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An assessment of different user–BS association policies for green HetNets in off-grid environments

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Abstract
Previous research has shown the relationship between the number of users connected to a cellular network base station (BS) and its energy consumption. For this reason, the study of optimal mechanisms that balance the load of users over the available BSs is a key element in the field of energy efficiency in cellular networks. The target of this paper is to propose and assess different user–BS association mechanisms to reduce grid consumption in heterogeneous cellular networks powered by hybrid energy sources (grid and renewable energy). These schemes are compared with the traditional best-signal-level mechanism and evaluated via simulation by using key performance indicators related to grid consumption, number of users served, and average transmission rate per user. Our results show that the new proposed user allocation policies improve grid electricity consumption while reducing unserved users compared with the traditional association scheme.

1 | INTRODUCTION

Green cellular networks are a field of great interest today, especially when we consider that mobile communication networks consume about 0.5% of the global energy supply.[1,2] For this reason, different projects have studied the energy consumption of cellular networks and ways to reduce it, eg, ICT-EARTH,[3] TREND,[4] and 5GrEEn.[5]

The major sources of energy consumption in a cellular network are base stations (BSs), whose consumption depends on the number of active users in a given time slot.[6] For this reason, a balance of downlink traffic loads among BSs by an appropriate user–BS association mechanism is needed to minimize on-grid consumption.

Renewable energy (RE) is also a good option to reduce the use of the grid and to deploy infrastructure in scenarios with connection limits or without grid connection (off-grid), eg, in developing countries. Some studies examining the feasibility of using RE sources in heterogeneous cellular networks (HetNets) have shown a reduction in network costs (CAPEX/OPEX)[7-9] and an improvement in environmental factors.[10] However, the integration of RE in next-generation cellular networks presents various challenges related to network architecture and energy sources.[11]

In the literature, it is possible to find several approximations to solve the load balancing problem in HetNets. Andrews et al presented a survey of different approaches for load balancing in HetNets.[12] There is a need for exploring new load balancing mechanisms different from traditional optimization techniques, because the problem of associating users to BSs is NP-hard and may not be tractable even for small-sized HetNets. From the optimization viewpoint, several load balancing approaches to increase energy efficiency in cellular networks have been proposed in recent years. Han and Ansari[13] presented a virtually distributed algorithm named vGALA to reach a balance between network utilities and green energy utilization in software-defined radio access networks powered by hybrid energy sources. Likewise, Zhou et al proposed a heuristic algorithm for target cell selection combined with a power control algorithm for coverage optimization to guide users toward BSs with RE supply in the handover process.[14] Likewise, Han and Ansari proposed the optimization of the utilization of green energy in cellular networks by cell size optimization.[15] To this end, they decomposed the problem into 2 parts: a multistage energy allocation problem and a multi-BS energy balancing problem. Liu et al[16] proposed an offline algorithm to optimize green energy allocation across different time slots to minimize the on-grid energy consumption of a BS. Ye et al[17] presented a low-complexity distributed algorithm to solve the association problem jointly with resource allocation in an on-grid HetNet. They assumed that users can be associated with more than 1 BS at the same time, as a relaxation of the NP-hard problem. In addition, a general approach can be found in the work of Kim et al[18] where different distributed user association policies in cellular networks with spatially inhomogeneous traffic are presented. Silva et al used the classic optimal transportation approach to study the mobile association problem in cellular networks.[19] Game theory has also been used to solve the user–BS association problem. Chekroun et al[20] presented a scheme based on a game of 2 players moving between a macro BS (MBS) and a small-cell BS (SCBS), with both BSs connected to the grid. To take the association decision, players use a distributed algorithm in trying to maximize their utilities independently. In the work of Hajijamali et al,[21] the user–BS association problem in HetNets is modeled as a noncooperative game and solved with a distributed algorithm inspired by machine learning techniques.

Furthermore, to reach energy efficiency in cellular networks, other approximations have been proposed,[22] with one of them being the utilization of renewable power sources.[23] This approach is particularly interesting for developing and Third World countries. For example, according to the International Energy Agency, 18% of the global population (1.3 billion people) lived without electricity in 2012.[24] This highlights the need for solutions that allow the deployment of telecommunications infrastructure in areas without access to conventional electricity.

In this work, 5 different alternatives are evaluated to analyze energy consumption on a given case study, including 3 new approaches: a green heuristic approach, another based on traffic flow, and one inspired by market behavior. The first of the 5 alternatives is a traditional scheme where users select the BS with a better signal level.[25] The second is a basic heuristic connection policy that modifies the BS selection procedure by prioritizing user association with a green BS over a grid-powered BS. The third scheme uses a discrete branch-and-bound optimizer to assign users to BSs. The fourth uses a traffic flow perspective to relax the discrete optimization problem and improve computational time.[26] Our final proposal models the system as a green market where users and BSs have the role of buyers and sellers.

To evaluate the proposed mechanisms, we use a 2-tier HetNet where SCBSs are powered only by RE. Wind is the only green energy source considered, and its behavior is modeled using real data of a geographical area in Medellín, Colombia.

Our proposal differs from previous works because our target is energy efficiency through grid consumption reduction. Moreover, our off-grid SCBSs are powered exclusively by wind energy and have no battery support, requiring more demanding control strategies to guarantee quality-of-service (QoS) levels. Conversely to other works where photovoltaic power generation is assumed,[13,27,28] we deal here with real wind data. Finally, we test different alternatives in a complex scenario (37 BSs/750 users).

In this work, we propose some heuristic user allocation policies that outperform classic mechanisms and are simple and tractable enough to be implemented in real systems. Moreover, our simulations in a simplified case study show that their optimality is on the order of that of exhaustive search methods, which are NP-hard and, hence, are not suitable for real-world applications.

The main contributions of this paper are the novel user–BS association schemes proposed to reduce grid consumption in HetNets powered by hybrid sources. In particular, we relax the problem by using traffic flow and a market approach that reduce grid consumption in a tractable way. The simplicity of these mechanisms and their good computation times allow for easier implementation in more complex scenarios.

The outline of the rest of this paper is as follows. In Section 2, the problem setting is described. Section 3 presents the proposed user–BS connection schemes. Section 4 describes the simulation scenario. In Section 5, the performance of the proposed schemes is evaluated, including the analysis of results. Finally, in Section 6, conclusions are provided.

