

Solar-Enabled Green Base Stations: Cost versus Utility

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Abstract—Solar-enabled cellular base stations are getting significant attention because they avoid greenhouse gas emission as well as easily available. Dimensioning of base station is a very important issue where the photo-voltaic (PV) panel size and storage capacity are determined to operate the system for a long time with minimum energy black out.

In this work we look into energy outage aware system cost as well as utility of solar-enabled base stations. Hourly harvested energy and traffic dependent hourly consumed energy are considered for analysis. First, the quantized profile of harvested and consumed energy are obtained. Subsequently, the lower bound on PV panel and storage capacity is determined which provides dimensioning information a priori and at reduced complexity. To calculate the outage probability, a discrete-time Markov chain is formed with different energy levels of the battery as the system states. The state transition probabilities depend on the harvested and consumed energy profile. It is observed that, with more stringent outage constraint, the harvested energy which is neither utilized nor stored increases significantly. To this end, we suggest the system other than cost optimal where the excess energy is sold to the intelligent smart power grid to generate revenue. Harvested and consumed energies of the three cities situated at different geographical locations are considered to verify the results.

I. INTRODUCTION

In recent years pollution is a very severe issue faced by various countries [1]. It is reported that China, USA, and India are the three major greenhouse gas emitters across the globe [2]. One of the major sources of greenhouse emission is diesel generators used to power the base stations. On an average 1500 liters of diesel are consumed by a base station monthly [3]. Apart from pollution, varying cost as well as transportation are also the constraints associated with diesel-dependent base stations, especially in remote areas where electrical power is either unreliable or unavailable.

Now-a-days renewable sources of energy, such as, solar and wind, are considered to be promising resources for base stations in order to provide the mobile access. Easy availability, environmental friendliness, cost-effectiveness, and less maintenance are some key features of renewable sources which encourage to adopt this solution for energy generation. These ambient energy resources are also very helpful in emergency situations, such as, complete blackout of power and disasters.

Several industry leaders have been taking keen interest in installing solar-enabled base stations, particularly in the regions which are not connected to the outside world. Some recent initiatives, such as, Orange in rural Africa, Eltek in South Africa, Arab, and Gulf countries, Huawei in China and Pakistan, Dialog Telekom in Sri Lanka, Ameresco in the USA, have gained considerable attention. Very recently, with the help

of government of India, Vihaan Network Limited has set up nearly 2200 solar-powered mobile communication towers in under-developed, inaccessible, and heavily forested areas in order to connect more than 18 million citizens with nearly 3.9 million mobile connections [4].

A solar-enabled base station is equipped mainly with photo-voltaic (PV) panel, battery and inverter. The energy harvested from solar radiation is supplied to the load via inverter. The excess energy is stored in the battery whereas energy is drawn from battery whenever required by the load.

A. Related Work and Scope

Since the solar energy is available during day time only, dimensioning of PV panel as well as battery is an important issue of research interest for ensuring that the energy blackout can be minimized. Intuitively, under-dimensioning leads to frequent power outages, whereas over-dimensioning leads to unnecessary increased capital cost.

Days of autonomy criteria is used to dimension the storage capacity for a given PV panel size [5], [6], where days of autonomy is the consecutive number of days over which the energy generated is less than a predefined threshold. This is not a cost-optimal system and the threshold strongly depends on the geographical location. Also there is chances of over-dimensioning the system.

Intensive computation based cost optimal systems are designed in [3], [7]–[11] to meet the required power outage probability. The system is dimensioned using loss of power supply in cost-optimal sense [7], [8]. In [9], a multistate Markov model is presented to dimension the system where extensive simulations are used for computation of the required outage probability. Zero grid Energy Networking (ZEN) concept is presented in [3] which is based on a networks of base stations that are solely powered with renewable energy sources.

Typical Metrological Year of a given location is used for dimensioning the solar-enabled base station system. A hybrid base station is dimensioned in a way that primarily depends on solar resource, but energy is purchased from power grid whenever required [10]. The aim is to minimize the capital expenditure (CAPEX) which accounts for the cost of PV panel and battery, and operational expenditure (OPEX) which accounts for power purchased from grid. In [11], using a Markov model the synthetic radiation data is first generated, and then storage energy is iteratively evaluated for a given panel size. This iterative process does not have any basis to

choose the initial values, and as a result the process tends to become computationally intensive.

Outage probability is a key performance parameter in dimensioning the solar-enabled system. A few methods are reported to compute the outage probability analytically rather than via iterations. In [12], outage probability is evaluated using Beta distribution based modeling. In [13], solar radiation data is generated using Monte Carlo method and modeled using exponential distribution. These approaches however provide rough estimation because it is difficult to capture the variation of solar data through a well known distribution as it depends on geographic location as well as environmental condition which is changing rapidly.

