

Exploiting Coexistence Between UMTS and LTE for Greener Cellular Networks with Particle Swarm Optimization

Mohammed H. Alsharif¹ · Rosdiadee Nordin¹ · Mahamod Ismail¹

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Abstract Switching base stations (BSs) off is considered an effective method for improving energy efficiency. This switch-off approach is a system-level approach that can be applied to an area covered by multiple cells, even if those cells use different radio access technologies. This study focuses on exploiting the coexistence of universal mobile telecommunications system and long-term evolution to achieve a balance between network performance (meeting the demands for high data rates at peak traffic hours) and energy efficiency based on traffic load variations while guaranteeing maximum coverage for the region. Particle swarm optimization has been adopted to maximize the cells' coverage area during a switch-off session with constraints for the transmission power of the BS (P_{tx}), the total antenna gain (*G*), the signal-to-interference-plus-noise ratio, and shadow fading (σ). Moreover, the modulation and coding scheme and data rate are considered in this study. The results show that daily energy savings of up to 27.86 % can be achieved while guaranteeing cell coverage.

Keywords Multiple radio access technologies \cdot Base station cooperation \cdot Cell switch on/ off \cdot Energy efficiency \cdot Green networks

1 Introduction

More than ever, energy efficiency in wireless networks has represented a challenge to researchers, vendors, and mobile operators. Current efforts toward creating green cellular networks focus on base stations (BSs) because they are considered the primary source of

Rosdiadee Nordin adee@eng.ukm.my

Mahamod Ismail mahamod@eng.ukm.my

Mohammed H. Alsharif moh859@gmail.com

¹ Department of Electrical, Electronics and System Engineering, Faculty of Engineering and Built Environment, University Kebangsaan Malaysia, 43600 Bangi, Selangor, Malaysia

energy consumption in cellular networks, therein accounting for 57 % of the total energy consumed [1]. From the perspective of cellular network operators, reducing electrical energy consumption is considered an economically important issue because a significant portion of the operational expenditures (OPEXs) of a cellular network are electricity costs as a result of the significant increase in the number of BSs in networks, which are not being used in the best and most efficient way [2]. According to [3], it is estimated that cellular network OPEXs for electricity globally reached \$22 billion in 2013. Moreover, energy efficiency in cellular networks is a growing concern for cellular network operators not only for maintaining profitability but also reducing the overall environment effects. A consensus is being drawn that the cellular network sector has emerged as a significant contributor of greenhouse gas (GHG) emission. According to [4], the amount of carbon dioxide (CO₂) that is emitted by the mobile sector is expected to increase to 179 Mt CO₂ by 2020, which represents 51 % of the information and communication technologies (ICT) sector's carbon footprint. This emission puts mobile operators under immense pressure to meet the demands of both environmental conservation and cost reduction.

Accordingly, a critical need for improvements in energy efficiency in cellular networks has emerged. Saving energy in BSs is considered the primary focus to realize greener networks. The main goal of green BSs is reducing energy consumption, OPEXs, and polluting gas generation while guaranteeing service and coverage for users and ensuring the adaptability of the BS for evolution. Many interesting studies have attempted to address this issue using 'greener' cellular networks that are less expensive to operate. Two approaches can generally be used to reduce environmental impacts and costs. In the first approach, power-efficient hardware is used to reduce BS power consumption. In the second approach, the intelligent management of network elements is adopted based on traffic load variations [5]. However, switching BSs off is considered an effective method of improving energy efficiency for two reasons: (1) the key source of energy usage in cellular networks is the operation of BS equipment, and (2) the infrastructure of cellular networks is designed to support daytime traffic. Traffic loads during the day differ from those at night. Therefore, the amount of energy that is wasted because of the inefficient use of resources cannot be neglected, particularly for low and idle loads [6, 7].

The BS switch-off approach is a system-level approach that can be applied to an area covered by multiple cells, wherein those cells may use different radio access technologies [GSM, universal mobile telecommunications system (UMTS), and long-term evolution (LTE)], which provide different levels of service. The present study focuses on taking advantage of the coexistence of multiple radio access technologies to achieve a balance between network performance (meeting the demands of high data rates at peak traffic hours) and energy efficiency based on traffic load variations while guaranteeing maximum coverage for the entire region. With the proliferation of wireless data applications, we are witnessing an unprecedented demand for high bandwidths. Therefore, this study focuses on the coexistence of cellular network technologies that offer wireless data delivery: UMTS and LTE.