2 | PROBLEM SETTING

The proposed connection policies will be evaluated in a 2-tier downlink HetNet such as that in Figure 1, which is composed of 1 MBS and multiple SCBSs. On-grid energy powers the MBS, and the SCBSs are powered exclusively by wind. The MBS provides basic coverage, whereas the SCBSs are deployed to enhance network capacity and absorb traffic load. To reduce

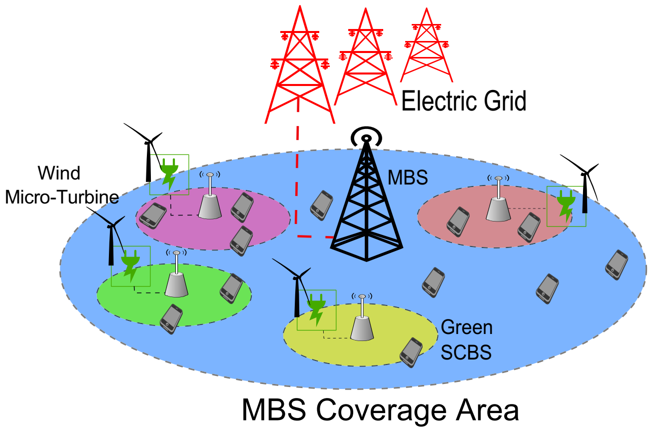

FIGURE 1 Scenario: a heterogeneous cellular network powered by hybrid energy sources. MBS, macro base station; SCBS, small-cell base station

maintenance, environmental, and production costs and to ease their deployment, SCBSs are assumed not to include batteries.

Our goal is to minimize on-grid consumption by balancing downlink traffic loads among BSs using an adequate user association scheme. To this end, let us define a geographical area $L \subset R^2$ that contains B BSs and U users. Let $x \in L$ denote a location and $j \in B$ be the BS index, where $j = 1$ represents the MBS. Time is divided into T time slots of length τ seconds, and $t \in T$ denotes the tth time slot. Each SCBS updates its cell size every τ seconds by changing the transmission power according to the amount of RE available at its location. For simplicity, we drop the time slot index t for the rest of this paper.

2.1 | Traffic model

Traffic requests are modeled as an inhomogeneous Poisson point process. The arrival rate per area $\lambda(x)$ and the traffic size are independently distributed with mean $\mu(x)$ to capture the spatial traffic variability.[18] The number of active users in a time slot is given by U_A.

A mobile user at location x associated with a BS j in the tth time slot has a transmission rate $r_j(x)$, which can be expressed according to the resource blocks (RBs) assigned and its modulation scheme[29] as

$$r_j(x) = bits_{\text{mod}}(x) \times 12_{\text{subc}} \times 7_{\text{symb}} \times 1_{\text{slot(ms)}}, \tag{1}$$

where the first term is the number of bits to use defined by the modulation scheme, followed by the number of subframe subcarriers in a 20-MHz bandwidth channel, the number of orthogonal frequency-division multiple-access symbols, and, finally, the time slots that will be assigned. This way, according to the received signal, the transmission rate is fixed in a given time slot depending on the mobile user modulation scheme. The received signal by a user in location x from BS j is given by the signal-to-interference-plus-noise ratio ($\text{SINR}_j(x)$), and it must be higher than a threshold φ. This is calculated as

$$\text{SINR}_j(x) = \frac{P_j g_j(x)}{\sigma^2 + \sum_{k=1,k\neq j}^{B} P_k g_k(x)}, \tag{2}$$

where P_j is the transmission power of BS j, σ^2 denotes the noise power level, and $g_j(x)$ is the channel gain between the jth BS and the user at location x. Note that the channel gain here reflects only the slow fading; fast fading is not considered.

Each small cell can only serve U_j^M users simultaneously; although, for simplicity, the MBS has no limit for the amount of associated users.

Assuming that mobile users are uniformly distributed in the coverage area of all BSs, the traffic load of the jth BS in the tth time slot can be expressed as

$$\begin{aligned}\rho_1 &= \frac{\sum_{i=1}^{U} y_{i,1}}{U_A}\\ \rho_j &= \frac{\sum_{i=1}^{U} y_{i,j}}{U_M},\end{aligned} \tag{3}$$

where $y_{i,j}$ is the user association indicator. If user i is associated with BS j in the tth time slot, $y_{i,j} = 1$; otherwise, $y_{i,j} = 0$. Note that $0 \leq \rho_j \leq 1$ for all $j \in \{1, 2, \ldots, B\}$.

It is also assumed that at each time slot, a user can be associated with the jth BS if the signal level received $s_{i,j}$ is greater than a threshold φ.

Finally, U_S is the number of users using the systems in a time slot, and it will be a QoS objective. It is expressed as

$$U_S = \frac{\sum_{j=1}^{B} \sum_{i=1}^{U} y_{i,j}}{U_A}. \tag{4}$$

2.2 | Energy consumption model

In this paper, the energy consumption model is based on the results of project EARTH.[6] This is a simple but general model of energy consumption that has been widely used in works related to energy efficiency in cellular networks, as can be seen in previous works.[13,27,30] The EARTH model states that the energy consumption of a BS consists of 2 parts: the static power consumption and the dynamic power consumption. It can be expressed as

$$C_j = \Delta_j \times \rho_j \times P_j \times \tau + E_j^S, \tag{5}$$

where Δ_j is the slope of the load-dependent energy consumption of BS j, P_j is the transmission power of BS j at the tth time slot, ρ_j is the traffic load of BS j at the tth time slot, and E_j^S is the static energy consumption of BS j in each time slot. Static power consumption is related to the energy required for the normal operation of a BS, and the dynamic power consumption is the additional energy demand caused by the traffic load, which is approximated by a linear function of the load.

Here, the total energy consumption of the network scenario in a given time slot is the sum of the grid consumption (due to MBSs) and the green consumption (due to SCBSs). Hence, the reduction of consumption in BS 1 (MBS) is key to increasing energy efficiency.

2.3 | Renewable energy model

Introducing RE power sources in a cellular network requires an understanding of RE dynamics and their relationship with energy consumption at a BS. In this work, we consider wind as the source of renewable power. In particular, real data are used to define a Weibull probability distribution that represents the expected wind speed at a specific location and time interval. The Weibull distribution used in an eolic system design is

$$p(v) = \frac{k}{c}\left(\frac{v}{c}\right)^{k-1} e^{-\left(\frac{v}{c}\right)^k}, \tag{6}$$

where v is the wind speed in meters per second, c is the scale parameter of the distribution, and k is the shape parameter.[31] In this case, these parameters are fitted from real data of Medellín city (Colombia).[32] This allows for a calculation of the amount of energy that can be produced by a microturbine in a period.

