( \gamma_1 \) and \( \gamma_2 \) is that S1 and S2 denote very bad and bad weather days, respectively, where the solar energy harvested during the day is less than the energy required to power the BS for a day. With this choice of \( \gamma_1 \) and \( \gamma_2 \), the energy harvested in S1 days is less than half of the energy required to power the BS over the day, and while S2 days harvest more energy than S1 days, it is still less than that required to power the BS during the entire day.

Next, we obtain the hourly harvested solar energy profile for the three day types by calculating the average hourly harvested energy of the days with that day type. Figure 7(a) shows an example value of the average harvested energy profiles for the different day types for Jaipur, India for the month of September. Also from the statistical data we compute the transition probabilities \( p_{ij} \), \( 1 \leq i, j \leq 3 \), of going from a day type to another. These state transition probabilities are used to calculate the steady state probabilities of being in a given solar day type (i.e. the probabilities \( P_1, P_2 \) and \( P_3 \)). After the parameter estimation is done individually for every month of the year, the corresponding outage probability for that month for a given PV-battery configuration may be evaluated using the framework developed in this paper. The outage probability for each month is averaged to obtain the overall outage probability for the given PV-Battery configuration.

For the load profiles we use the data from a large scale cellular traffic study in [29] as discussed in Section III-A. The traffic load from [29] is scaled based on the year of operation (resulting in a peak normalized traffic of 0.02 in the first year, increasing at 50% CAGR, thus giving a peak traffic of 0.768 in the tenth year of operation). The normalized traffic thus obtained is used in Eqn. (1) to calculate the BS power consumption. Note that the traffic volumes are lower on a low

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Algorithm 2 PATH TRACKING (PATR) Algorithm

```plaintext
1: function PATR(N, n, k, φ, f, g, N_{sl}, N_{sh})
2:  for i = 1 to 4 do
3:     φ' = [φ N_s];
4:     f' = [f ceil(i/2)];
5:     if i = 1 or i = 3 then
6:        g' = [g 1];
7:     else
8:        g' = [g 2];
9:     end if
10:    T = N_s + k(i);
11:    if T > N_{sl} and (i = 1 or i = 3) then
12:        T(i) = N_{sl};
13:    end if
14:    if T > N_{sh} and (i = 2 or i = 4) then
15:        T(i) = N_{sh};
16:    end if
17:    if T \leq N' then
18:        T(i) = N';
19:    end if
20:    if T = n then
21:       φ = [φ'; φ'];
22:       F = [F; f'];
23:       G = [G; g'];
24:    end if
25:    t = length(φ');
26:    if (T < N_s and T \geq N' and t < t_{max}) then
27:       PATR (T, n, k, φ', f', g', N_{sl}, N_{sh});
28:    end if
29: end for
30: end function
```
load day thus leading to lower BS power consumption. The traces of BS power consumption (load) are averaged on an hourly basis to calculate the hourly BS load profile for the days. This is done for both days with high load as well as low load. Figure 7(b) shows the average load profiles used in this paper for the two load day types during the tenth year of operation. The traces are also used to obtain the state transition probability between low load day and a high load day (i.e. $q_{ij}, 1 \leq i,j \leq 2$) and the steady state probabilities $Q_1$ and $Q_2$.

VI. COST OPTIMAL DIMENSIONING

This section presents a formulation for the cost optimal PV panel and battery dimensioning problem for a solar powered BS. The cost of the system depends on the size of the PV panel and the number of batteries required over the system lifetime. For any given values of $PV_w$ and $n_0$, the cost calculations are based on the calculation of the outage probabilities and the battery lifetime, as given by Eqn. (2). For a target system lifetime of $T_{run}$ years, the total system cost, $C$, is given by

$$C = N_{Bat}C_B + PV_wC_{PV}$$

where $C_B$ is the cost of one battery and $C_{PV}$ is the cost of PV panel per kW. $N_{Bat}$ represents the total number of batteries required over the desired system lifetime of $T_{run}$ years. Note that the calculation of $N_{Bat}$ is done taking into account the variation in the various system parameters such as increasing traffic and reduction in the PV panel efficiency as discussed in Sections III-A and IV-B.

The cost optimal system dimensioning problem is then given by

Minimize: $N_{Bat}C_B + PV_wC_{PV}$

Subject to: $\Omega < \lambda$

where $\lambda$ is the network operator’s specified limit on the tolerable outage probability. Standard techniques may be used to solve the optimization problem.

VII. SIMULATION RESULTS AND ANALYSIS

This section presents results to verify the proposed power outage estimation model and the framework for cost optimal system dimensioning of solar powered BSs.