The key contribution of our work is the development of a method that exploits the coexistence of UMTS and LTE networks that are managed by a single telecommunication operator to achieve a balance between network performance and energy efficiency by switching off/on LTE macro-BSs according to the traffic load conditions while guaranteeing service and coverage for users using UMTS macro-BSs. To secure the cell coverage area, particle swarm optimization (PSO) has been adopted to maximize the active UMTS cell coverage area during a switch-off session for LTE-BSs under constraints concerning the BS transmission power (P_{tx}), the total antenna gain (G), the signal-to-interference-plus-

noise ratio (*SINR*), and shadow fading (σ). Moreover, the modulation and coding scheme (MCS) and data rates are considered.

The remainder of this article is organized as follows. The site power consumption breakdown is described in Sect. 2. Mechanisms for the proposed BS-switching scheme are presented in Sect. 3. The system model and cell coverage area optimization problem are described in Sect. 4. The simulation setup and optimization programming are given in Sect. 5. Section 6 presents the results and discussion, and Sect. 7 concludes the paper.

2 Site Power Consumption Breakdown

A BS is a centrally located set of equipment used to communicate with mobile units and the backhaul network. It consists of multiple transceivers (TRXs), each of which serves one transmission antenna element. A TRX consists of a power amplifier (PA) that amplifies the input power, a radio-frequency (RF), small-signal transceiver section, a baseband (BB) for system processing and coding, a DC–DC power supply, a cooling system, and an AC–DC unit for connection to the electrical power grid [8]. Figure 1 shows a simplified block diagram of a complete BS that can be generalized to all BS types. Moreover, Table 1 summarizes and compares the power consumption of UMTS and LTE BSs. More details on the internal BS components can be found in [9].

The total power consumption using UMTS technology is higher than LTE; the main reason for this difference is that the PA efficiency in UMTS is less than that in LTE. However, in both technologies, PA consumes more energy than the other hardware elements. Consequently, highly efficient PAs are essential for OPEX cost reduction for the mobile network operators. The most efficient PA operating point is close to the maximum output power (near saturation). Unfortunately, non-linear effects and OFDM modulation with variable envelope signals in LTE force the PA to operate in a more linear region, i.e., 6–12 dB below saturation [9].

3 Mechanism of the Proposed BSs-Switching Scheme

This section presents an algorithm that attempts to reduce energy consumption in cellular networks by exploiting the coexistence of dual radio access technologies (DRAT), i.e., LTE and UMTS, while applying a dynamically BS switching-on/off approach. Other RAT



Fig. 1 Block diagram of a base station transceiver [8]

Item	Notation	Unit	LTE [5, 9]	UMTS [1, 10, 11]
PA	Max transmit (<i>rms</i>) power, P_{max}	(W)	40	40
	Max transmit (rms) power	(dBm)	46.0	46.0
	PA efficiency, μ	(%)	38.8	20
	Feeder loss, σ	(dB)	3.0	3.0
	Total PA $(P_{PA}) = \frac{P_{\text{max}}}{\mu}$	(W)	102.6	200
TRX	Total RF (P_{RF})	(W)	10.9	10.0
BB	Total BB (P_{BB})	(W)	14.8	18.0
DC–DC loss, σ_{DC}		(%)	6.0	9.0
Cooling loss, σ_{cool}		(%)	9.0	10.0
AC–DC (main supply) loss, σ_{MS}		(%)	7.0	8.0
Total per TRX = $\frac{P_{PA} + P_{RF} + P_{BB}}{(1 - \sigma_{DC})(1 - \sigma_{cool})(1 - \sigma_{MS})}$		(W)	160.8	303
Number of sectors		#	3.0	3.0
Number of antennas		#	2.0	2.0
Number of carriers		#	1.0	1.0
Total transceivers (N _{TRX})		#	6.0	6.0
Total N_{TRX} chains, $P_{in=} \: N_{TRX} \times$ Total per TRX		(W)	964.9	1818

Table 1 A comparison of the power consumption of the hardware elements for both UMTS and LTE BSs

can also be considered; however, the scope of our study is limited to these two RAT. We shall start with a motivational example in Fig. 2 that shows a real traffic profile from a cellular wireless access network [1].

