Resource Provisioning and Dimensioning for Solar Powered Cellular Base Stations

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***Abstract*—The deployment of cellular network infrastructure powered by renewable energy sources is gaining popularity as an avenue to provide coverage in areas without reliable grid power and also as a means to reduce the environmental impact of the telecommunications industry. To facilitate the deployment of such networks, this paper addresses the problem of resource provisioning and dimensioning solar powered base stations in terms of the required battery capacity and photo-voltaic (PV) panel sizing. The paper first develops a framework for evaluating the outage probability associated with a base station at a given location as a function of the battery and panel size, by using the solar energy and traffic profiles as inputs. A model is then proposed to evaluate the optimal battery and PV panel sizing, subject to the desired limit on the worst month outage probability. The proposed framework for dimensioning the base station's energy resource requirements has been evaluated using real solar irradiation data for multiple locations.**

I. Introduction

Developing countries currently contribute to the bulk of the worldwide growth in cellular networks [1]. In many such countries, reliable grid power is not available and many of the cellular base stations are operated by on-site fossil fuel (e.g. diesel) based generators [2]. In addition to increasing the pollution levels, they are also susceptible to variations in energy costs. In such scenarios, solar powered cellular base stations are a viable and attractive alternative. In addition, solar powered base stations may also be used in places where reliable grid power is available in order to reduce the energy costs and the carbon footprint of cellular networks. This paper addresses the problem of designing and provisioning solar powered cellular base stations in terms of the required battery capacity and photo-voltaic (PV) panel size, with the objective of minimizing the system cost.

Solar powered base stations are currently under development and deployment by a number of operators. For example, Orange has multiple deployments in the Middle East and Africa, while NTT DOCOMO in Japan and Grameenphone in Bangladesh are in various stages of deployment [3], [4]. While the initial experimental deployments serve as a proof of concept, a number of open problems still remain before "zero energy networks" become a reality [3]. The most fundamental of these problems include the dimensioning of solar powered base stations in terms of their energy harvesting and storage, design of routing and data transmission strategies, and strategies to guarantee uninterrupted service while minimizing energy consumption. While existing literature has investigated some aspects of this problem, the problem of resource dimensioning remains open.

In [3] the authors obtain the minimum required PV wattage and battery sizes for solar powered base stations by using the historical data of solar radiation in the Typical Meteorological Year (TMY) for a given location. In particular, the TMY data for the worst month is chosen to determine the PV wattage and number of batteries. Such an approach is not necessarily cost optimal. Also, due to seasonal variations over the years, TMY data is not very reliable when it comes to dimensioning a PV system. In other works [5], the authors model solar powered base stations, but do not use the long term weather data. Furthermore, the model presented only provides an estimate of the PV panel and battery dimension, and does not provide the cost optimal solution for a given outage probability.

This paper addresses the problem of developing a framework for dimensioning the resources required by a solar powered base station (BS) with the objective of minimizing the capital expenditure, while ensuring a probabilistic guarantee of uninterrupted service. The proposed framework is based on developing a model that combines historical data of solar irradiance along with traffic demands and BS energy consumption models to evaluate the outage probabilities associated with the choice of a PV panel size and number of batteries. The minimum cost base station configuration problem based on this model is then formulated. The proposed framework for dimensioning the resource requirements of solar powered base stations has been validated through extensive simulations.

The rest of the paper is organized as follows. Section II presents the background material and describes the system model. Section III presents the framework for evaluating the outage probability of a base station and determining the cost optimal PV panel and battery dimensions. Section IV presents the results to validate the proposed framework and Section V concludes the paper.

II. Background and System Model

This section we present the system model assumed in this paper and an overview of the background material.

