Radio resource management for improving energy self-sufficiency of green mobile networks

Mattia Dalmasso  
Department of Electronics and Telecommunications  
Politecnico di Torino, Italy  
mattia.dalmasso@studenti.polito.it

Michela Meo  
Department of Electronics and Telecommunications  
Politecnico di Torino, Italy  
michela.meo@polito.it

Daniela Renga  
Department of Electronics and Telecommunications  
Politecnico di Torino, Italy  
daniela.renga@polito.it

ABSTRACT

Three factors make power supply one of the most urgent and challenging issues for the future of mobile networks. First, the expected fast growth of mobile traffic raises doubts about the sustainability of mobile communications, that already account for 0.5% of the world-wide energy consumption. Second, power supply has become far the largest component of the operational costs of running a network. Third, the deployment of network infrastructures in emerging countries is strategic, but, in these countries, the power grid is not always reliable. Renewable energy sources can help to cope with these issues. However, one of their main drawbacks is the intermittent and difficult to predict energy generation profile. The feasibility of renewable power supply for base station (BS) powering depends then by the possibility to reduce the BS consumption and to adapt it to the amount of available energy.

In this paper, we consider a cluster of BSs powered with photovoltaic (PV) panels and equipped with energy storage units. Resource on Demand (RoD) strategies are implemented to reduce the cluster energy consumption and to adapt to energy availability. The results show that resource of demand can effectively be applied to make off-grid BS deployment feasible.

Keywords

Smart grid; Mobile access network; Resource on Demand; Energy efficiency

1. INTRODUCTION

The wide expansion of wireless data communications observed in recent years raises some major issues in relation to energy consumption and efficiency in mobile networks, that need to be properly addressed. Cellular networks are significant contributors to the global energy consumption, with a 0.5% share of the total energy supply worldwide [1]. A significant fraction of this consumption, between 60% and 80%, is accounted for by the access segment of 3G and LTE mobile networks [5]. Given the increasing deployment of mobile infrastructures, with the number of base station (BS) installations already exceeding 4 billions in 2012 [1], the need for reducing energy consumption and limiting the associated cost is becoming even more urgent. A promising solution is represented by the introduction of renewable energy (RE) to power BSs. RE power supply for BSs has been deployed especially in emerging countries, where the absence or unreliability of the traditional grid in remote areas has often led to diesel generators, with high cost for the fuel and its transportation. It is expected that in the period 2012-2020 more than 390,000 new RE powered BSs are installed worldwide [1].

Given the intermittent and unpredictable nature of RE production, the design of the BS power supply requires a careful dimensioning of the generators and energy storage capacity. Moreover, the possibility to introduce techniques to adapt the electric load of the BS (i.e., its consumption) to energy availability is very interesting. Among the works available in literature investigating the impact of using RE to power BSs, some are related to the proper dimensioning of photovoltaic (PV) panels and storage, based on solar radiation [1], others study the interaction with the grid, focusing on cost evaluation [7]. The introduction of RE alone may help to reduce the energy cost but it may not be sufficient to make the mobile network completely self-sufficient in terms of energy consumption. Typically, the traffic load in a mobile access network dynamically varies over time and peak loads are achieved only for limited periods. Hence, the deployed radio resources result to be redundant for a considerable fraction of time. RoD strategies allow to target this issue by dynamically adapting the available radio resources to the current actual energy need of the network [3]. Based on user demand, unnecessary BSs can be turned off when the load is low and energy can be saved. In this work, we study how the application of a RoD strategy affects the operation of a mobile access network in which BSs are powered by PV panels and equipped with energy storage units. We investigate the effectiveness of the RoD strategy in reducing the energy need of the green mobile system, and evaluate the impact of the strategy on the energy storage and PV panel dimensioning.

2. GREEN MOBILE ACCESS NETWORKS

In this study, a portion of a LTE mobile access network is considered, consisting in a cluster of one macro BS providing coverage over a wide area and N micro BSs providing additional capacity needed for peak demand. Besides receiving energy from the grid, this cluster of BSs can be powered by renewable energy produced by PV panels. RE production is typically intermittent and not always proportional to energy...
needs varying over time. Each BS is hence equipped with a storage device, where RE exceeding current BS demand can be saved for future usage. The system is now presented in more details, by considering first the BS consumption model and then describing the RE production and storage components.