Clearly, the traffic profile at night is much lower than during the day. Because the operators need to deploy their BSs to support the peak traffic, it is inevitable that the BSs will be under-utilized most of the time, especially at night, which explains why energy savings can be achieved using dynamically switching on/off BSs.

Figure 3 illustrates the DRAT deployment model of UMTS and LTE cells. LTE-BSs cover a smaller area than do UMTS-BSs. Generally, a UMTS-BS is deployed to provide continuous coverage of an area, whereas LTE-BSs increase capacity. The following basic



Fig. 2 The daily downlink traffic load pattern of a BS

questions naturally arise: (1) When and which BSs should be switched on/off? (2) What are the important parameters to consider when determining the switching status?

Operational on/off decisions depend on three considerations: (1) fulfilling the highspeed data needs of mobile subscribers at peak times; (2) provide full radio coverage to the neighboring cells, therein guaranteeing service during switch-off sessions; and (3) switching off the largest possible number of neighboring cells, which guarantees significant reductions in energy use. Here, two cases are considered.

• Case 1: high traffic load $(0.4 < \lambda \le 1)$

What do the subscribers need from the mobile operators at this stage? With the proliferation of wireless data applications, we are witnessing an unprecedented demand for high-bandwidth streaming video data. Therefore, the priority in this case is for a high data rate in addition to full radio coverage area with high QoS. Figure 4 illustrates the ultra-fast data transmission of both 3G and 4G. The LTE BSs should be active in this case to meet the demands for high data rates. In addition, the UMTS BSs should also be active to support the LTE cells and to guarantee coverage and radio services, especially at the edge of the LTE cells.

Moreover, LTE allows more users to use the same frequency in a cell, which results in an increase in the number of mobile broadband users. In addition, LTE offers higher data transfer rates, which result in higher download and upload rates. When the rate is increased, Internet connection lagging problems will also be reduced. In addition, LTE separates frequencies into different channels to protect against interference between



Fig. 3 Dual RAT cellular network topology considered in this study (*black cells* represent *case* 1, $R_{org} = 750$ m; *red cells* represent *case* 2, $R = 2R_{org} = 1.5$ km)





channels, which means overcoming path loss and other phenomena such as fading and noise. In addition, a radio transmitter and receiver are closer together because of the small cell size, which leads to a higher SINR and higher spectral efficiency.

However, this category of traffic continues for only 13 h (10 a.m.–11 p.m.), as shown in Fig. 2. After this period, the mobile traffic becomes <0.4, which represents a low-traffic-load case (energy saving period), i.e., the focus of our study.

• Case 2: low traffic load ($0 < \lambda \le 0.4$)

In this stage, the priorities of energy savings and power consumption grow proportionally with the number of cells. In this mode, LTE macro-BSs will be switched off, but service and coverage for users will be guaranteed using UMTS macro-BSs. Moreover, specific needs of subscribers can be met using UMTS technology, which has the following features:

- 1. The bandwidth is 5 MHz, which provides data rates of up to 14 Mbps (as shown in Fig. 4)
- 2. Large coverage area: because the receiver sensitivity power is low, the MCS decreases and the demodulation error rate increases as a result of the increase in both noise and the interference that often occurs at the edge of a cell. Low-order modulation, such as quadrature phase-shift keying (QPSK), is more robust and can tolerate higher levels of interference.

The switch-off\on procedures involve three steps (as shown in Fig. 5), which are described as follow:

- 1. Switching-off algorithm
- a. Pre-processing state

During the normal operation period, all BSs (UMTS and LTE) are active and operate with full functionality to provide the full coverage needed to guarantee radio service. LTE BSs monitor the traffic load periodically (i.e., every several minutes). Then, they determine if BSs can be turned off as follows: When the traffic load decreases below a certain threshold ($0 < \lambda \le 0.4$) and stays below the threshold for a certain period of time, the switch-off decision, which depends on only information about a BS and its neighboring BSs, is made.

b. Decision state



Fig. 5 Switching-off\on procedures

The switching-off decision depends on a decrease in traffic load below a certain threshold ($0 < \lambda \le 0.4$). Each LTE BS first sends a unicast control signal to a multi-RAT server,¹ which requests switching-off and only switches off when it receives a response to switch off from the multi-RAT server; immediately after, the LTE BSs begin to gradually decrease their transmission power. Meanwhile, UEs served by the switching-off LTE BSs are transferred to active UMTS BSs based on the UE BS signal strength path, which is a similar procedure to the conventional hand-over except that a group of UEs should be handed over at the same time. There has been an abundance of research on group hand-over. Most research has focused on supporting passengers on mass transportation systems such as buses and trains. The key to efficient group hand-over is to predict/prepare the hand-over a priori. A state-of-the-art group hand-over technique, such as in [13, 14], could be used alongside our switch-off algorithm to efficiently support the group hand-over.

c. Post-processing state

In this state, LTE BSs switch off and listen for the wake-up control signal from the MRAT server.