A discrete-time Markov process based model is presented in [14] to compute the energy outage probability of solar-enabled base station system. This model is based on several threshold parameters and evaluates outage probability for larger size of PV panels only. Markov chain based method is also used in [15], where the energy harvested by panel is estimated based on daily solar radiance level. However, the daily data based modeling may lead to inaccurate dimensioning.

To sum up, till now, dimensioning is done without any prior estimate of PV panel size and storage capacity. Further, in conventional outage-constrained solar-enabled base station dimensioning significant amount of excess energy is wasted which is unaccounted. Thus, to the best of our knowledge, although there have been a few recent studies [3], [9], [10], [14], [15] on dimensioning of solar-enabled base stations in terms of optimum panel size and storage cell requirement for an allowable power outage probability, optimality of system design from long-term utility viewpoint is still missing in the literature.

B. Contributions

In this work, the solar-enabled base station is analyzed using the hourly data set of harvested energy and traffic dependent hourly energy consumption profile. The key contributions of our work are as follows:

- 1) Lower bounds on PV panel size and storage capacity is obtained, which provides significant information towards dimensioning and reduces the computational complexity.
- 2) A simple discrete-time Markov chain is presented for evaluating the probability of energy outage and excess events. The evaluated outage and excess probability is compared with the simulation result of empirical data to validate the presented model.
- 3) The system is dimensioned to provide maximum utility by supplying the excess energy to the intelligent power grid while achieving the same outage constraint.

C. Paper Organization

The rest of the paper is organized as follows. Sustainable system design issues are presented in Section II, where lower bound on PV panel and storage capacity is obtained to aid system design. This is followed by outage and excess probability evaluation in Section III. Section IV contains the

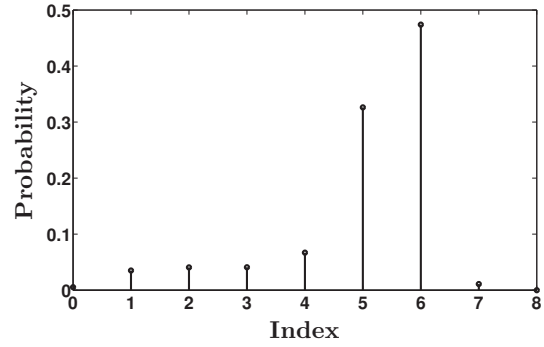


Fig. 1: The probability profile of harvested energy from a panel size of 10 KW rating at 12:00 noon in New Delhi. Energy level (in KWh) of horizontal axis = Index $\times$ Step Size.

outage performance results and discussion. The utility optimal dimensioning is presented in Section V, followed by the concluding remarks in Section VI.

II. SUSTAINABLE SYSTEM DESIGN

The statistical solar data of last 14 years available from National Renewable Energy Laboratory (http://www.nrel.gov/international/ra_india.html) are used for energy availability characterization. The data is fed into System Advisor Model (SAM) to get the hourly and daily energy generated by a panel size of 1 KW rating with default settings [16]. Lead acid batteries are used to store the energy.

Energy generated by the PV cell of size n_{PV} is given as:

$$E_{n_{PV}} = n_{PV} E_{1KW} \quad (1)$$

where E_{1KW} is the energy generated by a solar panel of rating 1 KW, which is taken as the reference panel. In this work the hourly energy harvested is considered for analysis.

Let E_{cons} denote the hourly energy consumption by base station. Hourly energy harvested by the panel of size n_{PV} and hourly consumption data profile are quantized with step size Δ . The profiles of energy harvested and energy consumed are obtained for each hour are denoted by $\mathbf{E}_{n_{PV}}^{(h)}$ and $\mathbf{E}_C^{(h)}$, respectively, where $h = \{0, \dots, 23\}$ denotes the hour of the day. $h = 0$ corresponds to 00:00 (12 midnight), whereas $h = 23$ corresponds to 23:00 (11 pm). One such profile of harvested energy is shown in Fig. 1. The variables represented in bold letters represent the probability profile.

A. Sustainable System

Usually a solar system is designed to operate for a longer time, for example, more than 15 years. The system is composed of PV panel and storage devices, such as a battery. The energy is extracted from the battery up to its lowest depth of discharge whenever the harvested energy is lesser than the required consumption. If instead the energy harvested is larger than the required consumption, then energy is added to the storage device up to its maximum capacity. To characterize

this phenomena, the residue energy profile in h^{th} hour with a panel size n_{PV} $\mathbf{E}_R^{(h)}$ is given as:

$$n_{PV} \mathbf{E}_R^{(h)} = \mathbf{E}_{n_{PV}}^{(h)} - \mathbf{E}_C^{(h)} \quad (2)$$

where $\mathbf{E}_{n_{PV}}^{(h)}$ is the energy harvested profile in h^{th} hour with a panel size n_{PV} , and $\mathbf{E}_C^{(h)}$ is the energy consumption profile in h^{th} hour.

The residue energy expressed by (2) characterize the energy added into or extracted from the storage device. Positive index of $n_{PV} \mathbf{E}_R^{(h)}$ represents the energy added to the storage, whereas negative index of $n_{PV} \mathbf{E}_R^{(h)}$ represents the energy extracted from the storage in h^{th} hour.

