On the Impact of Sleep Modes and BW Variation on the Energy Consumption of Radio Access Networks

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***Abstract*—This paper tries to analyze the energy saving capabilities of two common power saving techniques being suggested – introduction of sleep modes and bandwidth (BW) variation. The framework for this analysis assumes users and base stations (BSs) to be independently marked point processes in $\mathbb{R}^2$. The relationship between spatially averaged rate, user density, and base station density, which is an extension of findings in [1], is used in an affine power model to estimate the energy that can be saved by the two methods under consideration. The primary contribution of this paper constitutes an analytic relationship between spatially averaged rate, user density, BS density, transmit power, and the noise power. Another key contribution is a proof that shows that power saved by using sleep modes (or turning off BSs) is always greater than the power saved by varying the BW, for a system model implementing an affine power model (described here) when traffic densities below full load are considered.**

I. Introduction

Energy consumption analysis of wireless networks has garnered a lot of attention recently. This has been attributed to a multitude of factors, the most prominent of which is a conscious effort to make wireless networks more energy efficient to reduce environmental impact while continuing to cater to increasing user demands. Two, of the many, approaches that strive to achieve this goal are hardware improvements and the implementation of energy management strategies. Improvements in hardware, as shown in [2], are extremely beneficial for future upgrades or deployments that start anew. Energy management strategies, on the other hand, help minimize the energy consumption of existing and future networks by trying to find ways to use the minimum amount of resources (number of BSs per square kilometer, number of sub-carriers per BS, etc.) to satisfy user demands for a given traffic density. There are two prominent strategies for energy management – sleep modes and BW variation – and this paper compares one against the other. Adopting sleep modes involves turning off a significant portion of hardware in BSs which are not required to meet user demands for a given traffic density at any given time. As the name suggests, BW variation involves increasing or decreasing the BW depending on the traffic density while ensuring that user demands are always met by adapting network capacity to the load. Practical solutions that provide power savings (such as the ones mentioned above) form the basis of research carried out within the GreenTouch[1]consortium wherein, the idea of separating networks into signaling and data networks is being explored. The signaling network ensures coverage while the BSs responsible for satiating data requirements are subject to the methods hitherto described, to help minimize power consumption. Thereby, increasing the overall energy efficiency of the network. This paper aims to bring about a theoretic framework for what has, until now, been a simulation intensive analysis. The foundations for the results discussed in this paper are rooted in the principles of stochastic geometry which allows the introduction of randomness into network topologies. Randomness is introduced by considering users and BSs to be points of homogeneous Poisson point processes. This framework enables us to observe the utility of a particular energy conservation strategy by observing the average behavior that can be expected over a given area wherein averages over all possible cell topologies are included implicitly.

This paper considers the downlink of a wireless network and provides a relationship between spatially averaged rate, user density, BS density, transmit power, and noise power for a given path loss exponent. The work done in this paper can be considered an extension of the work done in [1] and [3]. Details pertaining to the differences between work done here and the aforementioned papers are given in Section II. The expression for spatially averaged rate derived here, along with a linear power model, provides the basis for energy consumption analysis in Section III. A theorem stating the results of a comparison between sleep modes and BW variation is given in Section III-A along with a numerical evaluation in Section III-B, to validate our findings. Concluding remarks and future work are detailed in Section IV.

II. Downlink System Model

The downlink system model considers *single antenna* BSs arranged according to some homogeneous point process Φ_b, with intensity λ_b (BS density) in $\mathbb{R}^2$. The users are located in the Euclidean plane according to an independent stationary Poisson point process Φ_u, with intensity λ_u (user density). User and BS densities are considered to be non-zero, and since there are more users in a network than BSs we assume $\lambda_u >$

