When Telecommunication Networks Meet Energy Grids: Cellular Networks with Energy Harvesting and Trading Capabilities

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Abstract

In this article, we cover eco-friendly cellular networks, discussing the benefits that ambient energy harvesting offers in terms of energy consumption and profit. We advocate for future networks where energy harvesting will be massively employed to power network elements and, even further, where communication networks will seamlessly blend with future power grids. This vision entails the fact that future base stations may trade some of the excess energy that they harvest so as to make profit and provide ancillary services to the electricity grid. We start discussing recent developments in the energy harvesting field, to then deliberate about the way future energy markets are expected to evolve and the new fundamental tradeoffs that arise when energy can be traded. Performance estimates are given throughout to support our arguments and open research issues are discussed for this emerging field.

Index Terms

Energy Harvesting, Energy Trading, Green Networking, Small Radio Cells, capex, opex, Network Deployment.

I. Introduction

Energy efficiency in cellular networks is becoming a key requirement for network operators to reduce their operative expenditure (opex) and to mitigate the footprint of Information and Communication Technologies (ICT) on the environment. Costs and greenhouse gases emissions due to ICT grew in the last few years due to the escalation of traffic demand from mobile devices such as smartphones and tablets. Cloud-based and Internet of Things (IoT) services are expected to exacerbate this negative trend [1].

Network designers have been addressing this by considering hierarchical cell structures, through the so called heterogeneous networks (HetNets), where small cells (i.e., micro or pico) are deployed to increase network coverage, capacity, and decrease the overall energy consumption [2].

In this article, we deliberate on scenarios where harvested ambient energy is employed to steer HetNets toward *nearly-zero* energy consumption and, more than that, where communication networks blend with future electricity grids. With the term nearly-zero we mean that, in the long run, the monetary costs incurred in operating the network are counterbalanced by the revenue from either grid energy savings or energy trading. This vision entails that future network elements may trade some of the energy that they harvest to make profit and provide ancillary services to the power grid. In pico deployments, for instance, this may occur in the form of supporting connected loads, such as street lighting or weather stations. Instead, selling energy to the grid operator may make sense for micro and macro cells where the amount of energy harvested easily matches or surpasses that of residential users.

Among other harvesting technologies, solar power is deemed the most appropriate due to the good efficiency of commercial photovoltaic (PV) panels [3] as well as the wide availability of the solar source for typical installations. The idea of using solar harvesters to power base stations (BSs) has been around since 2001, starting from 2G technology [4]. However, initial studies focused on rural scenarios, where connectivity to the power grid is impracticable. In the last few years, thanks to the reduced power constraints of small BSs and the reduction of the costs of energy harvesting technologies, PV sources are also becoming appealing for urban scenarios, as testified by the vivid literature on this topic [5].

The exploitation of other types of renewable energy, such as wind, is also possible. Due to the limited space, in this paper we will focus on PV technology but we remark that most of the following discussion applies as well to further energy sources.

The viability of a self-sustainable small cell networks has been discussed in [6] and can be achieved through the addition of rechargeable batteries and energy harvesting devices, such as solar panels. This makes it possible to reduce the opex, for what concerns the cost associated with the purchase of energy from the electricity grid. These facts have been analytically studied in [7] to identify availability regions, for uncoordinated BS operating strategies, where the network is energetically self-sufficient. Coordinated control algorithms for hybrid powered architectures are discussed in [8], where the consumption from the electricity grid is reduced through power control strategies and load balancing. Sleep mode control has been investigated in [9], to regulate the BS transmission power.

Here, we approach HetNets design from a fundamentally different angle. Following [10], we advocate for nearly-zero energy networks where the energy, besides being used for self-powering [6]–[9], can also be traded with the electricity grid or with other network elements. Moreover, we foresee that these HetNets will operate within an energy market where the price of energy changes hourly and is set a day-ahead (a contemporary example for this market is commented below). This allows for several new optimizations related to the way energy is consumed, purchased and possibly sold to the grid operator. The nature, benefits and open challenges related to these optimizations constitute the main objective of this article. We stress that, while energy harvesting technology for BSs has been investigated in the literature, energy trading with the smart grid entails a new design philosophy for energy management and networking algorithms, which should interact with or be aware of smart grid optimization procedures.