¹ The multi-RAT server is considered a brain for complex control, regulation and communication. In addition to the control functions, the server collects and analyzes data and uses this information to make a decision; data-logger and alarm memory capabilities are of high importance.

Here, the UMTS BSs are active and operate with full functionality to meet the needs of subscribers and guarantee radio service to the entire area while fulfilling data delivery requirements. However, the main concerns of cellular network operators are coverage issues and securing radio service for an entire area in response to the increased size of the UMTS to provide coverage for cell areas that are switched off. To this end, PSO, a bio-inspired computational method, has been adopted in this study to maximize the UMTS cell coverage area under constraints concerning the transmission power of the BS, the total antenna gain, the SINR, and shadow fading. Moreover, the MCS and the data rate are considered.

2. Switching-on algorithm

One way to implement the switching-on algorithm is to reverse the switching-off algorithm. The basic concept of the switching-on algorithm is that the BS should be switched on when the system load reaches the value at which the BS was originally switched off. However, the switched-off BS cannot make a switching-on decision because it does not have information about the current traffic load. Therefore, the switching-on process must rely on UMTS BS measurements of the traffic load and the multi-RAT server control signal. Similar to the switching-off algorithm, the switching-on algorithm also involves the following three parts:

a. Pre-processing state

The pre-processing state of the switching-on algorithm is operated with the post-processing state of the switching-off algorithm. Here, the UMTS BS is active and operates with full functionality to provide the full coverage needed to guarantee radio service. The UMTS BS periodically monitors the traffic load. When the traffic load becomes higher than the recorded traffic load ($\lambda > 0.4$) and maintains such a load for a certain period of time, the switch-on decision, which depends only on information from the UMTS BSs, is made.

b. Decision state

The UMTS BSs send unicast control signals to the multi-RAT server, which requests switching-on from LTE-BSs. Immediately after, the multi-RAT server sends multicast wake-up control signals to the LTE BSs. Then, the LTE BSs begin to gradually increase their transmission power and send unicast control signals containing the response to the multi-RAT server. Meanwhile, the UEs served by the UMTS BS are transferred to active LTE BSs based on the signal strength path of the UE BS. The UMTS BSs remain active to support the LTE BSs and provide extra coverage.

c. Post-processing state:

The post-processing state of the switching-on algorithm is operated based on the preprocessing state of the switching-off algorithm. The LTE BSs are active and operate with full functionality to provide the full coverage needed to guarantee radio service as well as to monitor the traffic load.

4 Mathematical Model and Problem Formulation

4.1 Propagation Model

Coverage depends on many parameters, and the most important parameters are the surrounding environment and the maximum radius of the cell, which have a significant impact on the received signal. However, three phenomena primarily affect the properties of the received signal: propagation path loss, multi-path (small-scale) fading, and shadow (large-scale) fading. Therefore, a basic propagation model for the received power (P_{rx}) can be written as follows [15]:

$$P_{rx} = P_{tx} + G - L_{Hata} - \sigma, \quad [dBm]$$
(1)

where P_{tx} and G denote the transmitted power and the total antenna gain, respectively; L_{Hata} represents the Hata path loss model; and σ is the shadow fading margin.

The Hata path loss model is expressed as a function that depends on the frequency (f), BS antenna height (h_b) , UE antenna height (h_m) , and radius of the cell (R). The basic formula for the Hata path loss is [15]

$$L_{Hata} = 69.55 + 26.16 Log_{10}(f_{\rm MHz}) - 13.82 Log_{10}(h_b) - a(h_m) + [44.9 - 6.55 Log_{10}(h_b)] \times Log_{10}(R_{\rm km}) - K_{\rm suburban} [dB]$$
(2)

$$a(h_m) = [1.1Log_{10}(f_{\rm MHz}) - 0.7] \times h_m - [1.56Log_{10}(f_{\rm MHz}) - 0.8]$$
(3)

$$K_{\rm suburban} = 4.78 [Log_{10}(f_{\rm MHz})]^2 - 18.33 Log_{10}(f_{\rm MHz}) + 40.94$$
(4)