2.4 | Optimization problem

Given that the objective is to reduce the overall system grid consumption, it is possible to formulate the following optimization problem:

$$\min_{y} \quad \sum_{t=1}^{T} \sum_{i=1}^{U} y_{i,1} \tag{7}$$

s.t.

$$\sum_{i=1}^{U} y_{i,j} \leq U_j^M \qquad j = 2, 3, \ldots, B \tag{8}$$

$$y_{i,j} \cdot s_{i,j} \geq \varphi \tag{9}$$

$$U_S = \frac{\sum_{j=1}^{B} \sum_{i=1}^{U} y_{i,j}}{U_A} \geq \varepsilon \tag{10}$$

$$\sum_{j \in B} y_{i,j} \leq 1 \qquad \forall i \in U \tag{11}$$

$$y_{i,j} \in \{0, 1\} \qquad \forall i, \forall j, \tag{12}$$

where Equation 7 is the objective function, which focuses on minimizing the consumption from the grid with an optimal assignment of active users to available BSs over each time slot. Equations 8 to 12 are the problem constraints: Equation 8 establishes that a small cell j can serve a maximum of U_j^M users simultaneously; Equation 9 is the user's received signal-level constraint, where $s_{i,j}$ is the signal level received by user i from BS j, and φ is the minimum signal level required by a user to have service; Equation 10 stands for the minimum percentage of users served (U_S), which is a QoS constraint; Equation 11 requires that a user is served only by 1 BS in a time slot; and Equation (12) establishes that $y_{i,j}$ is a binary variable.

The optimization is a binary integer problem, a well-known NP-hard problem,[33] where the search space is composed of a matrix $U \times B$. For example, the proposed scenario with $B = 2$ and $U = 30$ requires 2^{30} combinations to be evaluated, ie, a billion value computations, which limits the direct search of a solution.

3 | CELL SELECTION SCHEMES

To reduce the consumption from the grid in the HetNet, different user–BS connection policies are proposed. As stated previously, 5 different methodologies are presented and compared here. The first is based on traditional discrete optimization techniques. The second is the standard better-signal-level mechanism, which is introduced for the sake of comparison. The third is a greener version of this policy. The fourth uses a flow relaxation of the discrete problem. The fifth is a new green market model.

3.1 | Direct optimization

The optimal connection policy is attained solving Equation 7 by means of an integer linear optimization problem. To find a solution, a branch-and-bound method is used. Information preprocessing and previous knowledge of the problem are also helpful in reducing the computational burden. In particular, the following preprocessing was applied to the data given to the optimizer.

1. *Reduction of space search.* The matrix $S_{i,j}$ was simplified according to the number of active BSs (b) to reduce the search space from $U \times B$ to $U \times b$, where $b \leq B$ and with B being the number of BSs in the network.
2. *Time slot adjustment.* Since optimization is performed in each time slot, it is important that its length be sufficient to perform the calculations, but not too much, thus avoiding changes in the system being ignored.

3.2 | Best-signal-level policy

In traditional cellular networks, mobile users connect to the BS that offers the best SINR, which depends on BS power transmission, path loss, and interference from other BSs. However, this mechanism is not entirely adequate for HetNets, because SCBSs with available resources can be ignored by users when receiving a stronger signal from an MBS.[34] We will refer to this procedure as the traditional policy, and it will be the baseline for evaluating the performance of the proposed mechanisms. Note that, for simplicity, we used only path loss to determine the user's best received signal.

3.3 | Green policy algorithm

The second approach is a heuristic method proposed to reduce the consumption from the grid by first checking the possibility of attaching the user's request to SCBSs (green BSs), even if the received signal level of an MBS is better. The association process is managed jointly between the user and the network in a hybrid scheme. The main difference between this scheme and a proposal such as that presented in the work of Zhou et al,[14] where the priority of green BSs is established only during the handover process, is that we give priority to green BSs at any moment of the communication, not only during the handover.

The proposed user association algorithm can be summarized in the following steps:

1. The arrival of the users to the coverage area.
2. Definition of the initial signal level available for each user.
3. Inspection of the signal levels from green BSs.
4. Definition of the active users for each BS.
5. Association of users to green BSs.
6. Computation of grid consumption and the RB number of served users.

This mechanism guarantees that, at each time slot, the system consumes as much green energy as possible and uses grid energy only as a last resort.

3.4 | Traffic flow approximation

Approximation based on traffic flow was also considered in solving for the computational burden issues of integer optimization. This perspective uses a relaxation of the discrete problem and generates a solution with the optimal flow exchanged between BSs. This approach has been successfully applied to problems such as traffic management[35] and supply chains.[36]

Figure 2 presents an illustration of this perspective. The incorporation of a new virtual BS ($B+1$) can be observed, which is used to discard traffic according to the defined QoS level.

The mechanism uses input information from a matrix with the flow interactions that can be exchanged between BSs ($F_{i,j}$) in each time slot. This matrix is built from the received signal level of each user from each BS, the active BSs according to the wind speed, the BS adjacency matrix, and the number of users connected to each BS.

This matrix, the number of RBs available in each BS, and the QoS level are used as constraints of a linear optimization problem that minimizes the sum of flow interactions from any BS to the MBS (BS 1). Equations 13 to 18 present the formal description of the optimization problem, as follows:

$$\min_{x} \quad \sum_{t=1}^{T} \sum_{i=1}^{B+1} x_{i,1} \tag{13}$$

s.t.

$$\sum_{i=1}^{B+1} x_{i,j} \leq F_{i,j} \qquad j = 1, 2, 3, \ldots, B+1 \tag{14}$$

$$\frac{\sum_{j=1}^{B} \sum_{i=1}^{B} x_{i,j}}{U_A} \geq \varepsilon \times U_A \tag{15}$$