Our objective is to design a sustainable system (PV panel and storage capacity) in the sense that the system will operate for longer time with minimum energy black out.

Proposition 1: For a sustainable system with storage capacity, the mean daily harvested energy should be greater than or equal to the mean daily consumed energy.

Proof: Transfer of energy happens during each hour; it may be either added or extracted from the storage. If the storage energy is available in the hour of negative residue energy, energy outage is avoided. The 24 hours period constitutes a cycle of charging and discharging of storage.

The mean energy added or extracted from storage in h^{th} hour is $\mathbb{E}[n_{PV} \mathbf{E}_R^{(h)}]$, whereas the mean energy added or extracted from storage in each cycle, i.e., over 24 hours is $\sum_{h=0}^{23} \mathbb{E}[n_{PV} \mathbf{E}_R^{(h)}]$. The following two cases arise:

Case 1: $\sum_{h=0}^{23} \mathbb{E}[n_{PV} \mathbf{E}_R^{(h)}] > 0$

In this case the mean residue energy is positive which indicates that the energy is added to the storage in each cycle. The load demand can be fulfilled by the panel size n_{PV} and theoretically no energy outage occurs.

Case 2: $\sum_{h=0}^{23} \mathbb{E}[n_{PV} \mathbf{E}_R^{(h)}] \leq 0$

In this case energy is extracted from the storage in each 24 hours cycle. As a result, after some cycles the remaining storage energy depletes to zero, leading to energy outage.

Using (2) and the condition in Case 1, for a system to be sustainable, it must satisfy:

$$\sum_{h=0}^{23} \mathbb{E}[\mathbf{E}_{n_{PV}}^{(h)}] > \sum_{h=0}^{23} \mathbb{E}[\mathbf{E}_C^{(h)}]. \quad (3)$$

Thus, the system is said to be sustainable in the sense that it is reliable for operation over a long time when the mean harvested energy is larger than the mean consumed energy. ■

B. Lower Bound on System Design

Using Proposition 1, lower bound on PV panel size and storage capacity are obtained to help in dimensioning the solar-enabled base station system.

Using (3) and (1), it can written as,

$$n_{PV} > \frac{\sum_{h=0}^{23} \mathbb{E}[\mathbf{E}_C^{(h)}]}{\sum_{h=0}^{23} \mathbb{E}[\mathbf{E}_{I \text{ KW}}^{(h)}]} \stackrel{\text{def}}{=} n_{PV \text{ min}}. \quad (4)$$

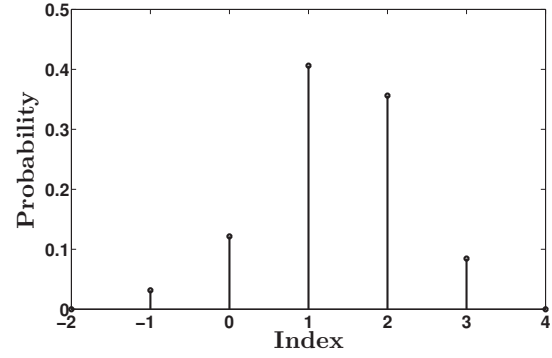


Fig. 2: Probability profile of residue energy $\mathbf{E}_R^{PV}$ with a panel size of 10 KW rating for New Delhi. Energy level (KWh) of horizontal axis = Index $\times$ Step Size.

Therefore, for a given load profile the PV panel size should be greater than the ratio of mean daily consumed energy and mean daily harvested energy by 1 KW solar panel size.

We now obtain the lower bound on energy storage capacity. The storage energy must be available whenever the base station requires energy. Using the residue energy profile $n_{PV} \mathbf{E}_R^{(h)}$, the storage capacity is given as,

$$S_{cap} \geq \left| \sum_{h=0}^{23} \left[\sum_{i<0} i \Pr \{ n_{PV} \mathbf{E}_R^{(h)} = i \} \right] \right| \stackrel{\text{def}}{=} S_{cap \text{ min}} \quad (5)$$

where $\Pr \{ n_{PV} \mathbf{E}_R^{(h)} \}$ is the probability profile of residue energy in h^{th} hour.

Assume each battery has capacity B_{cap} and maximum allowed depth of discharge δ . Then, $\delta N_B B_{cap} \geq S_{cap \text{ min}}$. Hence, the lower bound on number of batteries N_B is obtained as:

$$N_B \geq \frac{S_{cap \text{ min}}}{\delta B_{cap}} \stackrel{\text{def}}{=} N_{B \text{ min}}. \quad (6)$$

Thus, the lower bound on PV panel size is obtained (cf. (4)), and then the lower bound on the required number of batteries is obtained (cf. (6)). These two lower bounds provide significant prior information in designing the system.