The cell coverage area of a cellular system is defined as the percentage of the area within a cell that has received a signal at a power above a given minimum P_{min} . A cell requires a minimum received *SINR* for acceptable performance; the *SINR* requirement translates to a minimum P_{min} throughout the cell. The transmission power at the BS is designed for an average received power at the cell boundary of P_{min} . However, random shadowing and path loss will cause certain locations within the cell to have a received power below P_{min} . According to [16], the minimum received power P_{min} can be expressed as follows:

$$P_{\min} = N_o B w + N_f + SINR + IM \quad [dBm]$$
⁽⁵⁾

where $N_o BW$ represents the thermal noise level for a specified noise bandwidth, N_f is the noise figure for the receiver, and *IM* is the implementation margin.

4.2 Cell Coverage and Problem Formulation

It is important that a balance between coverage and energy consumption be achieved for cellular green networks. The closed-form solution for the cell coverage problem can be expressed as follows [17]:

$$C = Q(a) + \exp\left(\frac{2-2ab}{b^2}\right) Q\left(\frac{2-ab}{b}\right) \quad [\%]$$
(6)

$$a = \left(\frac{P_{\min} - P_{rx}(r)}{\sigma_{\phi}}\right), \ b = \left(\frac{10\alpha \log_{10}(\exp)}{\sigma_{\phi}}\right)$$
(7)

where σ_{ϕ} is the standard deviation of the shadow fading and α is a path loss exponent. In Eq. (6), the cell coverage area is expressed as a function $C = f(a, b) = f(P_{\min}, P_{rx}, \alpha, \sigma_{\phi})$, where the minimum received power is expressed as a function $P_{\min} = f(N_o, BW, N_f, SINR, IM)$ and the received power is $P_{rx} = f(P_{tx}, G, L, \sigma)$. The problem formulation is described as follows:

$$(p:) \underset{Ptx,G,SINR,\sigma}{\text{maximize}} \left[Q(a) + \exp\left(\frac{2-2ab}{b^2}\right) Q\left(\frac{2-ab}{b}\right) \right]$$
(8)

which is subject to the following constraints:

$$0 < P_{tx} \le P_{tx}^{\max} \tag{9}$$

$$G_{\min} \le G \le G_{\max} \tag{10}$$

$$SINR_{\min} \le SINR \le SINR_{\max}$$
 (11)

$$\sigma_{\min} \le \sigma \le \sigma_{\max}. \tag{12}$$

The problem posed in Eq. (8) is a nonlinear optimization problem. A PSO has been adopted to maximize the coverage under the constraints of P_{tx} , G, SINR, and σ . This algorithm has several advantages, such as lower computational costs, better performance, and fewer adjustable parameters, over other global optimization algorithms [18].

A PSO is initialized using a group of randomly positioned particles, which subsequently search for an optimal point; the position and velocity of each particle in the swarm with N decision parameters in the optimization problem are defined as $X_i = (x_{i1}, x_{i2}, ..., x_{in})$ and $V_i = (v_{i1}, v_{i2}, ..., v_{in})$, respectively. The best previous position of each particle is defined as $P_i = (p_{i1}, p_{i2}, ..., p_{in})$, and the global best position of all particles is represented by $P_g = (p_{g1}, p_{g2}, ..., p_{gn})$. Therefore, the velocity and position of each particle are updated as follows:

$$v_{new} = w \times v_{old} + c_1 \times r_1(p_{in} - x_{in}) + c_2 \times r_2(p_{gn} - x_{in})$$
(13)

where w is the inertia weight; r_1 and r_2 are random numbers, which are usually chosen between [0, 1]; c_1 is the self-recognition component coefficient, which is a positive constant; c_2 is the social component coefficient, which is a positive constant; and the choice of the values $c_1 = c_2 = 2$ is generally referred to as the learning factors. The following weighting function is usually utilized in Eq. (13):

$$w = \frac{w_{\max} - \left[(w_{\max} - w_{\min}) \times iter \right]}{iter_{\max}},$$
(14)

where w_{max} is the initial weight, usually chosen as a large value but less than 1; w_{min} is the final weight; *iter* is the current iteration number; and *iter_{max}* is the maximum iteration number. A large w enables a global search, whereas a small w enables a local search. Linearly decreasing the inertia weight from a relatively large value to a small value through the course of the PSO run provides the best PSO performance comparisons with fixed inertia weight settings.