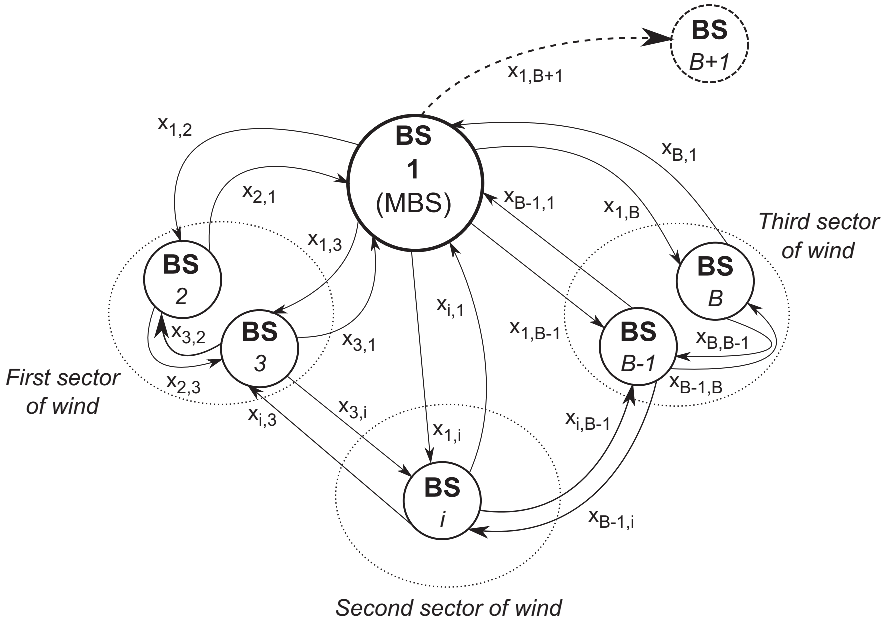

FIGURE 2 Traffic flow approximation. BS, base station; MBS, macro base station

$$\sum_{i=1}^{B+1} x_{i,j} \leq U_j^M \qquad j = 1, 2, \ldots, B+1 \tag{16}$$

$$\sum_{j \in B} x_{i,j} = x_i \qquad \forall i \tag{17}$$

$$0 \leq x_{i,j} \qquad \forall i, \forall j, \tag{18}$$

where $x_{i,j}$ is the traffic flow from BS i to BS j in a time slot. Equation 13 is the objective function, which seeks to minimize the flow interactions to the MBS and, hence, reduce the overall consumption from the grid of the cellular network. Constraint (14) specifies that the flow interactions between 2 BSs cannot exceed the limits established by the potential flow matrix. Equation 15 defines the QoS level and guarantees that the sum of all flow sequences is higher than the desired percentage of users served ε. Constraint (16) establishes the limit in the number of users to be served by a BS. This limit is defined by the number of RBs available in the destination BS in each time slot. Constraint (17) imposes flow conservation. This means that all users will be served, even by the $B+1$ BS or the same BS that originated the flow. Finally, Equation 18 defines that flow approximations must be positive.

Once the solution to this problem is found, a rounding process is executed to obtain integer values and assign users to BSs according to these values.

Finally, a remarkable feature of this approach is that it can be implemented easily in a distributed fashion.[37,38]

3.5 | Green market approach

This approximation is another contribution of this paper to the user–BS association schemes in HetNets powered by hybrid sources. Pindyck and Rubinfeld defined a market as "a collection of buyers and sellers that, through their actual or potential interactions, determine the price of a product."[39] The BSs are sellers, and the users are buyers, with both interacting through a market price by the RBs. When green BSs are active, the system works like a competitive market; when only the MBS is working, the market is a monopoly. In the competitive market, the price is defined depending on the technical characteristics of the offer and the demand. In the monopoly, it is necessary to include additional constraints to avoid abuses by the exclusive seller (MBS). This approach has been employed in other areas such as the electricity sector[40,41] and hydro storage systems,[42] where it is common to analyze the interaction between its actors using models that include the market behavior.

3.5.1 | Market definition

The market is composed of B BSs, acting like vendors, and U users, in the role of buyers. In each time slot, 4 key processes are implemented:

1. RB's price definition by sellers.
2. Utility function definition by customers.
3. Money assignment to active users.
4. Buying decision.

BSs establish the price of RBs according to the technical aspects of the network as follows:

$$p_{i,j} = \alpha_1 \times \psi_{i,j} + \alpha_2 \times \rho_j + \alpha_3 \times \vartheta + \alpha_4 \times \delta + \alpha_5 \times \xi_j^{BS}, \tag{19}$$

where $p_{i,j}$ is the price of a channel offered by BS j to user i; $\alpha_1, \dots, \alpha_5$ are the weights of network parameters over the market price; ψ is the index of modulation scheme offered to user i from BS j; ρ is the traffic load of BS j; $\vartheta = 1 - \frac{BS_{on}}{B}$ stands for BS scarcity; $\delta = \frac{U_A}{U}$ is the demand, where U_A is the number of active users in the time slot; and ξ^{BS} is the BS energy source. From Equation 19, it is possible to observe that if a channel of a BS powered by the grid is more expensive than a green channel, it is possible to establish an incentive to boost the use of green energy.

On the customer's side, we define a utility function for users according to the market characteristics, as follows:

$$\upsilon_{i,j} = \beta_1 \times \psi_{i,j} + \beta_2 \times \xi_j^U + \beta_3 \times \vartheta, \tag{20}$$

where $\upsilon_{i,j}$ is the utility perceived by user i for a channel offered by BS j, and $\beta_1, \dots, \beta_3$ are the weights of market characteristics over the utility function. From Equation 20, it is possible to observe that ξ^U can be an incentive for a user to buy a channel from a green BS. This utility function will be the key factor in making a buying decision.

3.5.2 | The monopoly case

When the RE source is insufficient to power any BS, only the MBS will be working. In this case, it is common to regulate prices. In our proposal, we implemented 2 control policies: a discount factor in the price function (ϕ) and a subsidy for users. The role of the discount factor is to reduce the price when the number of unserved users grows, ie,

$$p_{i,j}^M = p_{i,j} \times \left(1 - \phi \times \left(1 - \frac{U_{NA}}{U_A}\right)\right), \tag{21}$$

where $p_{i,j}^M$ is the monopoly price, $p_{i,j}$ is the competitive market price, U_{NA} is the unserved users, and U_A is the number of active users in the time slot. The discount factor is an incentive for users to buy at a lower price. The subsidy is an increase in the money assigned to active users.