In the following sections, we start discussing the requirements in terms of panel and battery size where BSs are operated off-grid and where they are grid-connected. We examine the related tradeoffs using realistic traces for the harvested energy, the price of the energy purchased from and sold to the grid and the users' demand profile.

Thus, we analyze whether the capex of providing these BSs with the needed solar add-on can be amortized and how long it takes to return the initial investments.

Finally, we present open research challenges concerning the integration of the foreseen BSs into future energy grids. These, involve the study of a system of systems that arises from the combination of telecommunication networks and electricity grids. According to this vision, telecommunication networks may become active players in the electricity market, providing ancillary services for the energy grid and/or support to connected loads [11]. These aspects are currently unexplored and require a great deal of work, both theoretical and applied.

II. Reference Framework

In Fig. 1 we show our reference diagram for a solar-powered BS. The solar energy is harvested through a solar panel. A management module orchestrates the use of this energy and in particular decides whether to accumulate it in a local energy storage or to sell it to the energy grid. The load corresponds to the BS elements in charge of managing the transmission and reception activities and their power consumption can be modulated as a function of the users' demand, as we detail shortly. Energy can be purchased from the electricity grid when the energy stored in the energy storage and that harvested are not sufficient to satisfy the current cell's load, but it can additionally be sold in case the energy inflow from the solar module is abundant. Similarly, energy can be locally stored, for example, when it is not convenient to sell it (e.g., when the energy price is high), and can be subsequently used to power the BS or sold to the grid operator.

For the moment, we assume that energy can be "sold" without specifying the nature of this action, i.e., whether energy is injected into the power grid or used to power a connected load. We elaborate on this below, where we identify open research challenges. For the energy storage, in the following discussion we consider lithium ion rechargeable batteries, which is the technology of choice at the time of writing. Nevertheless, we note that other options are viable, such as molten salt batteries and fuel cells.

[Fig. 1 about here.]

A detailed energy consumption model of LTE base stations has been proposed in the context of the European project EARTH [2], where the main sources of energy consumption have been identified and evaluated. The power consumption, P_c, of different types of BS considerably differs, ranging from about 1kW for a macro BS, to about 100W for a micro and 10W for pico (at full system load). Following [2], for P_c we consider a linear dependence on the (normalized) load factor ρ:

$$P_c(\rho) = P_0 + \alpha\rho\,,\ \rho \in [0, 1]\,, \tag{1}$$

where P_0 (Watts) is the minimum power consumption for the BS. Denoting the parameter vector by $\overline{p} = (P_0, \alpha)$, for macro, micro and pico cells we respectively have $\overline{p}_{\text{macro}} = (750, 600)$, $\overline{p}_{\text{micro}} = (105.6, 39)$, $\overline{p}_{\text{pico}} = (13.6, 1.1)$.

In the following sections, we discuss suitable models for the hourly price of energy, the amount of energy harvested and the demand profile.

[Fig. 2 about here.]

A. *Hourly Price of Energy and Energy Market*

Most likely, the energy price in future power grids will change hourly. This practice is not yet adopted worldwide but there are relevant programs that already use it. A relevant example can be found in Illinois, US, where electrical companies are offering new hourly electricity pricing programs where energy prices are set a day-ahead by the hourly wholesale electricity market run by the Midcontinent Independent System Operator (MISO). In this way, customers can optimize their usage patterns, saving money in their energy bills. In this article, we use publicly available historical energy price data from these programs to discuss suitable energy management policies.

In Fig. 2, we show a typical profile of the hourly energy prices for the first week of November 2010. The price dynamics follow a regular pattern with a bimodal shape within each day. Note that the price significantly increases during peak hours. In the summer months the price shows a different behavior, i.e., it is bell-shaped with a single maximum around midday. This is due to the impact of air conditioning, which is heavily used during the warmest hours.

A further important observation is in order. Up to now, communications networks have been mostly optimized for communication performance or in terms of energy efficiency, which entails a diminished cost in purchasing the energy required for operating the communication apparatuses. However, energy harvesting and future market policies will permit at least two additional optimization strategies. First, the system could adapt its behavior to the energy price, i.e., it could be energy frugal when the energy cost is high, whilst adopting more aggressive policies when the cost drops. Second, part of the energy that is accumulated could be sold or re-distributed among other network elements. As shown in Fig. 2, the peak in the energy harvested may not always occur when the price is maximum. Thus, as we show below, it may be worth temporarily saving the harvested energy for selling it later, thus achieving a higher revenue.