A. *Base Station Power Consumption*

The power consumption of a base station constitutes of two parts [6]: a fixed part which is due to the cooling system, signal processing, energy dissipated by cable feeders etc; and a variable part. The variable part of the power consumption comes from the power consumed by the power amplifier, and is proportional to the traffic at a given time. A base station is generally categorized into four categories according to its power consumption/coverage: a) macro b) micro c) pico d) femto. This paper considers a macro base station. This choice is only for illustration purposes and the techniques developed in this paper are also applicable to other BS types. As given in [6], the power consumption of a Long Term Evolution (LTE) base station, P_{BS}, can be modeled as

$$P_{BS} = N_{TRX}(P_0 + \Delta_p P_{max} K), \quad 0 \leq K \leq 1 \tag{1}$$

where N_{TRX} is the number of transceivers, P_0 is the power consumption at no load (zero traffic), Δ_p is a constant for a given BS, P_{max} is the output of the power amplifier at the maximum traffic, and K is the normalized traffic at the given time. The typical values of P_0, P_{max} and Δ_p for a macro base station are 118.7 W, 40 W and 2.66, respectively.

B. Traffic Model

From Eqn. (1) we note that the power consumption of a BS is dependent on the traffic load. In general, the traffic is non-stationary and varies depending on the the time of the day and the day of the week. To model the traffic, this paper uses the traffic models characterized in [7], wherein the call arrivals have been modeled as a Poisson process and the call durations are exponentially distributed. The number of calls in each hour are generated as a Poisson process whose rate depends on the hour of the day. Each call is assigned a hold time which is exponentially distributed with mean of 120 seconds [8]. The normalized traffic at a given time instant t of the day is given by

$$K(t) = N_t / N_{max} \tag{2}$$

where N_t is the number of active calls at time t and N_{max} is the maximum number of users which can be supported by the base station at a given point of time (which depends on the spectrum allocated to the BS). The normalized traffic is found on a per minute basis. We average the per minute normalized traffic for each of the hours to calculate the hourly normalized traffic.

Figure 1 shows the traffic generated using the above model for a period of one week. Note that the traffic volume follows a diurnal pattern with peak traffic during the day and relatively low loads at night. Also, the traffic values from the weekends are lower as compared to weekdays, as verified by large scale cellular data studies [9]. The hourly normalized traffic rates generated through our traffic model are used in Eqn. (1) to obtain the hourly base station power consumption values.

C. Solar Energy Resource

To develop and verify the proposed framework for dimensioning solar powered base stations, this paper uses hourly solar irradiance data provided by the National Renewable Energy Laboratory (NREL), USA [10]. This paper uses 10 years data from the NREL database for the following three locations: Mumbai (India), New Delhi (India) and Miami (USA). The data comprises of the hourly Direct Normal Irradiance (DNI) and Diffuse Horizontal Irradiance (DHI) values at the given location. This data is fed into the System Advisor Model (SAM) tool developed by NREL to calculate the hourly power generated by a given PV module based on the DNI and DHI values at a given hour. We assume a fixed PV panel with a DC-AC loss factor as 0.77 and the tilt of the PV panel as latitude of the location, which are the usual values [11].

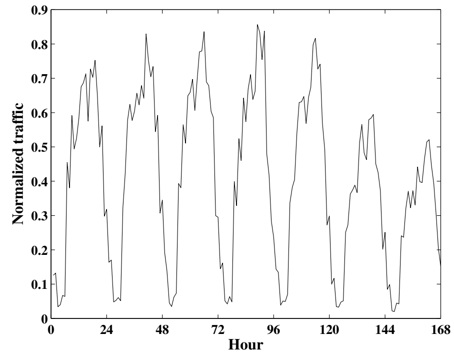

Fig. 1. Normalized traffic at a BS for a week.

D. Batteries

This paper assumes that flooded lead acid batteries are used by the base station. An important factor in configuring a solar powered BS is the lifetime of the batteries. The lifetime of a battery depends on its operating conditions and frequent discharges to very low values significantly reduces the lifetime. To calculate the lifetime of a battery, this paper uses a lifetime model based on the number of charge cycles to failure for various values of the depth of discharge (DoD). The DoD is the lowest level which the battery hits in a given cycle of discharging-charging. The relationship between the cycles to failure and the DoD is usually provided by the battery manufacturer and Figure 2 shows the characteristics for a typical lead acid battery [12].