A. Simulation Setup

We consider a LTE macro base station with 10 MHz bandwidth and $2 \times 2$ Multi Input Multi Output (MIMO) configuration. We assume that the BS has three sectors and each sector has two transceivers (thus, $\Upsilon_{TRX} = 6$). To validate the proposed framework, we consider two geographically diverse locations: San Diego (USA) and Jaipur (India). The various parameters for the solar energy model are obtained using the statistical solar energy data from NREL database and the methodology described in Section V-C. We use seven years of data (2000-2006) for parameter estimation and evaluate the performance using data for years 2007-2009. We assume that the BSs use 12 V, 205 Ah flooded lead acid batteries, each with a capacity of 2.46 kWh. $\xi$, the threshold state of charge which decides the point below which the batteries do not discharge is taken as 0.3. $\eta_c$ and $\eta_d$, the charging and the discharging efficiencies for the batteries have been taken as 0.9. For modeling the load profiles we use the methodology described in Section III-A and the various parameters were calculated as described in Section V-C. The average BS power consumption during a day, $\Gamma$, was taken as 22.8 kWh. $t_{max}$ for the PATR algorithm was taken as 6. As benchmarks for comparison, we consider results obtained using simulations with empirical traces for the solar energy and the traffic load as well as the model proposed in [5].

B. Power Outage Analysis

We begin with analyzing how the power outage probability is affected by the number of batteries. For both locations, we consider a PV panel with DC rating 12 kW installed at the BS site. The variation in the power outage with respect to the number of batteries is shown in Figure 8. It can be seen that the power outage probability estimated using our model has a close match with that obtained using simulations with empirical data. Also, the proposed model outperforms the model proposed in [5] in predicting the outage probability. Note that when the number of batteries becomes very small, the power outage probability rises sharply. This is on account of batteries being too small to hold sufficient charge to power the BS even when there is sufficient energy harvested. Further,

![Figure 8](image-url)  
**Fig. 8.** Power outage probability vs number of batteries (PV panel size: 12 kW).
C. Effect of PV Panel Size on Power Outage

We consider two PV panel sizes: 10 kW and 16 kW to study the impact of the PV panel size on the power outage probability. The power outage probability corresponding to the different PV panel sizes with respect to the number of batteries have been shown in Figures 9 and 10 for San-Diego and Jaipur, respectively. Note that for a higher PV panel size, the same power outage probability can be met with a lower number of batteries, as compared to the case of lower PV panel size. Again, from the plots we can see that proposed model outperforms the benchmark model in terms of predicting the power outage probability for a given battery size.

D. PV-Battery Configuration for a Given Power Outage Constraint

Given a power outage constraint, a network operator is usually interested in the minimum number of batteries required for different PV panel sizes. Note that these configurations of PV panel and battery sizes are prospective candidates for resource dimensioning for the BS, and the configuration with the lowest cost can be selected by the operator. We consider two target power outage values: 0.5% and 1%. Figures 11 and Fig. 12 show these PV panel-battery configurations for achieving the two target power outage values for the two locations.

E. Cost Optimal Configuration

The cost associated with the prospective PV-Battery configurations which meet the target outage probability can be calculated as described in Section VI. We consider a target operational time of \( T_{\text{run}} = 10 \) years. Also, based on the market statistics, we assume the cost of PV panels \( C_{PV} \) as US$ 1000 /kW and the cost of the lead acid batteries \( C_B \) has been assumed as US$ 280 [37]. The cost optimal configuration for the two target outage probabilities of 0.5% and 1% has been tabulated in Table II. We note that the results from the proposed model closely match the optimal configuration using simulations using empirical data and outperforms the benchmark model [5].

VIII. Conclusion

This paper proposed a framework for estimating the power outage probability for cellular BSs powered by solar energy. The harvested solar energy, base station load and the battery levels are modeled as discrete time Markov processes. These are further used to estimate the power outage probability associated with a given PV panel size and battery configuration. Using this estimate, we proposed a methodology for obtaining

---

**Table II**

<table>
<thead>
<tr>
<th>Location</th>
<th>PV ( n_b )</th>
<th>PV ( n_b )</th>
<th>PV ( n_b )</th>
<th>PV ( n_b )</th>
</tr>
</thead>
<tbody>
<tr>
<td>San Diego</td>
<td>11 36 12 22 10.5 34</td>
<td>( \lambda = 0.5% )</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Jaipur</td>
<td>14 16 12.5 18 14 18</td>
<td>( \lambda = 1% )</td>
<td></td>
<td></td>
</tr>
<tr>
<td>San Diego</td>
<td>14 25 12 20 13.5 23</td>
<td>( \lambda = 0.5% )</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Jaipur</td>
<td>10.5 20 10.5 20 10.5 20</td>
<td>( \lambda = 1% )</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Figures:**

- Fig. 10. Power outage vs number of batteries required for different PV panel sizes: Jaipur
- Fig. 11. PV panel size vs number of batteries required for different power outage probabilities (\( \lambda \)): San Diego.
- Fig. 12. PV panel size vs number of batteries required for different power outage probabilities (\( \lambda \)): Jaipur.
the cost optimal PV panel-battery for a solar powered BS. The proposed model is verified by comparing against simulation using empirical traces of solar energy and load data, and is shown to outperform existing models.

REFERENCES


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