2.1 BS consumption model

BS power models have a part that is fixed and independent on the traffic and a part that is load proportional. The proportionality with traffic load is mainly due to the Power Amplifier (PA) component of the transceiver, whose consumption scales down in case of lower traffic load. The load proportionality is more evident for macro BSs, where more than 55% of the overall power consumption at full load is accounted for by the PA. On the contrary, the PA component is responsible for less than 40% of the whole power consumption in a micro BS, making it less load dependent [2]. The BaseBand (BB) processor component of power consumption, which is load independent, amounts up to 38% in the latter case, almost 3 fold the value observed in macro BSs [2].

In our work, the input power required for the BS operation, denoted as $P_{in}$, is derived according to the linear model proposed in [2]:

$$P_{in} = N_{TRX} \cdot (P_0 + \Delta_p \cdot P_{out}), \quad 0 < P_{out} < P_{max}$$  \hspace{1cm} (1)

where $N_{TRX}$ is the number of transceivers, $P_{max}$ is the maximum radio frequency output power at maximum load, $P_0$ represents the power consumption when the radio frequency output power is null and $\Delta_p$ is the slope of the load dependent power consumption; denoting the load with $\rho$:

$$P_{out} = \rho \cdot P_{max}, \quad 0 \leq \rho \leq 1$$  \hspace{1cm} (2)

Table 1 shows the value of the parameters for macro and micro BSs [2].

In the following, we will also consider the case of micro BSs in sleep mode. The consumption of the BS in sleep mode is considered negligible.

2.2 RE production and storage

Each BS is equipped with PV panels made up by multiple PV modules, whose nominal capacity, expressed in peak W [Wp], is given by the maximum DC output power that can be produced, under standardized environmental conditions, for the conversion of sun radiation into electricity. Given a unitary capacity of 1 kWp, the physical area of the corresponding PV panel depends on the module efficiency which, in turns, varies according to the adopted PV technology and the environmental conditions. In our case, one of the most efficient crystalline silicon PV modules is considered: the efficiency is 19% and the PV panel area is about 5 m² per kWp [4]. In this work, we denote as $S_P$ the nominal capacity of the PV panels.

Data about RE production in a specific location are obtained by means of the tool PV-Watts [4]. They are derived based on real daily solar irradiation patterns, varying day by day across the typical meteorological year in the city of Turin, with a granularity of half an hour. The main typical losses occurring in a real PV system during the process of solar radiation conversion are taken into account.

For energy storage, lead-acid batteries are adopted here, one of the most commonly adopted storage technology for PV systems [8]. Unitary elements have capacity of 200 Ah and voltage 12 V. We denote as $S_B$ the storage capacity, defined as the number of battery units used in the system to save RE for future usage. To maximize the battery life-cycle duration and optimize the charging efficiency, a maximum Depth of Discharge (DOD) of 70% is considered in this study. This DOD value allows the battery to operate for more than 500-600 cycles before being replaced [1, 9]. Losses due to charging and discharging processes, responsible of a 25% loss in energy efficiency [6], are taken into account in the simulation.

Although PV panels and battery sets are assumed to be physically distributed among the various BSs of the cluster, a centralized management of these resources for RE production and storage is envisioned in our system, with a central controller handling the information exchange for proper system operation. Therefore, in the simulations, the distributed PV panels and batteries are treated as a unique PV system and a single storage unit, with which any BS can freely interact for both storing extra amounts of produced RE and draining energy. Storage losses occurring during energy transmission are neglected. The sizing of PV panels and storage is performed without taking into account the deterioration of PV module and battery efficiency occurring over years as time goes by.

3. RESOURCE ON DEMAND APPROACH

Resource on Demand (RoD) strategies are often used in wireless networks to reduce energy consumption, since they dynamically adapt the available radio resources to the varying user demand [3]. The application of RoD strategies to our scenario is expected to have an impact in both reducing the dependence on the traditional grid and limiting the dimensioning of PV panel and storage size, thus allowing more feasible solutions for a green mobile access network. According to the RoD strategy adopted in our scenario, the user demand is measured in terms of traffic load and unnecessary radio resources are turned off when traffic load is low.

