Dimensioning Stand-Alone Cellular Base Station using Series-of-Worst-Months Meteorological Data

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***Abstract*—This paper presents a methodology for dimensioning the photo-voltaic (PV) and battery requirements of stand-alone, solar-powered cellular base stations. In contrast to existing methodologies that use intuitive methods or are based on Typical Meteorological Year (TMY) data, this paper proposes the use of series-of-worst-months data for dimensioning the base station. The proposed approach has the advantages of higher accuracy as well as being computationally more efficient. The proposed methodology has been verified using real meteorological data for a number of geographical locations.**

I. Introduction

With the increasing demand and popularity of mobile communication services, the number of cellular networks deployed across the globe has been increasing over the last decade. In contrast to the developed nations which already have good cellular coverage, the increase has been more rapid in developing nations. Unfortunately, many parts of these developing nations suffer from unreliable grid supply and thus at times the base stations have to run on diesel generators. This increases both the operational cost as well as the contribution of the cellular network towards greenhouse gas emissions. In such scenarios, the use of renewable sources like solar and wind energy are viable avenues for powering cellular networks.

Among cellular network components, base stations typically consume the maximum energy (around 60-80%) [1]. Thus one of the key solutions for implementing green cellular networks is to use stand-alone base stations powered just by renewable energy, without using grid or depending on conventional sources. Also, previous studies have shown that such a base station can be implemented with lower capital cost as compared to using grid or conventional sources of energy [2]. Although some work has been done on designing cellular base stations powered by solar and wind energy, most lack elaborate use of weather statistics. Thus at times these designs lead to very optimistic configurations which fail when the system is actually deployed [3].

Intuitive approaches for dimensioning solar powered systems are simple and quick, and generally develop a system configuration such that the average energy produced exceeds the daily demand [4]. While such methods are simple, their solutions are usually neither cost-optimal nor do the provide any estimate of the outage probabilities [5]. Analytic approaches for dimensioning rely on the development and use of expression that relate the solar irradiance pattern for a given location to the system performance [6], [7], and are thus site-specific. On the other hand, numerical approaches for dimensioning solar powered systems use simulation tools that use long term solar irradiance data as their input [8], [9]. In addition to being computationally intensive, such methods are only useful for places for which long term solar irradiance data is available. As an alternative, Typical Meteorological Year (TMY) data that consists of synthetically generated, meteorological data for a year is used in many studies and simulation softwares [2], [10]. However, the averaging of weather conditions in TMY data leads to optimistic dimensioning solutions.

The fundamental problem in designing stand-alone solar powered systems is thus the tradeoff between reliability and complexity. While numerical methods provide highly reliable solutions, they are computationally intensive and are dependent on the existence of long-term meteorological data. On the other hand, TMY based approaches are faster, but at the cost of accuracy. To address this problem, this paper proposes a methodology for dimensioning stand-alone, solar powered cellular base station using series-of-worst-months (SWM) meteorological data that provides accurate PV panel and battery dimensions with low computational time requirements. The proposed method is based on selecting the worst month (in terms of solar irradiation) from each year for a given location, and then using these worst months in series as the input for a numerical simulation. To evaluate the proposed method, we consider three locations: Miami (USA), San Diego (USA) and Las Vegas (USA) and design the cost-optimal PV panel and battery requirements for a macro base station for these locations, for different tolerable worst month outages.

The rest of the paper is organized as follows. Section II presents the background and system model. Section III presents the proposed methodology for system dimensioning and Section IV presents evaluation results. Finally, Section V concludes the paper.

II. Background and System Model

This section presents the assumptions and underlying models used in this paper.