To model the battery lifetime, the entire range of DoD is split into N regions. For a period of operation over T years, the number of cycles corresponding to each DoD region is counted. The battery lifetime, L_b is then given by

$$L_{Bat} = T / (\sum_{i=1}^{N} \frac{Z_i}{CTF_i}), \tag{3}$$

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.

III. Framework for PV Panel and Battery Dimensioning

In this section we describe the proposed framework to dimension the PV panel size and number of batteries required by a solar powered cellular BS. The proposed framework is based on first evaluating the outage probability associated with any choice of PV panel and battery size. Next, we formulate

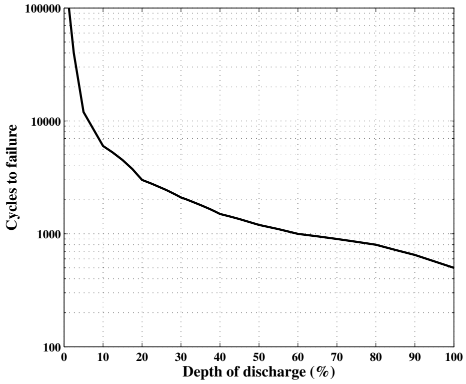

Fig. 2. Cycles to failure vs DoD for a typical lead acid battery.

an optimization problem that finds the least cost configuration that satisfies a given target outage probability.

A. BS Outage Probability

Let n_{PV} denote the number of PV panels used in a BS. Each of the PV panels has a DC rating which we denote by E_{panel}. Thus the PV resource dimension, with an overall DC rating PV_w can be expressed as

$$PV_w = n_{PV} E_{panel}. \tag{4}$$

Similarly, we denote the number of batteries used in the BS by n_b and each battery has a capacity given by E_{bat}. Thus the battery storage capacity, B_{cap} can be expressed as

$$B_{cap} = n_b E_{bat}. \tag{5}$$

Next we consider the problem of obtaining the outage probability associated with a given choice of PV_w and n_b. An outage is defined as the event that the battery level at the BS falls below a predefined DoD.

The PV panels harvest solar energy during the daytime. While part of the harvested energy is used to supply the instantaneous power demand of the BS, the excess is stored in the battery bank. During the time of low or no solar energy which may be either due to bad weather or at night, the BS is powered by the batteries. The BS load profile and the solar energy profile play key roles in dimensioning the PV and battery resources. In this paper we assume that the telecom operator has a model for the load profile as well as the historical data to characterize the solar energy profile for a given location.

It has been shown in previous work that the solar energy profile of any location may be modeled as a Markov process [13]. This paper refines such models by proposing a multi-state Markov model for the solar energy resource. In the proposed model, any day is classified as either "good" or "bad" weather day based on the level of energy that is harvested. For example, sunny days would be classified as good days. The fraction of all days that are classified as bad is denoted by α. Given that a day is either good or bad, the next day may be either good or bad, depending on the weather conditions. To capture the occurrence of consecutive good or bad weather days, the transition is modeled as a two-state, discrete time Markov process. The transition probability matrix of this Markov process is given by

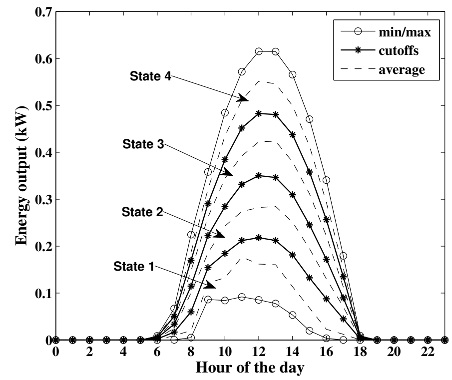

Fig. 3. Analysis for good day

$$\mathbf{T} = \begin{bmatrix} p_{gg} & p_{gb} \\ p_{bg} & p_{bb} \end{bmatrix} \tag{6}$$

where p_{gg} (resp. p_{bb}) is the probability of transition from a good (bad) day to a good (bad) day, and $p_{gb} = 1 - p_{gg}$ (resp. $p_{bg} = 1 - p_{bb}$) is the probability of transition from good (bad) day to bad (good) day.