3.5.3 | Money and buying decision

At each time slot, the system assigns to active users an amount of money, which allows them to buy channels and is sufficient to afford the price plus an extra percentage to cover variations. With the information about the costs of different channels, the utility function, and the money available, users take buying decisions. The selected option will maximize the consumer's surplus, ie,

$$C_{i,j} = \max(\upsilon_{i,j} - p_{i,j} \mid \mu_i \geq p_{i,j}), \tag{22}$$

where μ_i is the money of user i in the time slot. After buying, the user utilizes the channel along the time slot and returns it to the BS once the time is over. If in the next time slot the user still needs a channel, he or she can buy the same or select another that is cheaper.

4 | SIMULATION SCENARIO

The scenario described in Section 2 was implemented to evaluate the proposed alternatives regarding their consumption of energy. The case study considered is composed of 1 MBS and 36 overlapping SCBSs. This is the minimum number of SCBSs needed to cover the MBS area. In this scenario, the MBS is powered by on-grid energy, and it is always on, ensuring

TABLE 1 Simulation parameters

Parameter	Value
Coverage area	3.5 km^2
Number of users	750
System	LTE
BW LTE	20 MHz
RB per BS	100
N. macro base station	1
N. MBS sectors	1
N. SCBS	36
Intersite distance	500 m
Tx power MBS	43 dBm
Tx power SCBS	22 dBm
Static power cons. MBS	130 W
Static power cons. SCBS	6.8 W
Consumption slope MBS	4.7
Consumption slope SCBS	4.0
Path loss between MBS and user	Cost 231 model
Antenna gain	15 dBi
Max. active users simultaneously for an SCBS	100
Receiver sensitivity	−107.5 dBm
Size of request file	500 Kb
Time slot	2 s
Mobility model	Random walk point
Mobility speed	4 km/h

Abbreviations: BS, base station; BW, bandwidth; LTE, Long-Term Evolution; MBS, macro base station; RB, resource block; SCBS, small-cell base station.

constant coverage over the area. Each BS has 1 sector, and only large-scale loss is considered in the simulation. This case study presents different simplifications but is complex enough to show the potential of the methods proposed in the article.

Despite some simplifications made in the case study, it maintains generality and is representative of a real scenario where the complexity of the association process is caused in part by the number of BSs and active users.

The technical parameters of the simulation are defined according to an LTE system[43] with a geographical area of 3.5 km^2, with an intersite distance between BSs of 500 m and the environmental parameters of Medellín (Colombia). Furthermore, given the population density of this city (2500 hab/km^2) and the mobile Internet penetration in Colombia (10%), 750 users are considered in the experiments. Table 1 summarizes the parameters used in the simulation.

As mentioned previously, small cells are powered only by green energy. This way, to reduce the deployment cost and to mitigate the environmental impact, each SCBS has a microturbine that provides green energy without a battery system. The goal of each SCBS is to receive users from the MBS and, therefore, reduce its consumption from the grid.

4.1 | Renewable power potential

The simulation considers the behavior of the wind in Medellín, based on 3-year data provided by weather stations of SIATA.[32] Using @Risk7,[44] it was possible to define 3 sectors with different wind behaviors in the simulation area. It was found that sector 1 presents a mean wind speed of 1.787 m/s, sector 2 has a mean wind speed of 1.880 m/s, and sector 3 has a mean wind speed of 2.238 m/s.

According to the average wind speed, a microturbine was selected for the SCBSs with a start-up wind speed of 2 m/s and the power potential shown in Table 2.

The simulation is configured with different average wind speeds in the sectors under the coverage area of the MBS. Wind dynamics vary every minute. Therefore, there are 3 possible green energy scenarios (shown in Figure 3): (1) no SCBS has sufficient green energy, (2) the SCBSs of only 1 sector have green energy to work, and (3) more than 1 sector has green energy (this case could be even when all SCBSs have energy in the same period). In this Figure, the big red circle

TABLE 2 Energy potential of a microturbine

Wind Speed	Power Potential, W
< 2 m/s	0
2–3 m/s	26
3 m/s <	35

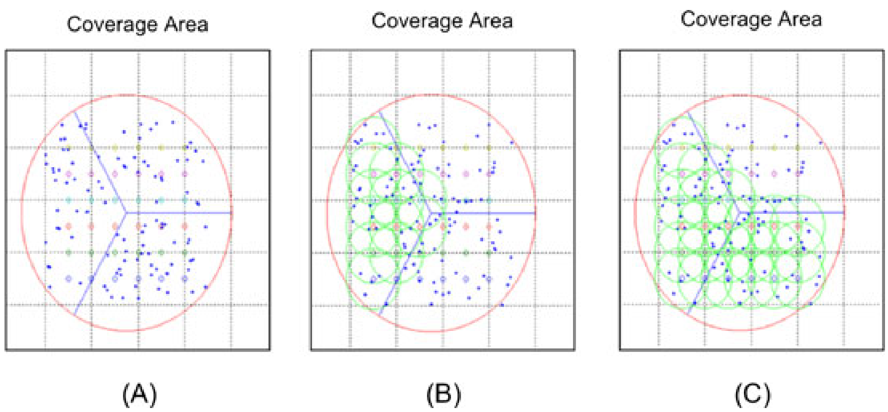

FIGURE 3 Green energy availability scenarios for the macro base station coverage area

TABLE 3 Modulation threshold

Threshold (Received Signal Level)	Modulation	Bits Per Symbol
> −65 dBm	QAM64	6
−65 to −85 dBm	QAM16	4
−85 to −107.5 dBm	QPSK	2

Abbreviations: QAM, quadrature amplitude modulation; QPSK, quaternary phase-shift keying.

represents the MBS coverage area, whereas the green smaller circles are the SCBS coverage areas. Users are represented as blue dots.

4.2 | User data rate

As mentioned previously, the user data rate depends on the amount of the RBs assigned by the BS and the modulation scheme used.

In this work, 3 received signal-level thresholds were defined for the simulation. These levels determine the modulation scheme used and, hence, the downlink user's data rate. The thresholds are shown in Table 3.

4.3 | Market characteristics

Table 4 shows the market parameters used in the simulation.

The weights α and β were chosen by trial and error but with the objective of fostering the green market. For this reason, the energy source factor has the higher value in function price and utility. The second most important element is the number of active BSs, reflecting how the scarcity of resources affects the price.