These facts may revolutionize the way we design communication systems, going from a solely communication-performance oriented approach to an energy-market oriented one.

B. Harvested Energy and Demand Profiles

Hourly energy generation traces from a solar source have been obtained for the cities of Los Angeles (CA) and Chicago (IL), US. For the solar modules, we have considered the commercially available Panasonic N235B photovoltaic (PV) technology. These panels have single cell efficiencies as high as 21.1%, which ranks them amongst the most efficient solar modules at the time of writing, delivering about 186W/m^2. For the results that we discuss in this article, raw irradiance data were collected from the National Renewable Energy Laboratory [12] and converted, accounting for this solar power technology, into harvested energy traces using the SolarStat tool of [13].

We note that energy harvesting traces are generally bell-shaped with a peak around midday, whereas the energy harvested during the night is negligible. We also note, as discussed in [13], that there may be a high variability in the energy harvested during the day and this also holds for the summer months. This means that, although the energy inflow pattern can be known to a certain extent, intelligent and adaptive algorithms that make their decisions based on current and past inflow patterns as well as predictions of future energy arrivals have to be designed. While these are being extensively studied by the wireless sensor networks community, much still has to be done for cellular systems.

For the demand profile, it is commonly accepted and confirmed by measurements that the energy use of base stations is time-correlated and daily periodic. In this article, we use the load profiles obtained within the EARTH project and reported in page 25 of [14].

III. OFF-GRID DEPLOYMENTS OF SOLAR POWERED BASE STATIONS

Next, we consider the setup of Fig. 1, where a BS collects renewable energy from a solar panel and uses it for self-powering. Some of the excess energy can be temporarily accumulated in a local energy buffer (battery) and used at a later time when the energy harvested is scarce or null. The BS operates off-grid and the above models are accounted for the energy harvested and the cell load. Here, we are concerned with the right sizing of solar panel and battery, so that the BS can be perpetually operated without having to buy energy from the electricity grid.

[Fig. 3 about here.]

With the term *outage probability* we refer to the fraction of time during which the BS is unable to serve the users' demand due to an insufficient energy reserve. In that case, the BS has to be momentarily switched off or put into a power saving mode. The contour plot for the outage probability for micro cells is shown in Fig. 3 considering solar traces from Los Angeles. Different colors are used to indicate outage probability regions (maximum outages are specified in the associated color map). The white filled area indicates the parameter region where the outage probability is smaller than 1%. The outage probability graphs for pico and macro cells are not given due to space constraints; the corresponding plots show a similar trend, rescaled to higher (macro) or smaller (pico) values along both axes.

From Fig. 3, we see that panels of size smaller than 15 square meters and battery capacities of at most 150Ah at 24V suffice for micro cells. For pico and macro deployments, solar panels range in size from 0.7 to 1.4 square meters (pico) and from 40 to 80 square meters (macro) and battery capacities form 20 to 90Ah at 12V (pico) and from 300 to 1500Ah at 48V (macro). Taking an outage of 1% as our design parameter, all the points on the boundary of the white-filled region are equally good. If we further consider the harvesting hardware cost (capex), the best solution additionally depends on the revenue that can be accrued when the BS is grid-connected and energy can be traded, as we shall see below.

The results for the city of Los Angeles are rather good, indicating that the nearly-zero energy is indeed a feasible goal. In fact, both battery and panel sizes are acceptable given the dimensions of typical installation sites for the considered BSs. Instead, for the city of Chicago the energy inflow is less abundant, and this is especially so during the winter months. In that case, reasonable panel and battery sizes (even slightly higher than those discussed for Los Angeles) lead to outages of 10% or higher. Due to this, grid-connected operation is required for locations where the energy inflow is moderate (especially during the winter).

IV. Grid-connected Deployments: Energy Trading and Optimization

A. *Energy trading policy*

Now, we take hourly energy prices into account (see Fig. 2) and consider a grid-connected BS. The system evolves in slotted time t, where the slot duration is one hour. At any given time t, the BS may sell or buy a certain amount of energy e_t, which is positive when energy is sold and negative when purchased. When energy $e_t < 0$ is purchased from the grid operator, a monetary cost $C(e_t)$ is incurred, which corresponds to the price of energy in slot t. Instead, when energy $e_t > 0$ is sold, a reward $R(e_t) = rC(-e_t)$ is accrued, with $r \leq 1$ being a discount factor. This means that the energy sold is paid less than that purchased, as this is usually the case in current energy markets and is expected to remain so for future ones. Also, we use $C(e_t) = 0$ for $e_t \geq 0$ and $R(e_t) = 0$ for $e_t \leq 0$, meaning that no cost is incurred when selling and no reward is accrued when buying.