III. OUTAGE AND EXCESS PROBABILITY ESTIMATION

With the knowledge of system lower bounds on PV panel size and battery storage capacity, we analyze the energy outage and excess probabilities. The system is in *outage* when the required energy is not supplied either by panel or storage. On the other hand, occurrence of an event when the harvested energy is surplus that cannot be added to the storage due to its fully-charged state is called *excess*. In this section we will evaluate the outage and excess probabilities for a given size of PV panel and number of battery.

With the hourly harvested data and hourly consumed data, the residue energy profile can be given as:

$$\mathbf{E}_R^{n_{PV}} = \mathbf{E}_{n_{PV}} - \mathbf{E}_C \quad (7)$$

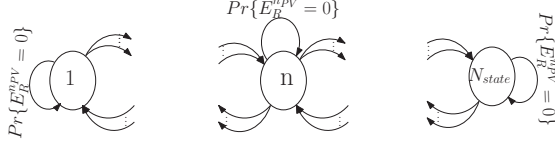


Fig. 3: Markov chain formed for different energy levels of battery using residue energy profile.

where $\mathbf{E}_{n_{PV}}$ is the hourly energy harvested profile and $\mathbf{E}_C$ is the hourly consumed profile. $\mathbf{E}_R^{npv}$ is different from $\mathbf{E}_{n_{PV}} \mathbf{E}_R^{(h)}$ which denotes the harvested energy over a particular hour h , whereas $\mathbf{E}_R^{npv}$ is the average which captures the variation of all hours in the data set. One such profile of residue energy is shown in Fig. 2.

The residue energy given in (7) added to the system. This residue energy profile indicates that the energy is drawn from the battery as well as energy is added to the battery. To capture the residue energy profile over time, a discrete-time Markov chain is formed with different storage energy levels of battery representing the states, as shown in Fig. 3.

Recall the notations that there are N_B batteries in the system along with the PV panel of size n_{PV} . Each battery have capacity B_{cap} with maximum allowed depth of discharge δ , and it is assumed that each battery performs with full efficiency. The energy level of first and last energy state of batteries are respectively $(1 - \delta)N_B B_{cap}$ and $N_B B_{cap}$. The total number of states in the Markov chain is:

$$N_{state} = \left\lfloor \frac{N_B B_{cap}}{\Delta} \right\rfloor - \left\lfloor \frac{(1 - \delta)N_B B_{cap}}{\Delta} \right\rfloor + 1 \quad (8)$$

where $\left\lfloor \frac{(1 - \delta)N_B B_{cap}}{\Delta} \right\rfloor$ and $\left\lfloor \frac{N_B B_{cap}}{\Delta} \right\rfloor$ denote the quantized energy levels of first and last state, respectively.

Let $L = [-l_1, l_2]$, $l_1 > 0$, $l_2 > 0$ is the domain of residue energy profile $\mathbf{E}_R^{npv}$. The elements of the transition matrix, i.e., the transition probabilities of the Markov chain, are calculated using (9) – (11) using residue energy profile. Steady state probabilities of the different energy states $\mathbf{E}_{Bat}$ of the battery can be obtained from the transition matrix.

As the residue energy is either added to or extracted from the battery, the total stored energy in the system is given as:

$$\mathbf{E}_{system}^{npv} = \mathbf{E}_R^{npv} + \mathbf{E}_{Bat}.$$

One such plot of cumulative probability profile of the system energy $\mathbf{E}_{system}^{npv}$ is shown in Fig. 4.

If residue energy is negative then the energy is extracted from the battery upto $(1 - \delta)N_B B_{cap}$, whereas if the residue energy is positive then the energy is added to the system maximum upto $N_B B_{cap}$. If the energy level goes below $(1 - \delta)N_B B_{cap}$, energy outage event happens. On the other hand, if the energy level goes above $N_B B_{cap}$, the excess power event occurs. Mathematically the outage and excess probabilities can be expressed as,

$$P_{out} = \Pr \left\{ \mathbf{E}_{system}^{npv} \leq \left\lfloor \frac{(1 - \delta)N_B B_{cap}}{\Delta} \right\rfloor \right\} \quad (12)$$

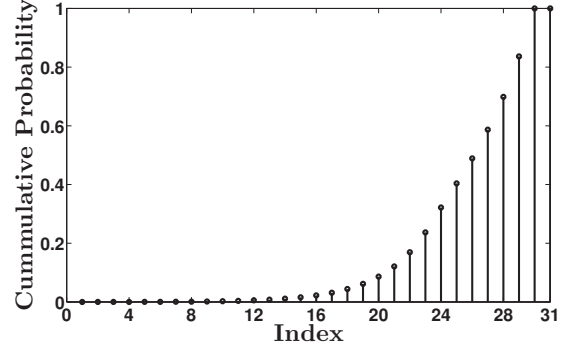


Fig. 4: Cumulative probability profile of system energy for a panel size of 10KW and number of battery $N_B = 12$ for New Delhi. Energy level (KWh) of X-axis = Index $\times$ Step Size.

$$P_{excess} = \Pr \left\{ \mathbf{E}_{system}^{npv} \geq \left\lfloor \frac{N_B B_{cap}}{\Delta} \right\rfloor \right\}. \quad (13)$$

IV. RESULTS AND DISCUSSION

For performance evaluation three cities of India, namely, New Delhi, Ahmedabad, and Itanagar – situated at different geographical locations are considered. Ahmedabad has the highest potential for solar energy whereas Itanagar has the lowest [17]. The energy harvested in each hour of the day is obtained from SAM for these places using solar data of last 14 years. Cost of PV panel size of rating 1 KW and cost of a lead acid battery are taken to be USD 1000 and USD 280, respectively. Depth of discharge δ is taken as 0.3.