A. Energy and Traffic Models

This paper considers a Long Term Evaluation (LTE) base station (BS). The base station power consumption comprises of a fixed part (which is due to air conditioners, losses in cable feeders etc.), and a variable part, which depends on the cellular traffic at a given point of time. In particular we consider a

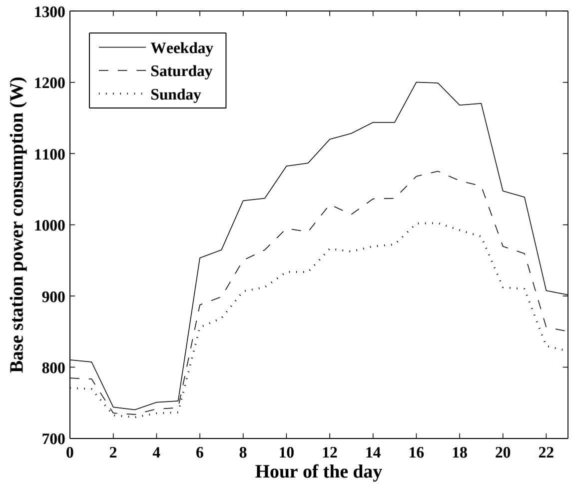

Fig. 1. Average hourly values of BS power consumption.

macro base station whose power consumption at time t is given by [11]

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

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 T 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.

To model the traffic, we use a call based model as proposed in [12]. The call arrivals are modeled as a Poisson process and the call durations are taken to be exponentially distributed. Based on this model, calls are generated on minutely basis with rate depending on the hour of the day. Each call is assigned a call duration which is exponentially distributed and has a mean value of 2 minutes. The normalized traffic denoted by T in Eqn. (1) at a given time is obtained by normalizing the instantaneous traffic by the maximum number of calls the base station can support at any given point of time. An example of the average base station power consumption profile for different days (based on data for 30,000 days) is shown in Figure 1. Note that the traffic levels during weekends are lower as compared to weekdays, which is in line with large scale cellular data studies [13].

B. *Solar Energy Data and Battery Model*

To characterize the harvested solar energy, this paper uses statistical weather data made available by National Renewable Energy Laboratories (NREL), USA [14]. In particular we use ten year's data for three different locations. This paper assumes a PV panel with a DC-AC loss factor 0.77 and tilt of the PV panel as latitude of the location, which are the default values [15].

This paper assumes that the base station uses lead acid batteries. Lead acid batteries are a popular choice because they are cheaper than other battery types. The life duration of a battery depends on its operating conditions and can be calculated based on the method of cycles counting [16], which involves counting the charge/discharge cycles for each range of depth of discharge (DOD) for a year. Let the entire range of DOD values (0-100) be divided into N non-overlapping regions. The battery lifetime (in years) is then given by

$$L_b = \frac{1}{\sum_{i=1}^{N} \frac{Z_i}{CTF_i}}, \tag{2}$$

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. The relationship between cycles to failure and the DOD is generally provided by the battery manufacturer.

III. PV Panel Size and Battery Dimensioning

This section presents the SWM based methodology for dimensioning solar powered base stations. We first describe our model for obtaining the outage probability for a base station with a given PV panel dimension and number of batteries. The model is then used to determine the cost optimal configuration of the PV panel and battery size for any desired bound on the outage probability using either SWM, TMY or empirical approaches.

A. *System Model*

Given n_{PV} number of PV panels installed in the BS site, each with DC rating E_{panel}, the overall DC rating of the PV panels for the site PV_w is given by

$$PV_w = n_{PV} E_{panel}. \tag{3}$$

Similarly, for n_b batteries installed, each with capacity E_{bat}, the battery bank capacity B_{cap} is given by

$$B_{cap} = n_b E_{bat}. \tag{4}$$

For a particular combination of PV_w and n_b, the outage probability can be calculated by using the energy produced by the PV panels (which depends on the solar irradiance profile at that location), BS power consumption (which is traffic dependent), and the battery charge/discharge dynamics under the influence of the two previous factors. In this paper we analyze the solar energy resource, base station power consumption and the energy stored in battery bank on an hourly basis.

For every time instant t (in hours), the solar data from NREL provides the solar power generated for a solar panel with DC rating of 1 kW, which we denote as $S(t)$. Thus for a PV panel with rating PV_w, the energy generated can be expressed as

$$E(t) = PV_w S(t). \tag{5}$$

We assume that the batteries are initially fully charged and have an efficiency of 80%. To avoid deep discharges which adversely affect the battery life, we disconnect the battery from the system when the overall charge level goes below 30% of its capacity. Based on these parameters, the level of the battery power at a given time instant is given by

$$B(t) = \begin{cases} B_{cap} & B(t) \geq B_{cap} \\ B(t-1) + E(t) - P_{BS}(t) & 0.3B_{cap} < B(t) < B_{cap} \\ 0.3B_{cap} & B(t) \leq 0.3B_{cap} \end{cases} \quad (6)$$