Next, to capture the hourly variations in the solar energy, we categorize each hour to belong to one of four possible categories. Each category is characterized by its energy level and the four categories for each hour of good and bad days are different. The overall state of the process representing the solar energy harvested at any hour is denoted by

$$S_t : S_t \in \{G_{x,y}, B_{x,y}\}, \qquad x \in \{1, 2...24\}, y \in \{1, 2, 3, 4\} \tag{7}$$

where G and B correspond to good and bad weather days respectively, x is the hour of the day and y is the state of the solar energy in that hour. Each state has a corresponding solar energy value which is the average hourly solar energy in that state as obtained from the empirical data, and is denoted by E_{S_t}. An example of the four states for each hour of good weather days is shown in Figure 3 and the methodology for obtaining the values of E_{S_t} and the other parameters used in our model is described in Section III-B. Note that while more than four states may be used to categorize any hour of the day, our experimental results show that the marginal improvement in accuracy by including additional states does not justify the increased complexity of the model.

According to the Markovian assumption for the solar energy, the state of solar energy at any hour only depends on the state of the solar energy in the previous hour and the transition probability of going from the previous state to the current state. Thus,

$$P[S_t | S_{t-1}, S_{t-2}, ...S_0] = P[S_t | S_{t-1}]. \tag{8}$$

Given that the solar energy is currently in a given state, in the next hour, the state may transition to any of four states in the next hour (for both bad and good weather days). For a good weather day, the transition probability matrix is given by

$$\mathbf{G} = \begin{bmatrix} g_{(1,1)(1,1)} & \cdots & g_{(1,1)(24,4)} \\ \vdots & \ddots & \vdots \\ g_{(24,4)(1,1)} & \cdots & g_{(24,4)(24,4)} \end{bmatrix} \tag{9}$$

with

$$g_{(i,j)(k,l)} = \begin{cases} r_{(i,j)(k,l)} & k = (i+1) \bmod 24;\ j,l \in \{1,2,3,4\} \\ 0 & \text{otherwise} \end{cases} \tag{10}$$

where $g_{(i,j)(k,l)}$ is the probability of transition from the j-th state in the i-th hour to the l-th state in k-th hour on a good weather day. Note that from a particular state in a given hour, the solar energy can just go to one of the states in the next hour. $r_{(i,j)(k,l)}$ denotes the numerical value of the transition probability and satisfies

$$\sum_{l=1}^{4} r_{(i,j)(k,l)} = 1, \qquad k = (i+1) \bmod 24, j \in \{1,2,3,4\}. \tag{11}$$

The transition probability matrix for a bad weather day is defined similarly.

The solar energy model defined above provides the solar energy harvested by a 1 kW PV panel at any given point of time. Thus the solar energy harvested by our PV panel with capacity PV_w for a given state S_t of the solar energy at time t is given by

$$E(t) = PV_w E_{S_t}. \tag{12}$$

Next, we consider the model for the state of the battery at any given point in time. We assume that the system starts with fully charged batteries (B_{cap}). To increase the operating lifetime of the batteries, we assume that the battery levels are not allowed to go below a pre-defined DoD (taken to be 70% in this paper). When the battery level starts to go below this particular value, it is automatically disconnected, and is reconnected to the load when we have enough solar resource to charge it above that level. Recall from Section II-B that the load (BS power consumption) is dynamic and depends on the traffic levels and we denote the load at time t by $L(t)$. Assuming a discrete time model with time in hours, the battery level at any time t, $B(t)$, is then given by