![Figure 1](image-url)  \hspace{1cm} Figure 1: Weekday normalized traffic profiles for Business and Consumer Area (BA and CA).
3.1 Traffic

To evaluate the effectiveness of RoD, the system has been investigated not only under real conditions of RE production but also of traffic. Real traffic traces obtained from an Italian network operator have been used for this study [3]. Two scenarios are considered: a consumer area (CA), dominated by residential users, and a business area (BA). Traffic data are provided with a granularity of half an hour. Fig. 1 reports the average daily traffic patterns during the weekdays and the weekend observed in a sample week. In a typical weekday, in the BA (continuous red curve, with circles) the traffic remains very low during the night hours, and sharply increases from 8 a.m. until lunchtime, when a temporary decrease is observed, then raising again before a new decrease starts at mid afternoon. The traffic pattern in the CA (continuous blue curve, with squares) shows a different behavior. A slow traffic increase is observed in the morning, lasting for the whole day, with peak in evening hours and some traffic persisting during night. During the weekend, in case of CA (dashed red curve, with circles), the traffic pattern results rather similar to weekdays, except for a steeper ascent during daytime hours, with an earlier peak; by converse, the BA traffic (dashed blue curve, with squares) results always very low in the weekend. These traffic patterns clearly show that outside the peak hours there are some periods of time during the day in which the radio resources are redundant with respect to the actual demand and a lot of energy is wasted. If the unnecessary resources can be turned off in case of low traffic, potentially high amounts of energy can be saved. The margin for saving energy may vary depending on the different day types and traffic areas. Furthermore, the potential amount of saving may be influenced by the traffic load varying for each BS, by the adopted RoD strategy and the configuration settings of its parameters.

Within each coverage area of any macro and micro BSs, the same pattern of normalized traffic load is assumed, either consumer or business. Each micro BS is in charge of handling the traffic share exchanged in its area of coverage. Although the shape of the normalized traffic is the same for all the N micro BSs, the amplitude of the actual traffic curve, hence the absolute value of peak traffic, may vary among the various micro BSs. The ratio between the traffic load of each micro BS and that of the macro BS is expressed among the various micro BSs. The ratio of traffic load of each micro BS and that of the macro BS is expressed by the parameter $\mu_i \in (0,1]$, with $i = 1, 2, ..., N$ and $N$ is the number of micro BSs in the cluster.

3.2 RoD strategy

The basic idea of the proposed RoD policy is quite simple. We define a time window over which the cluster can be reconfigured and some micro BSs can be switched off (we assume a time window of half an hour to avoid frequent system reconfigurations). At the beginning of each window, in case of low traffic, one or more micro BSs are put to sleep mode, i.e., they are turned off, and their traffic is moved to the macro BS, as long as the macro BS has enough capacity to handle the traffic. The same maximum capacity, denoted as $C$, is assumed for all the BSs. We, thus, define a threshold, $\rho_{\text{min}}$, over the traffic load of micro BSs. At every system check granularity, a set $S$ of BSs is switched off if the two following conditions hold:

$$\begin{align*}
\lambda_i \leq \rho_{\text{min}} \\
C_r = C - \lambda_M \geq \sum_{i \in S} \lambda_i
\end{align*}$$

where $\lambda_M$ is the current traffic load of the macro BS and $C_r$ represents the residual capacity in the macro BS.

For simplicity, we assume that micro BSs can be switched on and off in negligible time. Indeed, switching can take up to a few minutes and this time can be considered negligible with respect to the time window of half an hour that we use to decide possible system reconfigurations.

4. PERFORMANCE EVALUATION

The impact on our system of the application of the proposed RoD strategy has been investigated by performing several simulations over one year in a scenario with 1 macro and 6 micro BSs, either in a CA and in a BA. Different configuration settings in terms of $\mu_i$, $\rho_{\text{min}}$, PV panel size ($S_P$) and storage capacity ($S_g$) have been tested. The deployed simulator operates with a 30 minutes time slot granularity. At the beginning of each simulation, the batteries are assumed to be completely full.

4.1 Finding optimal thresholds for RoD

We first study the impact of the parameter $\rho_{\text{min}}$ that defines the threshold on the load of the micro BSs below which a micro BS is switched off and its traffic moved to the macro BS. Fig. 2 shows the total energy consumption with respect to the case with all the BSs always active for increasing values of $\rho_{\text{min}}$. Each curve corresponds to a different scenario in terms of relative traffic load; the values of $\mu_i$ are reported in the legend. Both the cases of CA and BA are considered. When no strategy is applied, the yearly overall consumption, denoted as $E$, is similar in the CA (12.148 MWh) and in the BA (11.672 MWh). Nevertheless, under RoD, up to 38% of energy can be saved in the BA, almost twice the maximum saving obtained in CA. Due to the steeper transition between peak and off-peak periods and to the low traffic load during the weekend, the business traffic profile leads to lower energy consumption than the CA profile.