Power consumption profile of an LTE macro base station can be written as [18]:

$$P_{BS}(t) = N_{TRX}(P_o + \partial_p \rho(t) P_{max})$$

where N_{TRX} is the number of transceivers. Here 2×2 Multi Input Multi Output (MIMO) configuration with 3 sectors are considered, i.e. we have $N_{TRX} = 6$. The traffic profile $0 \leq \rho(t) \leq 1$ is generated according to the procedure described in [19]. $P_o = 118.7$ W is the circuit power consumption to run the amplifiers, $\partial_p = 2.66$ is the slope and $P_{max} = 40$ W is the maximum power transmitted. Power consumption profile over one week is shown in Fig. 5.

The outage probability obtained from empirical data is calculated using (14). where $B(t)$ is the current battery level at hour t , $B(t - 1)$ is the battery level on previous hour $t - 1$, $E_{BS}[t]$ is the energy consumption by the base station on hour t and $E_{n_{PV}}[t]$ is the energy harvested by solar panel on hour t . The outage probability is the ratio of number of times the battery capacity goes below $(1 - \delta)B_{cap}$ of the total number of days. Battery discharge up to 70% depth, i.e., $\delta = 0.7$, is considered in computing the outage performance results.

A. Verification of Sustainable System

With the power consumption profile shown in Fig. 5, the lower bound on PV panel size is obtained as: $n_{PV_{min}} \approx 5.4$ for Ahmedabad, $n_{PV_{min}} \approx 5.8$ for New Delhi, and $n_{PV_{min}} \approx$

$$P[i, j] = \begin{cases} \Pr\{\mathbf{E}_R^{n_{PV}} = j - i\}, & \text{if } 1 < i < N, 1 < j < N, j - i \in L \\ 0, & \text{otherwise} \end{cases} \quad (9)$$

$$P[i, 1] = \begin{cases} \sum_{z=l_1}^{1-i} \Pr\{\mathbf{E}_R^{n_{PV}} = z\}, & \text{if } 1 \leq i \leq N, 1 - i \in L \\ 0, & \text{otherwise} \end{cases} \quad (10)$$

$$P[i, N] = \begin{cases} \sum_{z=N-i}^{l_2} \Pr\{\mathbf{E}_R^{n_{PV}} = z\}, & \text{if } 1 \leq i \leq N, N - i \in L \\ 0, & \text{otherwise} \end{cases} \quad (11)$$

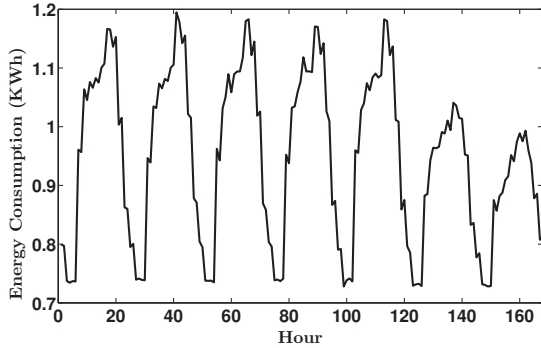


Fig. 5: Variation of hourly traffic dependent consumed energy for a week.

6.8 for Itanagar. Let us consider Ahmedabad city, whose outage probability calculated from the presented model and empirical data are plotted in Fig. 6 for $n_{PV} = 5$ KW panel against the number of battery ranging from 1 to 100. One can observe that, with very high number of batteries, up to 100, the outage probability stays near 0.1, i.e., 10 % of times the system is in outage. This performance is not acceptable because the system experiences outage for nearly two and half hours per day. The energy required to operate the system as well as to recharge the battery is not adequate, causing a very high outage probability. Theoretically infinite storage capacity is required in such scenarios, which is far from practical implementation.

The lower bound on storage capacity against different panel size is shown in Fig. 7. It can be observed that, as the size of PV panel increases, the lower bound on storage capacity decreases. This can be thought as if the storage required has two parts: one during solar radiation and other in absence of radiation. If the panel size is increased, the storage required during radiation hours decreases but it does not affect the storage required in absence of radiation. For very large panel size the storage required during radiation hours reduces to zero, and storage requirement remains only for absence of radiation. This observation is made in Fig. 7. It is also noticed that the minimum storage required for Ahmedabad is lowest, whereas it is the highest for Itanagar. This also verifies the fact that Ahmedabad has highest solar potential.