with $B(0) = B_{cap}$. Note that the model assumes that the battery is disconnected when the overall charge level of the battery goes below $0.3B_{cap}$. The disconnection of the battery leads to an outage event at the base station. This outage continues until there is sufficient solar energy to support the base station while keeping the overall charge of battery above $0.3B_{cap}$. The outage probability in the worst month is denoted by O and is given by

$$O = H_{outage}/H \quad (7)$$

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

The optimal PV panel and battery problem is to determine the least cost configuration in order to satisfy a limit on the worst month outage probability. The outage probability in the worst month is used in this paper as a constraint since for telecommunication applications which require high reliability, the worst month outage is a major concern for network operators [3]. The cost optimization problem can then be expressed as

$$\text{Minimize:} \quad N_{Bat}C_B + PV_w C_{PV} \quad (8)$$

$$\text{Subject to:} \quad O < \beta \quad (9)$$

where C_B is the capital cost of one battery, C_{PV} is the cost of PV panel per kW, and β is the operator's desired limit on the worst month outage probability. The total number of batteries (N_{bat}) required over the desired time period T_{run} is given by

$$N_{Bat} = n_b(T_{run}/L_{Bat}) \quad (10)$$

where n_b is the number of batteries powering the base station at a given point of time. L_{Bat} is the battery life time for the given PV wattage (PV_w) and number of batteries (n_b) configuration. The value of T_{run} is typically taken as 20-25 years. The optimization problem can be solved using standard techniques.

B. Worst Month Estimation

The methodology described above uses the outage probability in the worst month of the year. To determine the worst month in a year, we use the historical solar irradiance data to calculate the average daily solar irradiation value for each month and denote the month with the minimum value as the worst month. Table I shows the worst months for some specific years for three different locations which have been considered in this paper.

TABLE I
WORST MONTH FOR MIAMI, SAN DIEGO AND LAS VEGAS

Year	Worst month		
	Miami	San Diego	Las Vegas
2000	December	December	January
2001	September	November	January
2002	June	October	December
2003	December	December	December
2004	December	December	December
2005	June	January	January
2006	December	May	December
2007	October	November	December
2008	December	December	December
2009	December	December	December
TMY	November	December	December

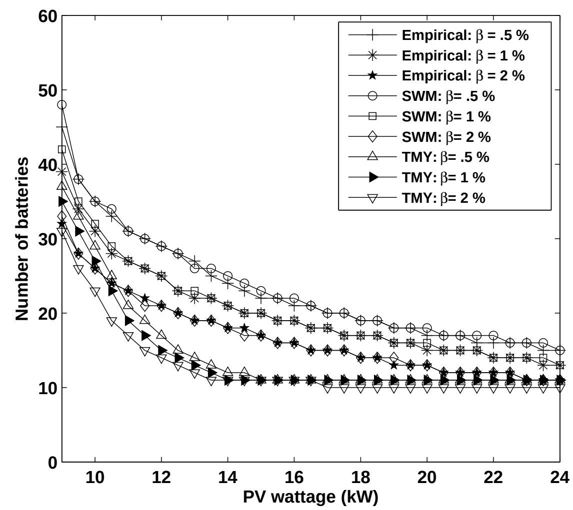

Fig. 2. Batteries required vs PV panel dimension comparison between empirical, TMY and SWM approaches for Miami.

C. Dimensioning with SWM Data

For this approach we consider ten years worth of meteorological data for the desired location and first determine the worst month for each of the years (using Section III-B). The data from these ten worst months are then combined, and the series of ten months' data is given as input to the model described in Section III-A. For any choice of the PV panel and battery bank size, the model then outputs the outage probability in the worst month. The solution to the optimization problem in Section III-A then provides the lowest cost PV panel and battery configuration that achieves the tolerable worst month outage.