Figure 2: Energy consumption in CA and BA, in different scenarios of traffic load distribution among micro BSs: $\mu_{\text{array}} = [\mu_1, \mu_2, ..., \mu_6]$

For low values of $\rho_{\text{min}}$, the energy consumption rapidly decreases as $\rho_{\text{min}}$ increases; indeed, the RoD kicks into play...
often and for long periods of time. For the same reason, the steep decrease becomes more evident for those scenarios in which some BSs are less loaded. The advantage of RoD stabilizes for larger values of \( \rho_{min} \). This is due to the different relative cost of carrying traffic through the macro and micro BSs. To investigate this, consider the total power consumption \( P_{tot} \) of the macro and micro BSs carrying a traffic \( \lambda \).

The consumption consists in a constant component and a load proportional component and can be expressed by using two coefficients, \( A \) and \( B \), according to the following formula:

\[
P_{in} = A + B \cdot \lambda
\]

where \( A = N_{TRX} \cdot P_0 \) and \( B = N_{RX} \cdot \Delta P \cdot \rho_{max} \). Denote by \( G \) the cost, in terms of energy, derived from switching off the \( i^{th} \) micro BS and transferring its traffic load \( \lambda_i \) on the macro BS:

\[
G = E_{off} - E_{on}
\]

where \( E_{off} \) is the energy consumption when the traffic of the micro BS is moved to the macro BS, while \( E_{on} \) is the consumption when both BSs are kept active. Hence:

\[
G = A_M + B_M \cdot (\lambda_M + \lambda_i) - (A_M + B_M \cdot \lambda_M + A_m + B_m \cdot \lambda_i)
\]

(6)

where \( M \) and \( m \) stand for macro and micro BS respectively. A negative cost (i.e., a saving) is guaranteed for \( G < 0 \), hence for:

\[
B_M \cdot \lambda_i - A_m - B_m \cdot \lambda_i < 0
\]

(7)

\[
\lambda_i < \frac{A_m}{B_m - B_m}
\]

(8)

When (8) is not satisfied, the additional cost to carry the traffic of the micro BS through the macro BS does not compensate the saving that can be achieved by switching off the micro BS. Hence, switching off is of no advantage. On the contrary, switching off is effective as long as (8) holds. The optimal choice for \( \rho_{min} \), denoted by \( \rho_{opt}^* \), is then,

\[
\rho_{min} = \frac{A_m}{B_M - B_m}
\]

(9)

Adopting the parameter values reported in Tab. 1, \( \rho_{opt}^* = 0.37 \). This value is adopted for all the results that will be presented below.

Finally, from the same figure observe that for values of \( \rho_{min} > \rho_{opt}^* \), only a slight increase in energy consumption can be observed. The tiny increase (almost invisible in the figure) can be explained by two reasons. On the one hand, even though a high value of \( \rho_{min} \) is used, the traffic load \( \lambda_i \) remains smaller than \( \rho_{opt}^* \) for long periods of time, especially when \( \mu_i < 1 \). On the other hand, most importantly, the total capacity of the macro BS imposes a limit on the maximum traffic load that can be transferred from the micro BSs.

4.2 Trading off system size and grid demand

In this section, we investigate how the RoD strategy affects the PV panel and storage dimensioning and the energy self-sufficiency of the system. Let us assume \( \mu_i = 1 \) for all the BSs and \( \rho_{min} = \rho_{opt}^* \). Fig. 3 reports the total energy demand from the smart grid over one year, denoted as \( E_G \), for increasing values of the PV panels, \( S_p \), both without any RoD strategy (Fig. 3a) and under RoD (Fig. 3b). Each curve corresponds to a different value of the capacity of the battery, \( S_B \), either in CA or BA. In general, larger batteries allow to reduce \( E_G \). When no RoD is applied, \( E_G \) can be reduced below 50 kW only with \( S_p > 40 \text{kWp} \). Under RoD, \( E_G \) is remarkably decreased for any PV size. Noticeably in CA, \( E_G < 50 \text{kWh} \) can be provided with much lower \( S_p \) than in BA and the largest \( S_B \) allows to achieve this target with a \( S_p \) resulting 34% smaller than under no RoD.