$$B(t) = \begin{cases} B_{cap} & B(t) \geq B_{cap} \\ B(t-1) + E(t) - L(t) & 0.3B_{cap} < B(t) < B_{cap} \\ 0.3B_{cap} & B(t) \leq 0.3B_{cap} \end{cases} \tag{13}$$

with $B(0) = B_{cap}$. The hours for which the battery level is either less than or equal to $0.3B_{cap}$ correspond to an outage event. The outage probability is denoted by O and is given by

$$O = H_{outage}/H \tag{14}$$

where H_{outage} is the number of outage hours and H is the total number of hours of operation.

B. Parameter Estimation

To obtain the parameters for the model described above, we use historical data of solar energy, such as that provided by NREL. For any given location, we consider 10 years worth of data, and in order to capture the impact of the worst weather conditions, we only consider the worst month of the year (in terms of solar irradiance levels). For each day of the 10 worst months (one from each year), we then calculate the total solar energy harvested by a PV panel of unit wattage. The days are then sorted based on the solar energy harvested, and the fraction α of days with the lowest harvested energy are marked as bad weather days while the remaining are marked as good. The data is then used to calculate the transition probabilities of going from a bad day to bad day, and good day to good day, in order to obtain the transition probabilities p_{gg}, p_{gb}, p_{bb} and p_{bg} for Eqn. (6).

To obtain the average energy harvested in each of the four possible states of each hour, we first analyze the data to record the hourly minimum and maximum values of solar energy generated for both good and bad weather days. The region between the minimum and maximum solar energy generated for each of these is divided by defining cutoffs that uniformly partition the region into four sub-regions. Each of the four sub-regions specifies a state of solar energy at that hour and the average hourly solar energy in each of those states is then obtained from the empirical data.

C. Optimal System Dimensioning

Our design problem is to find the optimal PV panel size and the number of batteries (i.e. values of PV_w and n_b) such that any given outage probability constraint is satisfied, with the objective of minimizing the overall cost of the system. The cost of the system depends on two factors: the cost of the PV panels and the cost of the batteries (the cost of other equipment such as the base station is treated as a constant and does not factor in the design). The system is designed with a target operational lifetime and the cost should include factors such as the need for replacing batteries.

To model the system cost for a given choice of PV_w and n_b, we first use the methodology of Section III-A to find the corresponding outage probability. In addition, we also compute the battery lifetime for the particular configuration as given by Eqn. (3). Then the total cost, C, of the battery and PV resources for a desired system lifetime of T_{run} years is given by

$$C = N_{Bat} C_B + PV_w C_{PV} \tag{15}$$

where C_B is the capital cost of one battery and C_{PV} is the cost of PV panel per kW. The total number of batteries (N_{bat}) required over the desired time period T_{run} is given by

$$N_{Bat} = n_b (T_{run}/L_{Bat}) \tag{16}$$

where n_b is the number of batteries powering the base station at a given point of time and L_{Bat} is the battery life time for the given PV wattage (PV_w) and number of batteries (n_b) configuration.

The cost optimization problem can then be expressed as

$$\begin{aligned} \text{Minimize:} \quad & N_{Bat}C_B + PV_w C_{PV} \\ \text{Subject to:} \quad & O < \beta \end{aligned}$$

where β is the operator's desired limit on the outage probability in the worst month. The optimization problem can be solved using standard techniques.

IV. Results

In this section we verify the solar powered BS dimensioning framework developed in this paper.