At each time t, the demand d_t has to be fully served and the energy required to do so is harvested, taken from the battery or bought from the grid. The energy manager of Fig. 1 intelligently chooses in which amounts and when energy e_t (the decision variable) has to be purchased or sold so that the system maximizes its profit. This corresponds to maximizing the total monetary reward, expressed as $f(T) = \sum_{t=0}^{T}[R(e_t) - C(e_t)]$, over the time horizon of interest $t \in \mathcal{T}$ (with $\mathcal{T} = \{0, 1, \ldots, T\}$). The solution to this problem amounts to finding the optimal allocation $\{e_t^*\}_{t\in\mathcal{T}}$ for all time slots $t \in \mathcal{T}$. Here, we do so through dynamic programming considering the above traces for hourly energy prices, user demand and harvested energy.

In Fig. 4, we show the optimal allocation e_t^* for the third week of November 2010 for the city of Los Angeles, considering a discount factor $r = 0.5$ for the energy sold and a micro cell with a panel of 10 square meters and a battery of 90Ah (at 24V). For the sake of illustration, the temporal traces of energy price ($cent/kWh) battery state (Ah) and harvested current (Ah) are also shown. From these results, various interesting observations can be made.

[Fig. 4 about here.]

During Monday and Wednesday (see labels (a) and (c) in the figure) it is optimal to sell energy during the day and, correspondingly, e_t^* shows two positive peaks. The first occurs because the energy inflow is abundant and the price of energy is also high. Note that not selling in this case would imply to discard the excess energy as the battery size is insufficient to store it in full; this is inefficient and would lead to a loss of revenue. For the second (smaller) peak, the BS sells part of the energy that has been previously accumulated and this is done in correspondence of the second maximum for the price. However, not all the energy is sold, but a certain amount of it is retained to power the BS during the night, where the harvested energy inflow is null (see (d)). For Tuesday (b), we have an additional small peak in e_t^* in the early morning as the price of energy is high and there is some residual energy in the battery. For Thursday (labels (d) and (e)), e_t^* shows a single positive peak: here, the inflow is so abundant that cannot be entirely stored in the battery and not selling it would imply a loss of revenue, as seen for (a) and (c). Moreover, there are no further selling events because the energy harvested during the next two days is modest. Thus, the optimal policy prefers to retain energy in the battery (see (d)) to keep the BS operational. Note also that (see (e)) some additional energy has to be purchased (see the negative peak in e_t^*) and this occurs during the night, where the price of energy is minimum. Finally, for Saturday (f) we have again two positive peaks but the first is considerably smaller due to the smaller amount of energy harvested in this day.

Note that these results are obtained offline, given a full knowledge of all processes for the considered time horizon. Online and predictive algorithms are still an open research topic.

B. Amortizing the capex

Here, we additionally consider the solar panel size and the battery capacity as optimization variables. Our task is to dimension the solar add-on in order to maximize the net profit, considering an amortization period T of ten years and given that the optimal policy e_t^* is used throughout. The net profit over this period is obtained summing the revenue $f(T)$ to the cost incurred when the BS is powered in full by the energy grid, and subtracting the capex associated with the resulting harvesting hardware.

For the following example results, we have accounted for the current price of solar panels, which is about 0.5\$/kWh and a battery cost of 300\$/kWh. Tab. I shows the 10-year net income for pico, micro and macro cells. According to the considered capex cost, optimal designs tend to pick smaller battery capacities and invest more on solar modules. In the table, two designs D1 and D2 are shown for each type of BS, where D2 returns the maximum net profit within the considered parameter range. Notably, a positive income is accrued in almost all cases. As expected, Los Angeles allows for higher revenues due to the more abundant energy inflow that is experienced at that location. D1 was added to show that even a suboptimal design, which may be required due to space limitations, still provides positive incomes and is a sensible alternative. The only case returning a negative net profit is Chicago for Macro BSs, where an additional year (eleven years) would be required to amortize the capex.