From Eq. (13), a particle decides where to move next, considering its own experience, i.e., the memory of its best past position and the experience of the most successful particle in the swarm. The new position is then determined using the previous position and the new velocity and can be written as

$$x_{in_new} = x_{in_old} + v_{new}.$$
(15)

5 Simulation Setup and Optimization Programming

The simulation layout involves three LTE-hexagon cells (radius = 750 m) and covers a smaller area than do UMTS cells (radius = 1.5 km) (as shown in Fig. 3). The LTE BSs are active for only 13 h (10 a.m.-11 p.m.) at peak times (as shown in Fig. 2) and are in sleep

mode the remainder of the time. The power consumption of the LTE-BS is 965 W in active mode [9] and 10 W in sleep mode [6]. The simulation model has been implemented in Matlab. Table 2 summarizes the simulation parameters.

The model that has been applied in this study is described in Fig. 6. In addition, the pseudocode of the PSO algorithm is shown in Fig. 7.

6 Results and Discussion

The PSO has been used to maximize the UMTS cell coverage area subject to four different constraints: (1) the transmission power of the BS, P_{tx} ; (2) the total antenna gain, G; (3) the SINR; and (4) shadow fading, σ . The impact of these parameters on the cell coverage area is shown in Fig. 8.

 P_{tx} and G are considered the most important parameters for maintaining coverage at the edge of a cell, where the *SINR* is low and the shadowing is high. When these parameters increase, the coverage also increases, as shown in Fig. 9. The optimal transmission power P_{tx} and antenna gain G provided maximum coverage with a maximum radius of 1.5 km, where the *SINR* was the lowest, at -5 dB, and the shadowing, at 5 dB, is 46 dB_m and 6.1 dB.

For the downlink data transmissions, the BSs typically select the MCS based on the channel quality indicator (CQI) feedback characteristics of the UE's receiver, i.e., the

Item	Parameter	Acronym	Value	Unit	
Network parameters	Carrier frequency	f_c	2.1	GHz	
	Bandwidth	BW	5	MHz	
	Max. cell radius	R _{UMTS}	1.5	km	
		R_{LTE}	0.750		
Base station parameters	Max. BS transmission power	P_{tx}^{\max}	46	dBm	
	BS antenna height	h_b	25	m	
	Tx antenna gain	G	5-10	dB	
	Number of antennas	Nant	2	#	
	Number of sectors	Nsec	3	#	
	Max. total power consumption	$P^{BS}_{\max_tot.}$	1819	W	
Mobile station parameters	Thermal noise density	N_o	174	dBm/Hz	
	Noise figure	N_f	9	dB	
	Implementation margin	IM	3	dB	
	UE antenna height	h_m	1.5	m	
Propagation losses	Morphology	Suburban			
	Propagation model	Hata path lo	Hata path loss model		
	SINR	SINR _{min}	-5	dB	
		SINR _{max}	20		
	Shadow fading margin	σ	4-8	dB	
	Exponent path loss	α	3.7	#	
	Standard deviation of the shadow	σ_{ϕ}	4	dB	

 Table 2
 List of simulation parameters

Inputs	• Initialize network parameters (f_c , BW , h_b , h_m , N_o , N_f , α , σ_{ϕ} , IM).	
	• Initialize PSO parameters, Number of particles ($N=20$), Learning factors ($c_1 = c_2 = 2$), Dimension of particles ($D=5$), Stopping condition (<i>Iter.</i> = 50), Initial weight ($w_{max} = 0.9$), and Final weight ($w_{min} = 0.4$).	
Constraints	• $SINR_{min}$ = -5, $SINR_{max}$ = 20; G_{min} = 5, G_{max} = 10; σ_{min} = 4, σ_{max} = 8; P_{tx_max} = 46 dBm.	
Main algorithm	• Finding the best optimized coverage subject to constraints of P_{tx} , G_{ty} , SINR, and σ .	
Outputs	• Given optimal solution best global fitness (<i>Max. coverage</i>) and the best global position (P_{rec} G. SINR, and σ).	

Fig. 6 Model of maximized coverage programming

SINR, via a link adaptation procedure. The SINR requirement translates into a minimum received power P_{min} throughout the cell. Figure 10 shows the relationship between the radius of the cell, P_{min} and the MCS.