A. Simulation Setup

This paper considers a LTE base station system with 10 MHz Bandwidth and 2×2 Multi Input Multi Output (MIMO) configuration. We assume 3 sectors for our macro BS, each with 2 transceivers, thus giving us $N_{TRX} = 6$. We model the traffic using the methodology described in Section II and assume that 12 V, 205 Ah flooded lead acid batteries are used by the BS. The efficiency of the battery is taken as 0.8. To validate the methodology presented in this paper, we consider three locations: Mumbai (India), Delhi (India) and Miami (USA). The solar data for these locations was obtained from the NREL database and used in the SAM tool to obtain hourly values of the solar power generated. We used $\alpha = 0.2$ for all the three locations. To validate the proposed framework, we conducted and compared simulations based on the empirical solar energy data and also the solar energy values predicted by our model.

B. Battery Lifetime

To evaluate the proposed framework, we first evaluate the battery lifetime obtained through our model and compare it against the lifetime obtained using simulations with empirical data. For these results, for a given PV panel size, we vary the number of batteries and observe the resulting battery lifetime. Figure 4 shows the battery lifetime obtained from the empirical data and our model for a PV wattage of 14 kW, and we note that our model predicts the battery lifetime quite accurately for all three locations. We also observe that as the number of batteries decreases, the battery lifetime decreases. This is because with fewer batteries, the batteries are more likely to go through deeper discharge cycles, which reduces their lifetime.

C. Battery Sizing

Next we evaluate the performance of the proposed model in terms of the battery requirements for achieving a given outage probability. For various PV panel dimensions, the number of batteries required to achieve 1 %, 2 % and 3 % outage rates are shown in Tables I and II for Delhi and Miami, respectively. The values of batteries required for the case of Mumbai can be seen in Figure 6. In addition, Figure 5 shows the battery requirements for the three cities for a PV panel of 14 kW for various values of outage probabilities. Note that an outage of 1 % corresponds to 7.44 hours of outage in the worst month. The results predicted by our model have a close match with

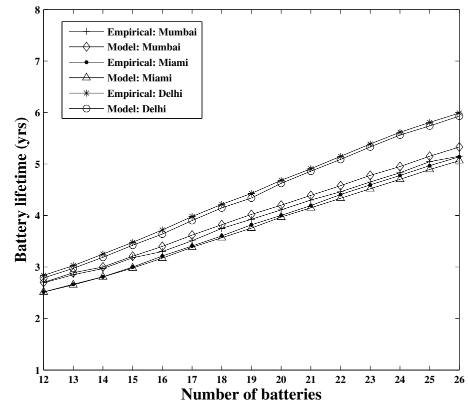

Fig. 4. Battery lifetime versus number of batteries for the three locations for PV wattage of 14 kW

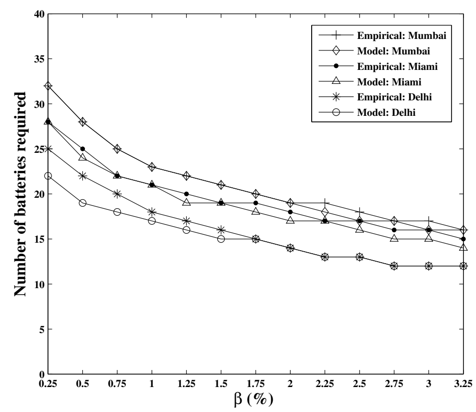

Fig. 5. Number of batteries required for a given tolerable worst month outage probability (β) for the three locations for PV wattage of 14 kW

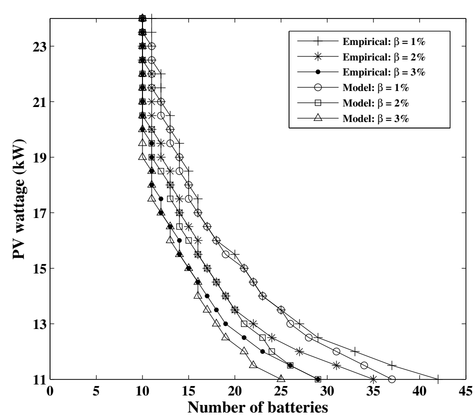

Fig. 6. PV wattage versus number of batteries required for various outage probabilities for Mumbai.