IV. RESULTS

This section presents simulation results to validate the proposed methodology. In addition to the SWM based methodology proposed in this paper, we consider two other approaches that are based on data types used in existing literature. In the

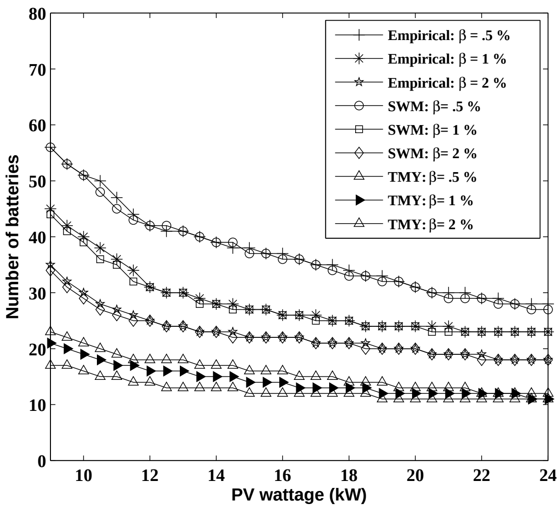

Fig. 3. Batteries required vs PV panel dimension comparison between empirical, TMY and SWM approaches for San-Diego.

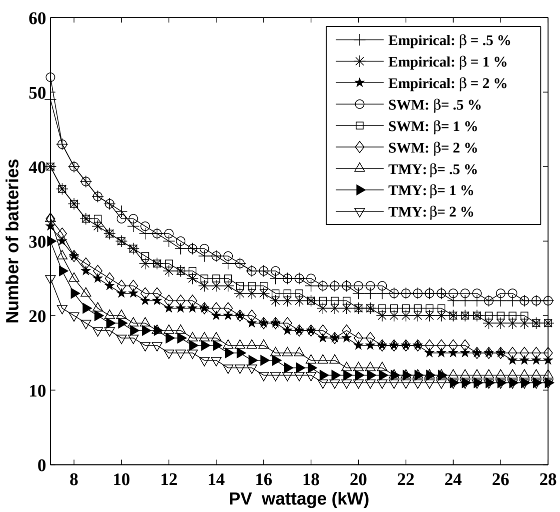

Fig. 4. Batteries required vs PV panel dimension comparison between empirical, TMY and SWM approaches for Las Vegas.

TMY based approach, the TMY year data for the given location is used as the input to the model and optimization framework of Section III-A, while in the *empirical* approach, the solar irradiance data for ten years (120 months) is used as the input. Note that the empirical approach gives the most accurate results since it is based on actual yearly data. However, it is computationally expensive since it requires the use of longer data streams.

The simulations assume a LTE base station with 10 MHz Bandwidth and 2×2 Multi Input Multi Output (MIMO) configuration. The base station is assumed to have three sectors, each with 2 transceivers ($N_{TRX} = 6$). We assume that 12 V, 205 Ah flooded lead acid batteries are used in the BS. The BS traffic profile was generated as described in Section II-A. This model dynamically generates the normalized load on a given day and for a given hour of the day which is used

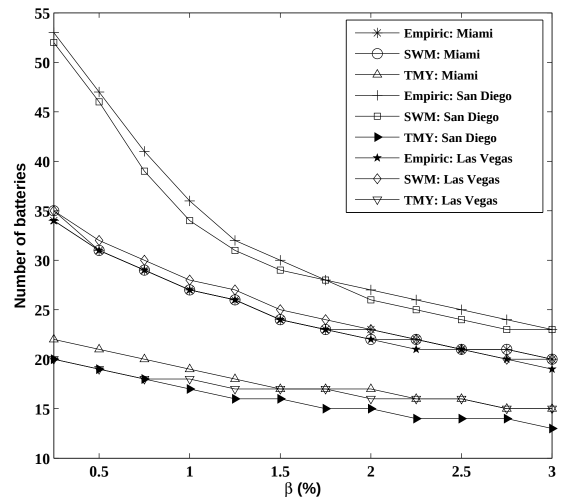

Fig. 5. Batteries required with 11 kW PV panel for given tolerable worst month outage : comparison between empiric, TMY and SWM