When P_{min} decreases, the MCS decreases because the demodulation error rate increases as a result of the increase in both the noise and the interference that often occurs at the edge of a cell. QPSK is more robust and can tolerate higher levels of interference but provides a lower transmission bit rate. However, the bit rate and data rate depend on the MCS, BW, and number of antennas. Assuming that the physical capacity is modeled as the Shannon capacity, i.e., $BW \log_2 (1 + SINR)$, increasing the radius can cause the data rate to decrease because of the low SINR, high path loss, and low MCS level. Figure 11 highlights the data rate versus macro-cell radii with $P_{tx} = 46$ dBm and BW = 5 MHz.

This study focuses on a cell radius of 1.5 km, which corresponds to that of a cell in a low-traffic case; the lowest modulation rate (QPSK, 1/3 rate) supports a 1.5-km cell radius, with the lowest data rate of 0.3 Mbps for the cell edge users.

Finally, we will briefly discuss the energy savings that are achieved using the proposed approach. The simulation layout involves three LTE hexagon cells and covers a smaller area than does the UMTS cell (as shown in Fig. 3). LTE-BSs are active for only 13 h (10 a.m.-11 p.m.) during peak time (as shown in Fig. 2) and are in sleep mode at other times. The power consumption of an LTE BS is 965 W in active mode [9] and 10 W in sleep mode [6]. The UMTS BSs are active all of the time; during high-traffic periods, they ensure coverage and support the LTE BSs, whereas during low-traffic periods, UMTS BSs have two functions: data delivery and ensuring maximum coverage and radio service. The network-wide power consumption can be expressed as

$$P_{Cons}^{day} = hr_{high_traffic}(a) + hr_{low_traffic}(a) \quad (Watt)$$

where hr refers to the hours per day and a is

$$a = N_{BS}^{active} \times P_{tot}^{macro} - BS$$

(a) Before implementing the switch-off solution, both the LTE UMTS BSs were active for 24 h, and the daily power consumption was

$$P_{Cons}^{day} = \left(N_{BS}^{active} \times P_{tot}^{macro} - BS\right) \times day \ time = \underbrace{(3 \times 965) \times 24}_{LTE - BSs} + \underbrace{(1 \times 1818) \times 24}_{UMTS - BS}$$
$$= 113.12 \text{ kW/day}.$$

Fig. 7 Pseudocode of the considered PSO algorithm

Algorithm of the proposed scheme		
1:	Initialize PSO parameters, Number of particles (N = 20), Learning factors (c_1 = c_2 = 2), Dimension of particles (D = 5), Stopping condition (<i>Iter.</i> = 50), Initial weight (w_{max} = 0.9), and Final weight (w_{min} =0.4).	
2:	Initial populations of particles $X_i = (P_{tor} G, SINR, \sigma)$ with random positions and zero velocities V_i .	
3:	Comparing the position of each particle with constrains	
4:	if $(X_i > \max. \text{ constrains})$ then	
5:	$X_i = \max$. constrains	
6:	end if	
7:	if $(X_i < \min. \text{ constrains})$ then	
8:	$X_i = \min.$ constrains	
9:	end if	
10:	Evaluate the initial fitness values $f(X_i)$ of each particle according to Eq. (8),	
11:	Store the best initial fitness value and both Pbest (P_i) and Gbest (P_g) .	
12:	while <i>i</i> < <i>iter</i> do	
13:	$r_1 = \text{rand ()}; r_2 = \text{rand ()};$	
14:	Calculate <i>w</i> according to Eq. (14),	
15:	Update V_i according to Eq. (13),	
16:	Update X_i according to Eq. (15),	
17:	Comparing the position of each particle subject to constraints	
18:	Repeat steps 3 – 9	
19:	Evaluate the new fitness values $f(X_i)$ of each particle	
20:	Compare each particle's fitness evaluation with the current particle's to obtain the individual best position	
21:	Compare fitness evaluation with the population's overall previous best to obtain the global best position	
22:	end while	
23:	Given optimal solution best global fitness (<i>Max. coverage</i>) and best global position (P_{tx} , <i>G</i> , <i>SINR</i> , σ).	