![Figure 3: Yearly grid energy, \( E_G \), versus \( S_p \) in Consumer and Business area (CA and BA), for different values of the energy storage capacity.](image)

Even though larger PV panel sizes allow to reduce \( E_G \), hence making the system more self-sufficient, this occurs at the price of increasing the RE waste, especially in summer. We denote as \( E_W \) the wasted energy over a year, i.e. the yearly amount of RE production exceeding the BS need that cannot be completely stored in the battery, due to capacity overflow. In Fig. 4, \( E_W \) is reported with respect to \( S_p \) in the CA, with \( S_B = 40 \). As \( S_p \) increases, \( E_W \) has an opposite and mirroring trend, as shown in the same figure on the right-hand side y-axis.

It is to be noted that a very large \( S_B \) is required, \( \geq 80 \text{kWp} \), in order to achieve \( E_G \approx 0 \text{kWh} \). By denoting as \( f_C \) the frequency of energy requests from the smart grid over one year (measured considering the time granularity of half an hour that is used in our simulator), this condition corresponds to \( f_C \approx 0\% \). However, if the constraint on \( f_C \) is only slightly relaxed, for instance by admitting the less tight constraint \( f_C < 1\% \), a consistent reduction (of 41.3%) of the minimum PV panel size can be achieved. Further relaxations of the...
constraint on $f_G$ do not provide such a remarkable further reduction of $S_p$. This is evident also when other values of $S_p$ are assumed, as it can be seen from Fig. 5, reporting the values of $S_p$ required to target various $f_G$ constraints for different $S_B$, in case of a CA. The gain obtained by softening the constraint on $f_G$ is even more significant when a smaller storage is used. A similar behaviour is confirmed in the BA, although smaller $S_B$ are sufficient to satisfy the same constraints on maximum $f_G$. By converse, the energy waste as measured by $E_W$ tends to be rather high even with loose constraints on the maximum $f_G$. This means that relaxing the constraint on the maximum permitted $f_G$ by just one percentage point allows to significantly reduce the required PV panel capacity, while the RE waste is not decreased to the same extent. If the system is dimensioned to be efficient in the cold season, it clearly results to be oversized in summer. In a smart grid integrated system, the extra amounts of RE that cannot be stored for future usage may be sold to the grid, receiving a reward for the energy exchange.

$$S_p \text{ needed to satisfy the constraint } f_G < f_{G_{Max}} \text{ for increasing values of } f_{G_{Max}} \text{ and for different storage sizes.}$$

Similar considerations can be drawn for storage capacity dimensioning given PV panel capacity (data table not reported here for the sake of brevity).

### 4.3 Feasibility and costs

When trading off independence from the grid and PV panel and battery dimensioning, feasibility and cost issues should be considered as well. In particular, the PV module efficiency affects the PV panel area per kWp. Considering a module efficiency of 19%, a total capacity of 120 kWp might not be feasible even with a distributed PV system, since it would require a total area of about 600 m². In this section, we make a preliminary analysis of the impact of RoD on the costs of the powering system, considering both Capital Expenditure (CAPEX) of the PV panels and batteries and Operational Expenditure (OPEX) due to energy purchase from the grid when production is not enough and the batteries are discharged.

Denote by $c$ the cost per year of a system with a given combination of $S_p$ and $S_B$. The cost can be evaluated from:

$$c = \frac{S_p \cdot c_P}{l_p} + \frac{S_B \cdot c_B}{l_B} + c_G \cdot E_G$$

where $c_P$ is the cost for 1 kWp of PV panel capacity, $c_B$ is the cost for a 200 Ah-12 V lead-acid battery, $c_G$ is the cost for 1 kWh of energy bought from the grid, $l_p$ is the lifecycle of a PV panel (in years), $l_B$ is the expected lifespan of the set of batteries (in years) and $E_G$ is the yearly amount of energy taken from the grid. The lifecycle of a PV panel, $l_p$, can be estimated to be around 25 years, whereas the sets of batteries need to be replaced more frequently and their lifetime duration is highly influenced by the number of charge/discharge cycles they undergo. Assume that the set of batteries is replaced after 500 cycles [9], hence $l_B = \frac{500}{n}$, where $n$ is the number of battery cycles during one year of system operation. A lower value of $n$ implies a lower frequency of battery replacement, hence less need for human maintenance. The introduction of the RoD strategy determines a considerable reduction in $n$ with respect to the no RoD case. The decrease may amount up to 16.6% in CA, while it becomes even more remarkable in BA, where $n$ can be reduced by percentages as high as 85%. In addition, $n$ may vary depending on the number of batteries, $S_B$. For small to intermediate $S_p$, $n$ tends to sharply increase as $S_p$ grows larger. By converse, for intermediate to very large PV panel sizes, $n$ slightly decreases as $S_p$ increases, according to a roughly inverse proportionality. In our simulations, the maximum value of $n$ achieved under the RoD strategy results to be higher in CA ($n=180.2$) rather than in BA ($n=121.6$). Given the same $S_B$, the batteries lifespan $l_B$ tends to be higher in the BA scenario, with worst-case values over 4 years, against only 2.8 years in the CA case. For the price of panels, batteries and electricity we assume $c_P=750 \, €/kWp$, $c_B=140 \, €/battery$ and a rather high $c_G=0.223 \, €/kWh$ (as for the Italian electricity market).