[TABLE 1 about here.]

As one may expect, the actual sizing for the solar add-on depends on the energy selling price as well as on the location. Nevertheless, the rather good results that we have shown here are encouraging. These, are due to the modest cost of PV technology, that has been plummeting over the last decade (10-fold reduction). In addition, we observe that while commercial panels at the time of writing have maximum efficiencies of about 21%, new developments with efficiencies as high as 44% are on the way [3]. The battery cost is still rather high, but trends are encouraging for it as well. As an example, since 2008, the cost reduction has been of about one third for lithium ion cells, which is the technology of choice at the time of writing. These facts can be found in numerous reports, see, e.g., [15] and allow us to assert that the scenarios envisioned here are already feasible and are expected to become even more appealing in the near future, as the harvesting capex will further drop and PV efficiencies will improve.

The following observations are in order. First, we note that further optimizations in the BS energy consumption model, although not considered here, are possible. For example, the design of energy efficient sleeping modes is expected to be a very effective means to further reduce the energy consumption figure. Their exploitation could lead to further savings by selectively switching-off some of the BSs (note that sleeping modes should be designed to allow for quick transitions into the active state as soon as new traffic is detected). Second, we remark that with the advent of 5G mobile systems, the cell demand is expected to further increase with respect to the traffic volume that we have considered here. This will not affect the energy consumption of small cells, as their energy expenditure only marginally depends on the load ρ, and will have a minor impact on micro cells (see (1)). The results for macro deployment may however be affected by a higher load, due to their larger α parameter (see again (1)). However, this may be partially mitigated by the massive deployment of small cells, which are expected to offload macro BSs and by further optimizations that are among the objectives of 5G.

V. Research Challenges

Building on the above discussion, we believe that nearly-zero energy cellular networks are fertile ground for research, both theoretical and applied.

Research challenges go from the optimal energy management of federations of small cells to their active involvement as actors of future energy grids and new energy trading models. Moreover, while some technical work has been performed on the energy management (in terms of, e.g., load balancing and BS ON/OFF switching) for federations of small cells, much still has to be done for the scenario of this article, where cells harvest ambient energy and sell or transfer part of it to other network elements. To the best of our knowledge, these aspects are currently unexplored. Next, a few fundamental problems are identified and discussed.

A. Optimal Energy Management of Federations of Small Cells

Here, we envision a network setup where hierarchical cell structures are deployed within the same geographical area (e.g., a district), and possibly operated off-grid. Modulating the user profile has a modest impact for pico cells (variations in the load ρ only marginally affect their energy consumption). Thus, it may make sense to think of installations where some BSs are temporarily put into some power saving state. The cells that are still active will provide the needed coverage, whereas the remaining ones will recharge their batteries. This dynamic management is required as the renewable energy inflow may differ from cell to cell depending on obstructions from objects, which will cause partial shading of the irradiated solar power.

This calls for smart algorithms that take into considerations aspects such as load balancing among the cells and the need for offloading some of the traffic from the macro cells in the area. Note also that, although no energy can be traded by the cells when these are operated off-grid, their presence is expected to relieve some demand from the macro cells in the area by substantially reducing the energy that the latter purchase from the power grid. Hence, although no direct energy transfer occurs, the discussed offloading mechanism is expected to provide economical savings for macro-BS operators.

B. QoE and Energy Harvesting Aware Streaming

There is a large body of work concerning the optimization of routing for multimedia traffic for an increased Quality of Experience (QoE). This has to do with the selection of the access point, but also with routing strategies within the fixed portion of the network. These algorithms are usually based on measures of congestion and on the on-the-fly estimation of the quality perceived by the end users. Current adaptation strategies act on the degree of compression of audio/video streams (video coding rate), their transmission rate, power and, possibly, their routing path.

Here, we support the use of additional information to model the residual energy at the mobile user and at the base station(s), and the status of the corresponding energy harvesting process(es). Future adaptation policies could then take these further aspects into account, to deliver the expected target QoE at the end user side, under the energy sustainability constraints of the system.

C. Blending Mobile Networks with Power Grids

With the possibility of trading energy with the grid, future communication networks will become active actors in future smart energy grids. The energy injected by BS deployments could be used to provide ancillary services for power grids such as load balancing and compensation, peak shaving or, e.g., the reduction of power distribution losses through the injection of controlled amounts of power [16]. This especially holds for micro and macro cells, whose generated energy will easily surpass that of residential users. For pico deployments, we may imagine the support of connected loads, such as weather stations, street lightning or IoT networks for traffic control in smart cities. In addition, we may think of massive installations where energy aggregators will be in charge of trading the energy generated by a myriad of distributed small cells.