After implementing the switch-off solution, the LTE BSs are active for 13 h and in sleep mode for 11 h. The UMTS BSs experience no change; thus, the daily power consumption is



Fig. 8 The behavior of constraint parameters that impact the cell coverage area





$$P_{Cons}^{day} = \left(N_{BS}^{active} \times P_{tot}^{macro}_BS\right) \times day \ time = \underbrace{(3 \times 965) \times 13}_{LTE-BSs} + \underbrace{(3 \times 10) \times 11}_{LTE-BSs} + \underbrace{(1 \times 1818) \times 24}_{UMTS-RS} = 81.60 \text{ kW/day}.$$

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Fig. 10 Cell radii versus receiver sensitivity power for different MCSs with $P_{tx} = 46 \text{ dB}_{\text{m}}$ and BW = 5 MHz



Fig. 11 Data rate versus macro-cell radii with $P_{tx} = 46$ dBm and BW = 5 MHz

By applying the proposed scheme to the cellular system, the energy consumption can be reduced by 81.60 kW per day, which means that the network power requirements can be reduced by 27.86 %.

7 Concluding Remarks

This study investigated the possibility of reducing energy consumption by exploiting the coexistence of dual RAT cellular networks—UMTS and LTE—to achieve a balance between network performance (meeting the demands of high data rates during peak traffic hours) and energy efficiency by switching LTE macro-BSs off/on according to the traffic load conditions while guaranteeing service and coverage for users using UMTS macro-BSs. A PSO technique was used to maximize the coverage area for UMTS cells during low-traffic periods to achieve energy savings at the network level subject to constraints on the parameters that affect the cell coverage area: the transmission power of a BS, the total antenna gain, the SINR, and shadow fading. The simulation results show that when the cell coverage area increases, shadowing increases and the SINR decreases, translating into a minimum received power, which may impact the detected and decoded signals. However, the transmitted power and antenna gain ensure good coverage at the edge of the cell. This study demonstrated that daily energy savings of up to 27.86 % can be achieved while guaranteeing cell coverage.

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Mohammed H. Alsharif received his engineering degree in Communication and Control from the Electrical and Computer Engineering Department at the Islamic University of Gaza (IUG), Palestine, in 2008 and an M.S. degree in Computer and Communication Engineering from Universiti Kebangsaan Malaysia (UKM), Malaysia, in 2012. Alsharif is currently pursuing a Ph.D. degree in Electrical and Electronic Engineering at the Universiti Kebangsaan Malaysia. His research interests include wireless communications, green communication, cooperative communication, and multiple radio access technologies.





Rosdiadee Nordin received a B.Eng. degree in electrical, electronic and systems engineering from Universiti Kebangsaan Malaysia in 2001 and a Ph.D. degree in wireless engineering from the University of Bristol, United Kingdom in 2011. From 2002 to 2006, he was a telecommunication engineer with the Maxis Communications in Malaysia. His research interest includes energy efficient wireless communications, resource allocation, advanced Multiple-Input Multiple-Output (MIMO) techniques, fundamental study of TV White Spaces (TVWS) and indoor wireless localization. Dr. Nordin is a professional engineer with the Board of Engineers Malaysia (BEM), corporate member for Institute of Engineer Malaysia (IEM) and member of The Institute of Electronics, Information and Communication Engineers (IEICE), Japan. He is a senior member of IEEE and serves as a reviewer in some IEEE journals related to wireless communications. In addition, he has been appointed to technical committees in several IEEE Malaysia-sponsored conferences.

Mahamod Ismail joined the Department of Electrical, Electronics and System Engineering, Faculty of Engineering and Built Environment, University Kebangsaan Malaysia (UKM) in 1985. He is currently a Professor in Communication Engineering. He received a B.Sc. degree in Electrical and Electronics from University of Strathclyde, UK in 1985, an M.Sc. degree in Communication Engineering and Digital Electronics from University of Manchester Institute of Science and Technology (UMIST), Manchester UK in 1987, and a Ph.D. from University of Bradford, UK in 1996. He was with the fist Malaysia Microsatellite TiungSat Team Engineers in Surrey Satellite Technology Ltd. UK from June 1997 until March 1998. In the summer semester of 2003, he served as a Guest Professor in Computer Engineering in the University of Duisburg-Essen, Duisburg Germany funded by the German Academic Exchange Services (DAAD). His research interests include mobile and satellite communication, and wireless networking, particularly focusing on radio resource manage-

ment for next-generation wireless communication networks. He is a Senior Member of IEEE USA and was the chair of IEEE Malaysia Section from 2011 to 2013.