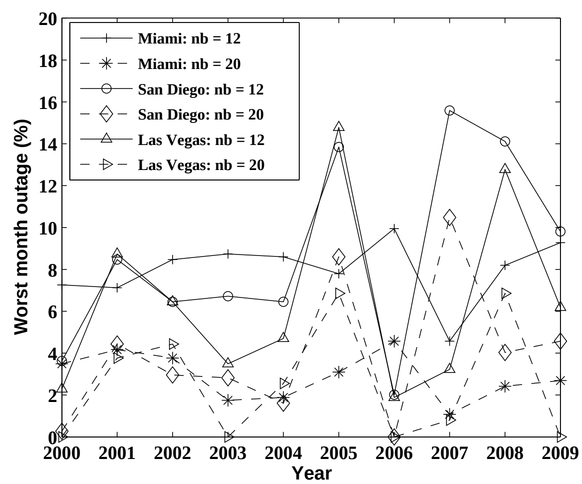

Fig. 6. Worst month outage in years 2000-2009 for the three cities for PV panel of 11 KW (nb: number of batteries)

in Eqn. (1) to determine the BS power consumption at that given time. To validate our proposed approach, we consider three cities: Miami (USA), San Diego (USA) and Las Vegas (USA). For each of these locations we considered the ten year period from 2000-2009 for this study. Table I shows the worst months for the different years for these locations.

A. PV-Battery Requirement for Given Outage Requirement

For three different values of the tolerable worst month outage probability: 0.5%, 1% and 2%, the number of batteries required for a given PV panel dimension as predicted by the TMY data, SWM data and the empirical data are shown in Figures 2, 3 and 4 for the three locations. We see that while the number of batteries predicted using TMY data are much lower for a given PV wattage as compared to that predicted by empirical data, the prediction made by using the SWM approach is quite close.

TABLE II
OPTIMAL CONFIGURATION FOR VARIOUS OUTAGE PROBABILITIES

Location	Empirical		SWM		TMY	
	PV	n_b	PV	n_b	PV	n_b
$\beta = .5\%$						
Miami	13	27	13	27	10.5	25
San Diego	11.5	44	11	45	9.5	22
Las Vegas	7.5	43	7.5	43	8	25
$\beta = 1\%$						
Miami	12.5	23	12.5	23	10.5	23
San Diego	9.5	42	9.5	41	9	21
Las Vegas	7.5	37	7.5	37	8	23
$\beta = 2\%$						
Miami	11.5	22	11	22	10	23
San Diego	11	27	11.5	25	9	17
Las Vegas	9	25	9.5	25	7.5	21

B. Battery Dimensioning

For different values of tolerable outages, the number of batteries required for a PV panel with dimension 11 kW as predicted by the empirical, SWM and TMY data is shown in Figure 5 for the three locations. We note that that while the required battery size predicted using TMY data for a given PV Wattage (here 11 kW) as compared to empirical data is much lower (leading to an optimistic design), the prediction made using SWM approach comes much closer.

C. Cost Optimization

For the results of the cost optimal PV panel and battery dimensioning, we assume that the the cost optimization is to be done over a period of $T_{run} = 20$ years. Based on market statistics, the unit cost of lead acid batteries, C_B, is assumed to be US$ 280 and the unit cost of PV panels, C_{PV}, is assumed to be US$ 1000 [17]. For the three different approaches (i.e. the Empirical, SWM and TMY), the cost optimal configurations are shown in Table II and we observe that the proposed SWM based method is more accurate that those based on TMY.

D. Data Complexity

The proposed SWM based approach achieves accuracy closer to that obtained from the use of empirical data, but at an order of magnitude lower data requirement. In the results presented in this section, the SWM based approach uses only 10 months' data while the empirical approach uses 120 months. Note that while the TMY approach uses 12 months data and thus has a data complexity closer to SWM data, its accuracy is significantly worse.

E. Outage Behavior Over the Observed Period

This section illustrates the importance of the requirement for 10 years meteorological data (or more years if available) for dimensioning purposes. Figure 6 shows the outage observed in the worst months for each of the ten years for the three locations. We observe that there are significant variations in the worst month outage in different years, thereby indicating that by in increasing the number of years under consideration, the reliability can be increased.

V. CONCLUSION

In this paper we proposed a new approach for PV panel and battery dimensioning for stand-alone, solar powered cellular base stations using series-of-worst-months meteorological data. The proposed methodology is more accurate as compared to approaches like using TMY data, and requires lower computational time as compared to numerical simulations using empirical data. The proposed methodology has been verified using extensive simulations for multiple locations.

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