According to this vision, telecommunication infrastructures will additionally manage their internal resources in terms of trading with the electricity grid, possibly benefiting its efficiency. This may benefit from the adoption of demand/response strategies managed by electric utilities [11]. Moreover, this will only work if proper pricing schemes will be in place, which should incentivize BSs to sell their excess energy, while also making these transactions convenient for the electricity grid.

These aspects are still unexplored and their study requires optimization frameworks that jointly account for telecommunication and grid aspects under radically new market models. In addition, co-simulation tools are essential to assess the performance of such a complex system.

VI. Concluding Remarks

In this article we have made the case for nearly-zero energy cellular networks, where excess energy can be traded with the electricity grid to make profit and provide ancillary services. To support this vision, we have provided quantitative performance examples, using real data traces, and have elaborated on challenging and new research issues. The foreseen technology positions itself at the intersection between the telecommunications and the power grid fields and its success requires cross-disciplinary research involving tools from telecommunications, operations research, economics and smart grids. The authors believe that this technology holds a huge potential and will lead to an exciting new field.

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VII. Biographies

Davide Zordan received the M.Sc. in telecommunications engineering and the Ph.D. degree from the University of Padova (Italy) in 2010 and 2014, respectively. He is currently a postodoctoral researcher at the Department of Information Engineering, University of Padova. His research interests include stochastic modeling and optimization, protocol design and performance evaluation for wireless networks, in-network processing techniques (including Compressive Sensing), energy efficient protocols and energy harvesting techniques for WSNs and wearable IoT devices.

Marco Miozzo is a researcher at the Centre Tecnològic de Telecomunicacions de Catalunya and a PhD student at the Technical University of Catalonia (Barcelona, Spain). His main research interests are in mobile networks, green communications, and mobile networks with energy harvesting capabilities. Marco Miozzo holds a Master in telecommunications engineering from the University of Ferrara, Italy.

Paolo Dini is with CTTC from 2006. His research interests encompass wireless networks modelling and optimization, with particular emphasis on energy saving and energy efficiency, integration of renewable energy sources in mobile network equipment, energy sustainable network architectures and protocols, self-organizing networks, cognitive networking, radio resource and mobility management, quality of service/experience provision. He is author of around 40 papers in scientific journals and international conferences.

Michele Rossi is an Assistant Professor at the Department of Information Engineering, University of Padova, IT. His current research interests are centered around Wireless Sensor Networks (WSN), Internet of Things (IoT), telecommunication and optimization aspects of Smart Power Grids and energy harvesting mobile networks. He has recently initiated a research line on signal processing (feature extraction and compression) for wearable IoT devices. In the last few years, he has been actively involved in EU projects on IoT technology and has collaborated with Worldsensing (Barcelona, ES) in the design of optimized WSN solutions for smart cities. He is author of more than 100 scientific papers published in international conferences, book chapters and journals and has been the recipient of four best paper awards from the IEEE. Dr. Rossi is currently serves on the Editorial Board of the IEEE

Transactions on Wireless Communications and is a Senior Member of the IEEE.