the results from the empirical data. We observe that for smaller PV panel sizes, the number of batteries required for a given outage is very high. The results from the tables show that the number of batteries required for a given outage decreases as the PV wattage increases, and after a certain point the required number of batteries starts saturating. This is because once we have sufficient energy harvested and stored in the batteires to

TABLE I
PV BATTERY DIMENSIONING FOR DELHI

PV Size (kW)	Number of Batteries					
	$\beta = 1\%$		$\beta = 2\%$		$\beta = 3\%$	
	Emp.	Mod.	Emp.	Mod.	Emp.	Mod.
9	39	34	30	28	26	23
11	25	24	20	20	18	17
13	19	18	16	15	13	13
15	17	16	13	13	11	11
17	15	13	12	11	11	10
19	13	12	11	11	10	10
21	12	11	10	10	10	10

meet an outage constraint, adding more batteries is pointless. Thus in these cases if the PV size is further increased, the energy is wasted. Also, as expected, the required number of batteries increases as the limit on the outage probability is decreased.

D. PV Wattage Requirements

In this section we evaluate the requirements on the PV sizing as a function of the number of batteries and outage probability. For Mumbai, Figure 6 shows the required PV wattage for outage probabilities of 1, 2 and 3% for various battery sizes. The nature of the results for Delhi and Miami are similar. The results show that as expected, the required PV wattage increases when the number of batteries is reduced. Also, when the number of batteries is reduced beyond a certain point, the required PV wattage tends to infinity. This is because while an increase in the PV wattage increases the solar energy harvested during the day, the small number of batteries implies that there are not enough batteries to store the energy. Consequenlty, outages occur frequently and it is not possible to keep the outage rates below the desired limit.

E. Cost Optimization

To compare the results for the cost optimal PV panel size and number of batteries, we consider a target operational lifetime of $T_{run} = 20$ years. Based on the market statistics for the cost of PV panels and lead acid batteries, we have assumed C_B as US$ 280 and C_{PV} as US$ 1000 [14]. The optimal configuration for various outage probabilities are shown in Tables III where the PV size is in kW and the cost is in thousands of US dollars. The battery lifetime and the cost corresponding to the optimal solutions have also been shown.

V. CONCLUSION

This paper presented a framework for determining the cost optimal PV panel and battery sizing for solar powered cellular base stations. The proposed framework is based on our model for evaluating the outage probability associated with a base station that uses historical solar irradiance data as the input. The proposed framework has been evaluated through data collected for three different geographical locations.

TABLE II
PV BATTERY DIMENSIONING FOR MIAMI

PV Size (kW)	Number of Batteries					
	$\beta = 1\%$		$\beta = 2\%$		$\beta = 3\%$	
	Emp.	Mod.	Emp.	Mod.	Emp.	Mod.
9	41	42	33	34	29	27
11	27	29	23	23	20	20
13	23	23	19	19	17	17
15	20	19	17	16	15	14
17	18	17	15	14	13	12
19	16	15	14	12	11	11
21	15	13	12	11	11	11

TABLE III
OPTIMAL CONFIGURATION

Location	Empirical				Model			
	PV	n_b	L_b	Cost	PV	n_b	L_b	Cost
$\beta = 1\%$								
Mumbai	16	18	4.0	41.4	14	23	4.8	40.9
Delhi	13	20	4.5	37.7	12	20	4.4	37.6
Miami	13.5	22	4.3	41.9	14.5	20	4	42.4
$\beta = 2\%$								
Mumbai	14	19	3.9	41.1	14	19	4.0	40.5
Delhi	12	18	3.9	37.6	12	17	3.7	37.5
Miami	13	19	3.7	41.7	13	19	3.7	42.1
$\beta = 3\%$								
Mumbai	14	17	3.6	40.7	13	18	3.8	40.0
Delhi	13	13	3.0	37.4	13	13	2.9	37.7
Miami	13	17	3.3	41.6	13	17	3.3	41.9

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