Now we consider very high panel size, up to 16 KW. The corresponding outage probability against the number of battery is plotted in Fig. 8. It can be observed that, even with very high

PV panel size outage performance is unacceptably high with small number of batteries. Thus, to achieve a better quality of service, proper combination of PV panel size and number of battery is required.

B. Outage Probability Estimation

The outage probability estimated with the presented model is compared with that obtained using empirical data. These are plotted in Fig. 9, with different panel sizes against the number of battery. As the number of battery increases, the outage probability decreases. The root mean square error (RMSE) for different quantization step size and different panel size are listed in Table I. The acceptable upper limit of RMSE is 0.07 [20]. The number of battery ranges from 6 to 40 for RMSE calculation. The listed values shown indicate a good match of outage probability obtained from the presented model and empirical data.

V. COST-OPTIMAL SYSTEM: MAY NOT BE BEST OPTION

Selection of PV panel size and storage capacity is conventionally based on cost optimality for a given performance constraint, e.g., outage probability [9], [14]. But as the performance constraint becomes more stringent, the excess energy significantly increases. This energy is not stored, and so ultimately it becomes useless. Two combinations of PV panel are listed in Table II along with the cost-optimal system with same performance constraint, i.e., outage probability $P_{out} \leq 0.001$. One can observe that the excess energy generated yearly is very high and increases with panel size. The variation of excess probability obtained from the presented model and empirical data is shown in Fig. 10 with panel size 9 KW and 10 KW for Ahmedabad city. Nearly more than 25 % of times the excess event occurs.

Significant advancements in power grid technology facilitates the bidirectional energy flow, i.e., energy can be purchased as well as sold back to the grid as required [21]. Assuming that these cities have such facility, the excess energy produced can be utilized to generate revenue at the base station. With this objective, we propose a framework where combinations other than the cost-optimal solution may be beneficial without degrading the performance.

Dimensioning is done to operate the system for long period of time. This includes the CAPEX accounts for initial installment whereas OPEX accounts mainly for battery replacement

$$B(t) = \begin{cases} N_B B_{cap} & \text{if } B(t) \geq N_B B_{cap} \\ B(t-1) + E(t) - E_{BS}(t), & \text{if } (1-\delta)B_{cap} < B(t) < N_B B_{cap} \\ (1-\delta)N_B B_{cap} & \text{if } B(t) \leq (1-\delta)N_B B_{cap} \end{cases} \quad (14)$$

TABLE I: RMSE FOR OUTAGE PROBABILITY CALCULATED FROM THE PRESENTED MODEL AND EMPIRICAL DATA WITH DIFFERENT PANEL SIZE FOR DIFFERENT CITIES.

	Ahmedabad			New Delhi			Itanagar		
n_{PV} (in KW)	10	11	12	10	11	12	10	11	12
$\Delta = 1$	0.0141	0.0133	0.0127	0.0156	0.0152	0.0142	0.0285	0.0255	0.0230
$\Delta = 1.5$	0.0078	0.0070	0.0068	0.0091	0.0076	0.0072	0.0346	0.0142	0.0097
$\Delta = 2$	0.0094	0.0086	0.0086	0.0097	0.0094	0.0104	0.0195	0.0175	0.0155

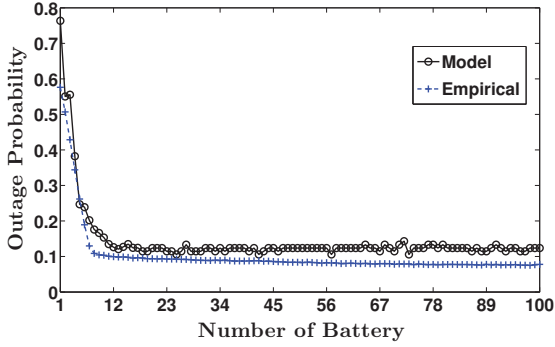


Fig. 6: Outage probability versus number of battery, with panel size $n_{PV} = 5 \text{ KW} < n_{PV_{min}}$ for Ahmedabad city.

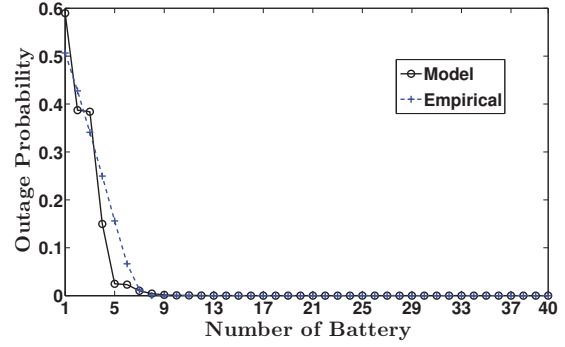


Fig. 8: Outage probability versus number of battery having a PV panel size 16 KW for Ahmedabad city.