Fig. 6 shows the values of the yearly cost $c$ together with the requested size of the PV panel, $S_p$, for some values of the percentage of energy requests to the grid, indicated as $f_{G_{Max}}$, that corresponds to the powering system design target. For example, the case $f_{G_{Max}} = 10\%$ corresponds to a design target that requires that no energy should be bought from the grid; the case $f_{G_{Max}} = 1\%$ allows that up to 1% of the times energy can be purchased from the grid.

When all the BSs are always kept active, $E$ is comparable in the CA and in the BA, but the energy saving that can be obtained under RoD in the BA (26.2%) is more than twice the saving achieved in the CA (11.5%). When the system is kept totally independent from the grid, the RoD strategy reduces $c$ by 17% in CA, against a 30% decrease obtained in BA, thanks to a larger decrease in $S_p$. When
up to 1% of requests from the grid are allowed, RoD never reduces c by more than 14.3% in CA, while a 41% reduction is observed in BA, thanks to the smaller required $S_P$. Under RoD strategy, the most significant contribution in improving the system feasibility in relation to $S_P$ and in terms of c reduction is obtained when the constraint on $f_G$ is slightly softened from a self-sufficiency system to $f_G < 1\%$, with up to 41.3% reduction in $S_P$. By converse, it is not very effective to further lessen the constraint on $f_G$. Finally, c could be further reduced by selling to the grid the amounts of produced RE exceeding the BS cluster energy demand and the storage capability, energy that would be otherwise wasted.

4.4 Comparing traffic patterns

From the presented results, it appears that, after introducing the traffic-based RoD strategy, higher energy savings can be achieved in BA rather than in CA. Moreover, the RoD strategy has a deeper impact on $S_P$ dimensioning and on c in case of BA with respect to CA. This behaviour can be explained by the fact that the traffic pattern in the BA almost follows the trend of sun irradiation during the day, like it can be seen from Fig. 1. This makes the usage of RE energy more effective and it reduces the need for energy storage support.

Finally, given the same total amount of traffic for the BS cluster, the load distribution among the different BSs highly influences the amount of energy saving that can be achieved through the RoD approach, even under the same setting of $S_P$ and $S_G$. This can be deduced, for instance, from Fig. 2, considering the case where all the micro BSs show $\mu_1 = 1$ except for $\mu_1 = 0.2$ and the case where 2 micro BSs show $\mu_1 = \mu_2 = 0.6$. The total normalized traffic is the same, but the curve representing the energy consumption in the latter case is almost always above the curve representing the first case.

5. CONCLUSION

In this paper, we have considered a cluster of BSs powered with a renewable based powering system composed of PV panels and energy storage units. In this context, the application of resource management, consisting in BS switching on and off based on demand, shows to be very promising to improve energy efficiency and system feasibility, to reduce costs, both operational and capital expenditure. Overall, this seems a promising way to mobile network self-sustainability.

In particular, the results of our simulations show that up to almost 40% of energy can be saved when RoD is applied under proper configuration settings, with a higher impact observed in traffic scenarios in which there is a better match between communication service demand and RE production. While a feasible PV panel and storage dimensioning can be achieved only with high costs and large powering systems, by slightly relaxing the constraint on self-sustainability it is possible to significantly reduce the size of the required PV panels, up to 41.3%, along with a reduction in the corresponding CAPEX and OPEX.

The combination of smart resource management of the communication system with new technologies, both for the communication devices and the power supply, is opening the way to self-sustainability of mobile access networks, a strategic important goal for the sustainability of future networks.

References