5 | RESULTS

Using MATLAB®[45] and IBM Cplex Optimizer,[46] it was possible to evaluate the different connection schemes and their impact on grid power consumption. The temporal variability of traffic on the cellular network was not considered. For

TABLE 4 Market parameters

Parameter	Value
$[\alpha_1, \alpha_2, \alpha_3, \alpha_4, \alpha_5]$	[15, 20, 20, 15, 25]
$[\beta_1, \beta_2, \beta_3]$	[40, 20, 40]
ψ	1 for QAM64 0.5 for QAM16 0.2 for QPSK
ξ^{BS}	1 for the grid (MBS) 0.2 for RE (SCBS)
ξ^{U}	0.2 for the grid (MBS) 1 for RE (SCBS)
ϕ	20%
Subsidy	10%
Money increase	Market price + 10%

Abbreviations: MBS, macro base station; QAM, quadrature amplitude modulation; QPSK, quaternary phase-shift keying; RE, renewable energy; SCBS, small-cell base station.

TABLE 5 Association scheme comparison

User Association Scheme	Average Grid Consumption, W/min	Users Served, %	Average Transmission Rate, Mb/s	% of Reduction	Bits/Watt
Signal-level policy	6055 ±24	85.8 ±0.1	265.76 ±5.1%	–	791.1
Green policy	5922 ±35	86 ±0.1	256.98 ±2.7%	2.2	801.6
Optimizer 80%	5542 ±18	80.8 ±0.7	166.76 ±2.5%	8.5	520.1
Optimizer 85%	5733 ±17	85.5 ±0.3	183.54 ±3.1%	5.3	578.1
Optimizer 90%	5903 ±16	90.2 ±0.1	207.46 ±1.8%	2.5	609.1
Traffic flow 85%	5765 ±11	86.1 ±0.2	194.37 ±2.2%	4.8	578.4
Green market	5724 ±51	85.4 ±2.1	168.23 ±3.2%	5.4	493.3

this reason, a simulation time of 15 minutes was used to assess the behavior of the proposed solutions. The active BSs along the corresponding 450 time slots define the $S_{i,j}$ matrix and the search space in each optimization.

To compare the performance of the mechanisms with the traditional best-signal-level scheme, 6 key performance indicators (KPIs) are proposed: average grid consumption (W/min), percentage of users served, average transmission rate (Mb/s), percentage of consumption reduction compared with the traditional scheme, transmitted bits per grid-consumed watts, and simulation time. Table 5 shows the KPI results for each scheme.

As can be seen, the green policy reduces the consumption by 2.2% compared with the traditional scheme and maintains similar levels of users served and average transmission rates, thus demonstrating itself as a good option to reduce consumption in the presence of RE sources. In addition, the green policy has the best bits-per-watt performance, followed by the signal-level policy and traffic flow.

The optimizer policy was implemented for 3 different QoS objectives, being equivalent to 85% of the baseline defined by the traditional scheme. We found a reduction in consumption with respect to the traditional connection scheme. In particular, the optimizer of 85% has good grid energy savings of 5.3% compared with the signal-level policy. Only when $U_S = 90\%$ do we observe that the optimizer grid consumption is close to the traditional scheme. However, the average transmission rate is lower. This is caused by the relation between the signal level and the modulation scheme. Therefore, if the best signal level is not the main criteria for selecting a BS, a reduction in the average rate can be achieved. It is important to remember that the optimizer does not have constraints or incentives related to the transmission rate.

Regarding traffic flow, it is possible to observe a reduction of the consumption from the grid to levels comparable to those of the discrete optimizer (4.8%). This result is very important because the discrete optimizer delivers the optimum consumption of the system according to a QoS level. The other key element is the QoS (U_S) in the system, which presents a small improvement if the traditional scheme is compared with the traffic flow. However, being a mechanism based only on grid consumption optimization, the average transmission rate is lower than signal level–based policies.

FIGURE 4 Green market behavior. BS, base station

TABLE 6 Computation time for the simulations [s]

User Association Scheme	500 Users	750 Users	1000 Users
Signal-level policy	210.99 ±15	287.28 ±12	261.13 ±11
Green policy	211.19 ±12	287.39 ±13	261.62 ±9
Optimizer 85%	506.46 ±9	1157.4 ±22	2077 ±32
Traffic flow 85%	391.53 ±10	553.64 ±25	507.28 ±28
Green market	195.28 ±15	215.69 ±15	217.5 ±18

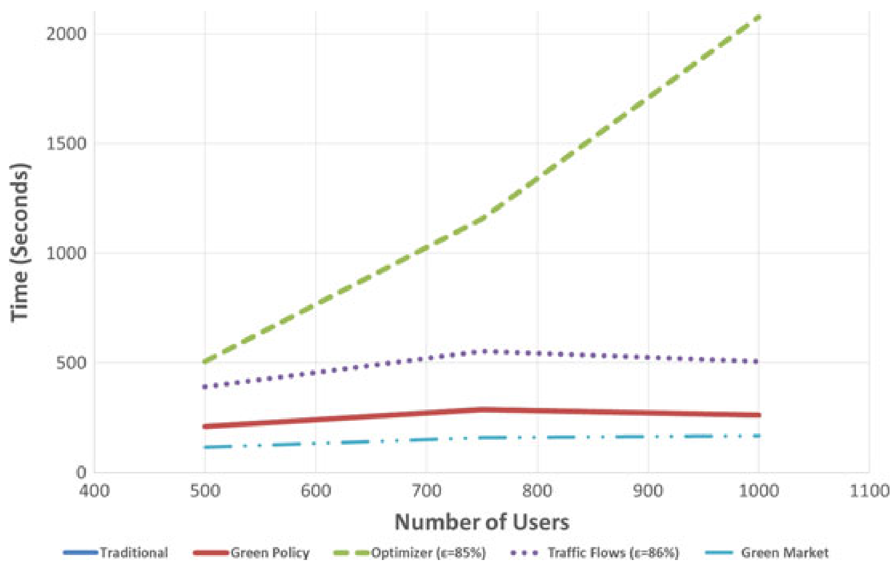

FIGURE 5 Comparison of computational time required to carry out the user–base station association policies

The green market scheme has 5.4% energy savings and a percentage of users served closer to 85%, but with high variation caused by market dependence on the number of active BSs. Its transmission rate is the lowest. This phenomenon, similar to the variation in served users, is caused by the high influence of the competition (number of active SCBSs) on the market price and buying decisions. Figure 4 shows the green market behavior. We observe a market price that is significantly influenced by the offer (number of active green BSs) and users sensitive to price variations. Furthermore, it is possible to see the control mechanism in the case of a monopoly and its function to avoid abuses in price and maintain buying tendencies.