List of Figures

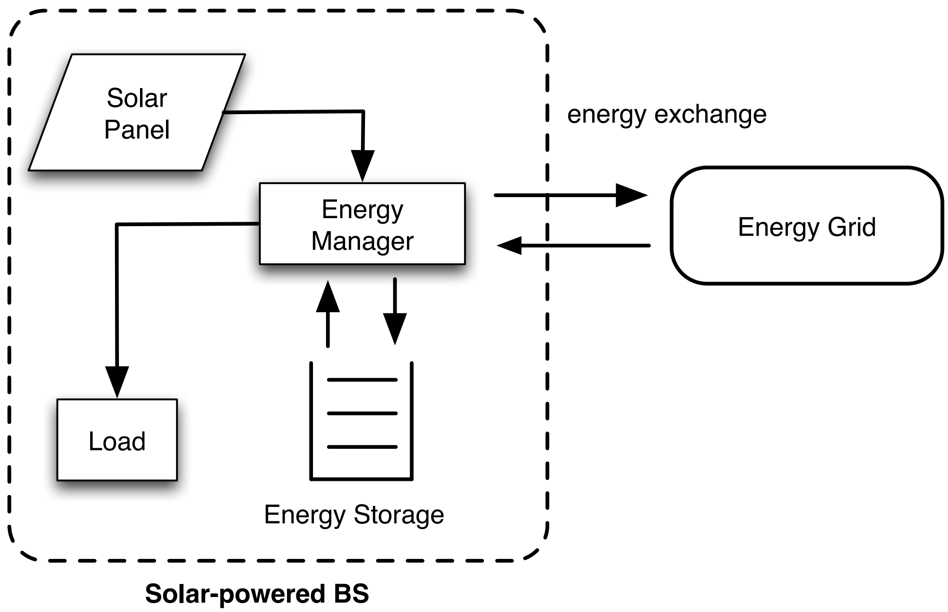

Fig. 1. Reference diagram for a solar-powered BS.

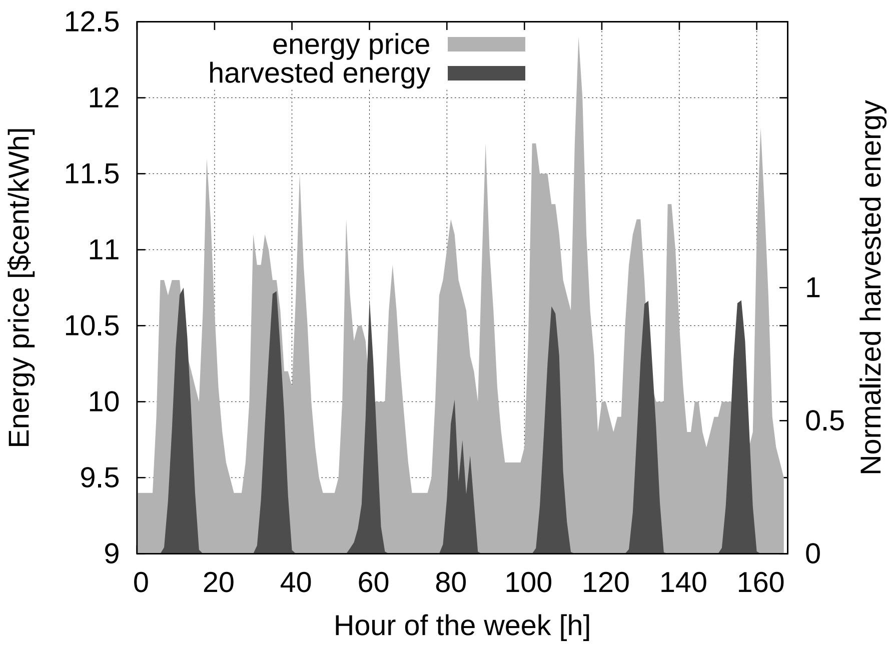

Fig. 2. Hourly energy price and harvested energy for the state of Illinois, US, during the first week of November 2010 (Monday goes from hour 0 to hour 23, Sunday goes from hour 145 to hour 168). The maximum harvested energy during the week is 123Wh for a solar panel of 1.2 square meters.