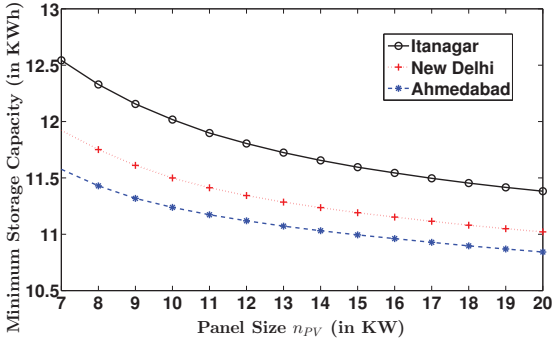


Fig. 7: Minimum storage required versus PV panel size for different cities.

cost. Using the lower bound on panel size and storage capacity, the cost optimal combination is chosen as,

$$\begin{aligned} & \text{minimize} && C_{n_{PV}} n_{PV} + C_B N_{B_T} \\ & \text{subject to:} && n_{PV} \geq n_{PV_{min}} \\ & && N_B \geq N_{B_{min}} \\ & && P_{out} \leq p \end{aligned} \quad (15)$$

TABLE II: COMPARISON OF THREE DIFFERENT COMBINATION OF PANEL SIZE AND NUMBER OF BATTERY HAVING OUTAGE PROBABILITY $P_{out} \leq 0.001$.

	Case 1	Case 2	Case 3
(n_{PV}, N_B)	(10,25)	(11,17)	(12,14)
$Cost_{system}$	17000	15760	15920
$Cost_{optimal}$		✓	
Excess Energy (yearly in KWh)	7.34 $\times 10^3$	9.00 $\times 10^3$	10.57 $\times 10^3$

where n_{PV} is the panel size, N_{B_T} is the total number of batteries used during the entire period of operation, and N_B is the number of battery used at any time in the system. $C_{n_{PV}}$ and C_B are the cost of 1 KW PV panel with 1 KW rating and 12 V 205 Ah lead-acid battery. The run time of 14 years is considered.

The battery life is limited which depends on the number of cycles as well as cycle's depth-of-discharge [22]. The number of cycle is counted using Rain-flow Counting Algorithm [23]. The variation of life of battery against the number of battery is plotted in Fig. 11. One can observe that, as the number of battery increases the battery life also increases. Moreover, a higher panel size leads to a longer battery life.

Let C_{opt} be the cost of the system $(n_{PV_{opt}}, N_{B_{opt}})$ with cost optimality criteria with given outage probability as dis-

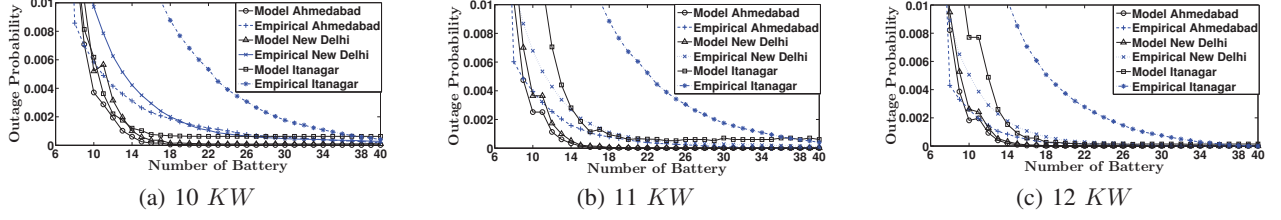


Fig. 9: Outage probability versus number of battery for three cities with different panel sizes (a) 10 KW, (b) 11 KW, and (c) 12 KW.

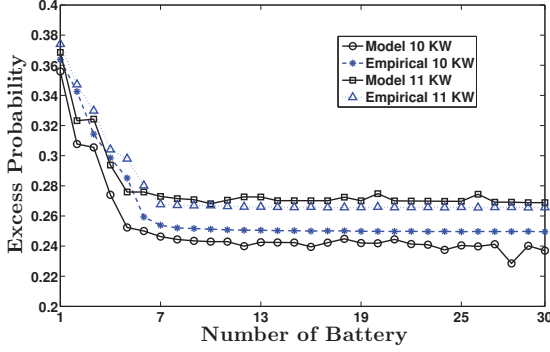


Fig. 10: Excess probability versus number of battery for Ahmedabad city with PV panel of ratings of 10 KW and 11 KW.

cussed in (15). Let $C_{Revenue}(n_{PV}, N_B)$ be the revenue earned by selling the energy back to the grid, which is given as:

$$C_{Revenue}(n_{PV}, N_B) = \sum_{14 \text{ years}} C_{sell}[i] E_{excess}[i]$$

where $C_{sell}[i]$ is the selling price of 1 KWh energy on hour i and $E_{excess}[i]$ is the excess energy generated (in KWh) on hour i with system combination (n_{PV}, N_B) .