Regarding the computational time required for the simulations, Table 6 shows a comparison of the results of implementing the different policies when different amounts of users are present in the network. It can be observed that the optimizer increases its computational time markedly when the number of users grows.

Another interesting result about the computational time is the similarity between the traditional policy and the green algorithm proposed (Figure 5). The processing time of the traffic flow and green market approaches is lower than that of the discrete optimizer and remains practically constant despite the growth of users, thus representing a good option for improving consumption and maintaining QoS levels in scenarios with a large number of users.

6 | CONCLUSIONS

The target of this paper was to study user–BS association techniques to reduce grid consumption in HetNets powered by hybrid sources. Five different user–BS association schemes were compared in a case study using real data of wind behavior. In particular, the traffic flow and green market policies deserve special attention in view of the obtained results and of their novelty. The simplicity of the green policy is also a good characteristic in complex scenarios.

Our simulations show that optimization-based schemes result in lower power grid consumption, but the average transmission rate is also lower because optimizer schemes prioritize grid consumption over the signal level.

Regarding the performance of the green policy algorithm, lower consumption was observed compared with the traditional scheme, but the optimizer performance at the same U_S level (85%) is better. However, the green algorithm can be a good option in scenarios with a large amount of users and active BSs, because its simplicity demands less computational resources than the optimizer.

The green market scheme is a good option in situations with many users and high wind speeds, since this increases the number of active small cells and encourages users to use green energy.

It is important to emphasize the good response of the traffic flow approximation, despite being a relaxation of the original optimization problem. It reaches KPI values closer to those of the discrete optimization. The possibility of implementing the traffic flow mechanism in a distributed scenario is another advantage, with it being difficult in discrete optimization–based schemes. Future work in this line can consider exploring alternatives to improve average transmission rates.

The case study has simplifications but is representative of a real scenario with an appropriate level of complexity due to the absence of batteries and the number of users and BSs considered in the simulations. Even when the results obtained are approximate due to the simplicity of the models used, they are an indication of the potential of the methods proposed.

The next stage in the study of alternatives for improving the energy consumption of these kinds of networks should include the analysis of delays in the user association process and their impact on the QoS of the system. Finally, it was demonstrated that by using mechanisms with low computation times, it is possible to reach levels of energy saving and QoS similar to those obtained with discrete optimization–based methods.

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REFERENCES

1. Lubritto C, Petraglia A, Vetromile C, et al. Energy and environmental aspects of mobile communication systems. *Energy*. 2011;36(2):1109-1114. https://doi.org/10.1016/j.energy.2010.11.039

2. Hasan Z, Boostanimehr H, BhargavaGhazzai V. Green cellular networks: a survey, some research issues and challenges. *IEEE Commun Surveys Tuts*. 2011;13(4):524-540. https://doi.org/10.1109/SURV.2011.092311.00031
3. ICT-EARTH. ICT-EARTH. https://www.ict-earth.eu. Accessed: January 6, 2016.
4. TREND. Towards Real Energy-efficient Network Design. http://www.fp7-trend.eu/. Accessed: January 2, 2017.
5. 5GrEEn. Towards Green 5G Mobile Networks. https://wireless.kth.se/5green/. Accessed: January 2, 2017.
6. Auer G, Giannini V, Desset C, et al. How much energy is needed to run a wireless network? *IEEE Wireless Commun*. 2011;18(5):40-49. https://doi.org/10.1109/MWC.2011.6056691
7. Morea F, Viciguerra G, Cucchi D, Valencia C. Life cycle cost evaluation of off-grid PV-wind hybrid power systems. Paper presented at: Intelec 07 - IEEE 29th International Telecommunications Energy Conference. IEEE; 2007; Rome. https://doi.org/10.1109/INTLEC.2007.4448814
8. Marsan M, Bucalo G, Di Caro A, Meo M, Zhang Y. Towards zero grid electricity networking: Powering BSs with renewable energy sources. Paper presented at: 2013 IEEE International Conference on Communications Workshops (ICC); 2013; Budapest, Hungary. https://doi.org/10.1109/ICCW.2013.6649303
9. Alsharif MH, Nordin R, Ismail M. Energy optimisation of hybrid off-grid system for remote telecommunication base station deployment in Malaysia. *EURASIP J Wireless Commun Netw*. 2015;2015(1):64. https://doi.org/10.1186/s13638-015-0284-7
10. Piro G, Miozzo M, Forte G, et al. Hetnets powered by renewable energy sources: sustainable next-generation cellular networks. *IEEE Internet Comput*. 2013;17(1):32-39. https://doi.org/10.1109/MIC.2012.124
11. Hassan HAH, Nuaymi L, Pelov A. Classification of renewable energy scenarios and objectives for cellular networks. Paper presented at: IEEE International Symposium on Personal, Indoor and Mobile Radio Communications, PIMRC. IEEE; 2013; London. https://doi.org/10.1109/PIMRC.2013.6666655
12. Andrews J, Singh S, Ye Q, Lin X, Dhillon H. An overview of load balancing in HetNets: old myths and open problems. *IEEE Wireless Commun*. 2014;21(2):18-25. https://doi.org/0.1109/MWC.2014.6812287
13. Han T, Ansari N. A traffic load balancing framework for software-defined radio access networks powered by hybrid energy sources. *IEEE/ACM Trans Netw*. 2016;24(2):1038-1051.
14. Zhou J, Li M, Liu L, She X, Chen L. Energy source aware target cell selection and coverage optimization for power saving in cellular networks. Paper presented at: IEEE/ACM International Conference on Green Computing and Communications and International Conference on Cyber, Physical and Social Computing. IEEE; 2010; Hangzhou. https://doi.org/10.1109/GreenCom-CPSCom.2010.56
15. Han T, Ansari N. On optimizing green energy utilization for cellular networks with hybrid energy supplies. *IEEE Trans Wireless Commun*. 2013;12(8):3872-3882. https://doi.org/10.1109/TCOMM.2013.051313.121249
16. Liu D, Chen Y, Chai KK, Zhang T, Pan C. Adaptive user association in HetNets with renewable energy powered base stations. Paper presented at: 21st International Conference on Telecommunications (ICT); 2014; Lisbon, Portugal. https://doi.org/10.1109/ICT.2014.6845087
17. Ye Q, Rong B, Chen Y, Al-Shalash M, Caramanis C, Andrews J. User association for load balancing in heterogeneous cellular networks. *IEEE Trans Wireless Commun*. 2013;12(6):2706-2716. https://doi.org/10.1109/TWC.2013.040413.120676
18. Kim H, de Veciana G, Yang X, Venkatachalam M. Distributed α-optimal user association and cell load balancing in wireless networks. *IEEE/ACM Trans Netw*. 2012;20(1):177-190. https://doi.org/10.1109/TNET.2011.2157937
19. Silva A, Tembine H, Altman E, Debbah M. Optimum and equilibrium in assignment problems with congestion: mobile terminals association to base stations. *IEEE Trans Autom Control*. 2013;58(8):2018-2031. https://doi.org/10.1109/TAC.2013.2250072
20. Chekroun S, Sabir E, Kobbane A, Tembine H, Bouyakhf EH, Ibrahimi K. A distributed open-close access for small-cell networks: A random matrix game analysis. Paper presented at: Wireless Communications and Mobile Computing Conference (IWCMC); 2015; Dubrovnik, Croatia.
21. Hajijamali A, Omidi MJ, Mehbodniya A, Adachi F. A distributed learning based user association for heterogeneous networks. *Trans Emerg Telecommun Technol*. 2017:1-13. https://doi.org/10.1002/ett.3192
22. Suarez L, Nuaymi L, Bonnin J-M. An overview and classification of research approaches in green wireless networks. *EURASIP J Wireless Commun Netw*. 2012;2012(1):142. https://doi.org/10.1186/1687-1499-2012-142
23. Dhillon HS, Ying L, Nuggehalli P, Zhouyue P, Andrews J. Fundamentals of heterogeneous cellular networks with energy harvesting. *IEEE Trans Wireless Commun*. 2014;13(5):2782-2797. https://doi.org/10.1109/TWC.2014.040214.131201
24. Conference Mondiale De L'Energie. World energy. World Energy Outlook. Paris: International Energy Agency; 2012. http://www.worldenergyoutlook.org/publications/weo-2012/
25. ETSI. LTE; general packet radio service (GPRS) enhancements for evolved universal terrestrial radio access network (E-UTRAN). Accessed 2011; http://www.etsi.org/
26. Orlin J, Magnanti T, Ahuja R. *Network Flows: Theory, Algorithms, and Applications*. 1st ed. New Jersey: Pearson; 1993.
27. Liu D, Chen Y, Chai K, Zhang T, Elkashlan M. Two-dimensional optimization on user association and green energy allocation for HetNets with hybrid energy sources. *IEEE Trans Commun*. 2015;6778(c):1-1. https://doi.org/10.1109/TCOMM.2015.2470659
28. Mao Y, Zhang J, Letaief K. A Lyapunov optimization approach for green cellular networks with hybrid energy supplies. *IEEE J Sel Areas Commun*. 2015;33(12):2463-2477. https://doi.org/10.1109/JSAC.2015.2481209
29. 3GPP. 3rd Generation Partnership Project; Technical Specification Group Radio Access Network; 3GPP TR 36.814-900, Evolved Universal Terrestrial Radio Access (E-UTRA): Further advancements for EUTRA physical layer aspects (Release 9); 2010.
30. Yang H, Geraci G, Quek T. Energy-efficient design of MIMO heterogeneous networks with wireless backhaul. *IEEE Trans Wireless Commun*. 2016;15(7):4914-4927.