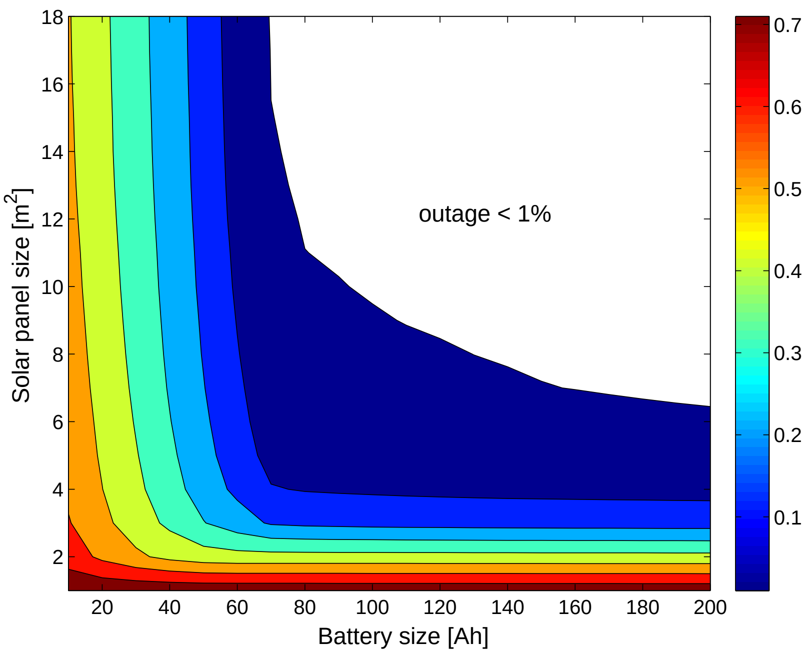

Fig. 3. Contour plot of the outage probability for a micro cell operated off-grid (battery voltage is 24V). Different colors indicate outage probability regions, whose maximum outage is specified in the color map in the right hand side of the plot. The white filled region indicates an outage probability smaller than 1%.

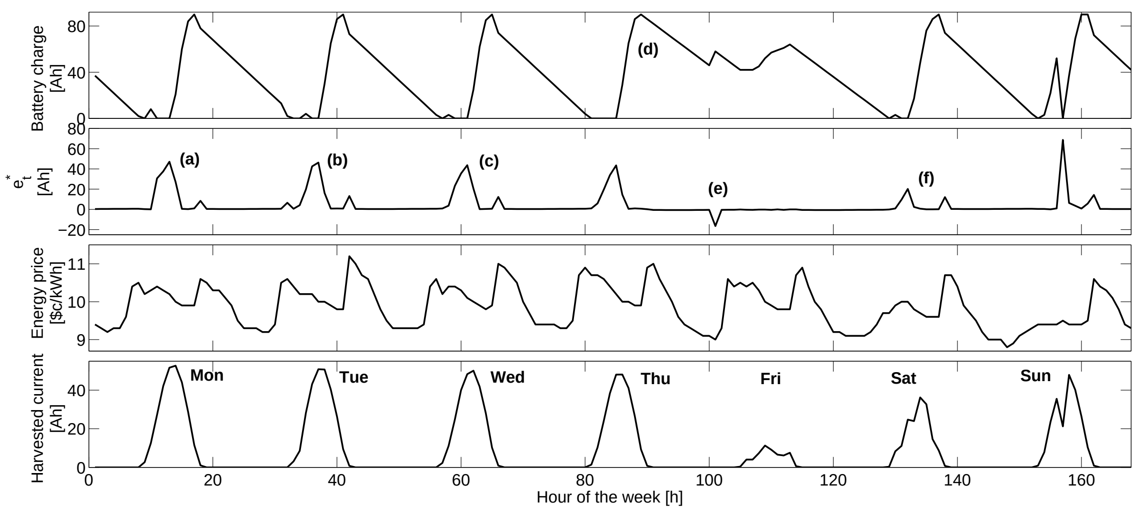

Fig. 4. Optimal energy trading policy for the third week of November 2010 (Monday goes from hour 0 to hour 23, Sunday goes from hour 145 to hour 168). Price data has been taken from the Power Smart Pricing program. Energy harvesting traces are for the city of Los Angeles, CA, US.

List of Tables

TABLE I

NET INCOME AND ANNUAL REVENUE FOR DIFFERENT CONFIGURATIONS. FOR THE NET INCOME THE NOTATION IS "$X\$$ (Y, Z)", WHERE X IS THE NET INCOME IN US DOLLARS, Y IS THE SOLAR PANEL SIZE (SQUARE METERS) AND Z IS THE BATTERY SIZE (AH). 12, 24 AND 48VOLT BATTERIES ARE RESPECTIVELY IMPLIED FOR PICO, MICRO AND MACRO BSS.

	Chicago			Los Angeles		
BS type	D1 (net income)	D2 (net income)	D2 (annual revenue)	D1 (net income)	D2 (net income)	D2 (annual revenue)
Pico	19\$ $(1, 20)$	58\$ $(2, 20)$	71\$	51\$ $(1, 20)$	117\$ $(2, 20)$	130\$
Micro	232\$ $(10, 80)$	607\$ $(20, 80)$	709\$	544\$ $(10, 80)$	1193\$ $(20, 80)$	1295\$
Macro	−1566\$ $(60, 500)$	−695\$ $(80, 500)$	1395\$	446\$ $(60, 500)$	1813\$ $(80, 500)$	2568\$