Accordingly, the total expenditure to run the system over 14 years with system dimension (n_{PV}, N_B) is given in (16). Here $C_{Ex}(n_{PV}, N_B)$ is total expenditure, $C_{CAPEX}(n_{PV}, N_B)$ is the capital expenditure, $C_{OPEX}(n_{PV}, N_B)$ is the operational expenditure, and $C_{Revenue}(n_{PV}, N_B)$ is the revenue generated by selling the energy.

The utility function is defined as,

$$U(n_{PV}, N_B) = C_{Ex}(n_{PV_{opt}}, N_{B_{opt}}) - C_{Ex}(n_{PV}, N_B) \quad (17)$$

This utility function accounts for net profit over cost-optimal system dimensioning in (15). Hence, our aim is to choose the system combination with maximum utility without degrading the performance. Using the lower bounds on system design,

the utility-optimal system combination is chosen as,

$$\begin{aligned} & \underset{n_{PV}, N_B}{\text{maximize}} && U(n_{PV}, N_B) \\ & \text{subject to:} && n_{PV_{min}} \leq n_{PV} \leq n_{PV_{max}} \\ & && N_B \geq N_{B_{min}} \\ & && P_{out} \leq p. \end{aligned} \quad (18)$$

where p is the outage probability constraint. It takes 5 m^2 space to install a 1 KW PV panel. Keeping this in mind the upper bound on PV panel size is kept $n_{PV_{max}}$. Here $n_{PV_{max}} = n_{PV_{opt}} + 4$ is considered for simulation.

For simulation purpose the cost of selling one unit of electricity i.e. $C_{sell}[i] = \$0.05$ is considered for the total period of operation. The utility-optimal and cost-optimal selections are listed in Table III for different performance constraints. One can observe that significant saving can be achieved if the system is dimensioned using the utility-optimal criteria. Usually the base stations are deployed in bulk by any operator. If the system dimensioning is done according to utility-optimal criteria then significant revenue can be earned without compromising with performance.

It may be noted that, currently the cost of PV panel and battery is higher. However, as the technology advances the efficiency will increase and the cost will decrease. The current analysis and the findings should motivate the operators to look for utility-optimal system design, so that they can earn in the long run without degrading the performance. Along with the economical utility, such systems have significant social impact as well, wherein the solar-enabled base stations assist in renewable energy generation while providing the wireless access support.

VI. CONCLUSIONS

The quantized version of hourly harvested solar energy and consumed energy have been used to analyze the system. The lower bounds obtained on PV panel size and storage capacity provide initial guess as well as reduce the complexity of dimensioning computation. It has been verified that the system performance with PV panel size and storage capacity below a lower bound is unacceptable. A discrete-time Markov chain based model has been presented to estimate the power outage probability. The transition probability depends on the profile of residue energy. A good match between the outage probability

$$C_{Ex}(n_{PV}, N_B) = C_{CAPEX}(n_{PV}, N_B) + C_{OPEX}(n_{PV}, N_B) - C_{Revenue}(n_{PV}, N_B). \quad (16)$$

TABLE III: DIMENSIONING OF SYSTEM ACCORDING TO COST-OPTIMALITY AND UTILITY-OPTIMALITY CRITERIA WITH DIFFERENT OUTAGE PROBABILITY CONSTRAINTS FOR DIFFERENT CITIES.

	Ahmedabad			New Delhi			Itanagar		
	Cost Opti- mal	Utility Optimal	utility (\$)	Cost Opti- mal	Utility Optimal	Utility (\$)	Cost Opti- mal	Utility Optimal	utility (\$)
$P_{out} \leq 0.01$	(8,14)	(12,8)	2076	(8,16)	(12,8)	2329	(13,17)	(16,14)	701
$P_{out} \leq 0.001$	(11,17)	(15,13)	972	(10,23)	(14,13)	1779	(13,24)	(16,17)	1264

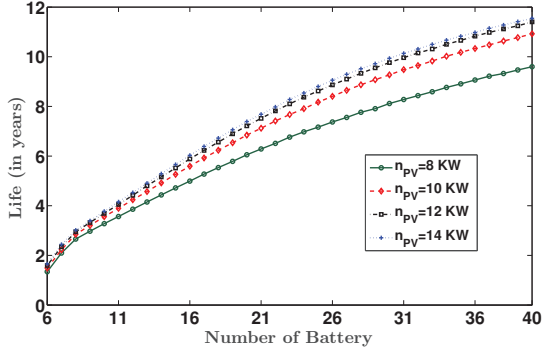


Fig. 11: Battery life versus number of battery for Ahmedabad city with different PV panel size.

obtained from the presented model and empirical data has validated the accuracy of model. It has been noted that, the excess energy produced is neither utilized nor stored, which increases significantly with stringent outage constraint. Taking advantage of smart grid technology, it has been proposed to over-dimension the system where the excess energy is sold back to the grid. A utility function has been defined which accounts for the net profit and the system is dimensioned aiming to maximize the utility. Simulation results have indicated that this simpler non-parametric model works well in efficient system operation.

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