31. Villarrubia M. *Ingeniería de la Energía Eólica*. 1st ed. Barcelona: Marcombo; 2012.

32. SIATA. Medellín and Aburrá Valley Early Warning System, A project of the Aburrá Valley Metropolitan Area and the City of Medellín. SIATA - Sistema de Alertas Tempranas. http://www.siata.gov.co/

33. Johnson D, Garey M. *Computers and Intractability: A Guide to the Theory of NP-Completeness*. 1st ed. New Jersey: Bell Telephone Laboratories, Incorporated; 1979.

34. Andrews JG. Seven ways that HetNets are a cellular paradigm shift. *IEEE Commun Mag*. 2013;51(3):136-144. https://doi.org/10.1109/MCOM.2013.6476878

35. Smulders S. Control of freeway traffic flow by variable speed signs. *Transp Res Part B: Methodol*. 1990;24(2):111-132. https://doi.org/10.1016/0191-2615(90)90023-R

36. Sarimveis H, Patrinos P, Tarantilis C, Kiranoudis C. Dynamic modeling and control of supply chain systems: a review. *Comput Oper Res*. 2008;35(11):3530-3561. https://doi.org/10.1016/0191-2615(90)90023-R

37. Camponogara E, Scherer H. Distributed optimization for model predictive control of linear dynamic networks with control-input and output constraints. *IEEE Trans Autom Sci Eng*. 2011;8(1):233-242. https://doi.org/10.1109/TASE.2010.2061842

38. Maestre JM, Negenborn RR. *Distributed Model Predictive Control Made Easy*. 1st ed. New Jersey: Springer Science & Business Media; 2014.

39. Pindyck R, Rubinfeld D. *Microeconomics*. 8th ed. Boston: Pearson; 2013.

40. Pinto T, Silva H, Vale Z, Santos G, Praca I. Pan-European electricity market simulation considering the European power network capacities. Paper presented at: 26th International Workshop on Database and Expert Systems Applications (DEXA); 2015. https://doi.org/10.1109/DEXA.2015.36

41. Maaz A, Grote F, Moser C. Agent-based price simulation of the German wholesale power market. Paper presented at: 12th International Conference on the European Energy Market (EEM); 2015; Lisbon, Portugal. https://doi.org/10.1109/EEM.2015.7216698

42. Gu Y, Bakke J, Zhou Z, Osborn D, Guo T, Bo R. A novel market simulation methodology on hydro storage. *IEEE Trans Smart Grid*. 2014;5(2):1119-1128. https://doi.org/10.1109/TSG.2013.2289915

43. 3GPP. LTE Evolved Universal Terrestrial Radio Access Network (E-UTRAN); Self-configuring and self-optimizing network (SON) use cases and solutions; 2014. http://www.3gpp.org/dynareport/36902.htm

44. Palisade Corporation. @Risk 7. http://www.palisade.com/risk/. Accessed: January 3, 2016.

45. The MathWorks. Matlab® R2012a. https://www.mathworks.com. Accessed: January 6, 2016.

46. IBM. IBM ILOG CPLEX Optimization Studio. https://www.ibm.com/software/commerce/optimization/cplex-optimizer/. Accessed: January 6, 2016.

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