[1] http://greentouch.org

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λ_b. The Euclidean plane is tessellated around the BS process, and the Voronoi cell is given by

$$\begin{aligned}\mathcal{C}_{X_b} &= \left\{y \in \mathbb{R}^2 : SINR_y \geq T\right\} \\ &= \left\{y \in \mathbb{R}^2 : L\left(y, x_i\right) \geq T\left(I_{\Phi_b}\left(y\right) + W\right)\right\}\end{aligned}$$

where $X_b = \{x_i\}$ is the set of BS locations, T is the threshold, and $SINR_y$ is the Signal-to-Interference-plus-Noise ratio at point y. $L(y, x_i)$ is power received at point y, W is the noise power, and $I_{\Phi_b}(y)$ is the interference at point y. The noise power is assumed to be additive and constant with σ^2, and no assumptions are made about its distribution. Inclusion of noise in the definition of the Voronoi cell is the main difference between the system model described here and in [1]. This model assumes that all BSs transmit with a constant average power. The received power and the interference are defined as

$$L(y, x_i) = \frac{Ph}{l\left(|y - x_i|\right)}, I_{\Phi_b}\left(y\right) = \sum_{x_j, j \neq i} L\left(y, x_j\right),$$

where P is the transmit power, h is a fading parameter defined as an exponential random variable with mean 1. So "Ph" can be considered to be the "virtual power" at point y that can be represented by an exponential random variable of mean P^{-1}. Finally, $l\left(|y - x_i|\right)$ is the omni-directional path loss function which can be represented as $l\left(r\right) = \left(Ar\right)^{\beta}$, for some constant $A > 0$ and the *path loss exponent* $\beta > 2$, where r is the distance between the point y and the BS at x_i. The interference received at a point y is also dependent on the number of users connected to a BS, an aspect which has not been included in [3]. The general expression derived in this paper includes this aforementioned aspect, and can therefore be considered an extension of their findings. The average number of users connected to a given BS has been shown to be $\mathbb{E}\left(N\right) = \lambda_u / \lambda_b$ in [4], where λ_u is the user density and λ_b is the BS density. Incorporating this fact, results in a "virtual power" that is exponentially distributed with mean $\left(\lambda_u P / \lambda_b\right)^{-1}$. The parameters described above are used to find the probability of coverage (i.e. probability that a point $y \in \mathbb{R}^2$ is covered by the nearest BS, $x_i \in X_b$) and the average rate provided by a system, which form a basis for energy analysis.

Theorem 1. *For $\beta = 4$, the probability of coverage for a threshold t is given by*

$$\begin{aligned}&p_c\left(\lambda_b, \lambda_u, t, P, \sigma^2\right) = \frac{\pi^{3/2}}{2}\lambda_b\sqrt{\frac{P\lambda_u}{\lambda_b t\sigma^2}}\times \\ &\mathrm{Erfc}\left[\frac{\pi}{2}\sqrt{\frac{P\lambda_u}{\lambda_b t\sigma^2}}\left\{\sqrt{\lambda_u\lambda_b t}\tan^{-1}\left(\sqrt{\frac{t\lambda_u}{\lambda_b}}\right) + \lambda_b\right\}\right]\times \\ &\quad\exp\left[\frac{\pi^2\lambda_u P\left\{\sqrt{\lambda_u\lambda_b t}\tan^{-1}\left(\sqrt{\frac{t\lambda_u}{\lambda_b}}\right) + \lambda_b\right\}^2}{4t\lambda_b\sigma^2}\right]. \quad (1)\end{aligned}$$

The spatially averaged rate, $\bar{R}_{\Phi_b}(\lambda_b, \lambda_u, P, \sigma^2)$ can then be approximated as

$$\frac{\pi^{5/2}}{2}\sqrt{\frac{\lambda_u\lambda_b P}{\sigma^2}}\,\mathrm{Erfc}\left[\frac{\pi^2\lambda_u}{4}\sqrt{\frac{P}{\sigma^2}}\right]\exp\left[\frac{\pi^4\lambda_u^2 P}{16\sigma^2}\right]. \quad (2)$$

Proof: The spatially averaged rate can be written as

$$\bar{R}_{\Phi_b}(\lambda_b, \lambda_u, P, \sigma^2) = \mathbb{E}^0\left[\log(1 + SINR_0) > \gamma\right]$$

where $\mathbb{E}^0$ is the Palm expectation, γ is the threshold, and $SINR_0$ is the Signal-to-Interference-plus-Noise ratio at the origin. For ease of computation, the origin is shifted to the point $y \in \mathbb{R}^2$ under consideration. The spatially average rate $\bar{R}_{\Phi_b}(\lambda_b, \lambda_u, P, \sigma^2)$ then becomes

$$\mathbb{E}^0\left[\log(1 + SINR_0) > \gamma\right] = \mathbb{E}^0\left[SINR_0 > e^{\gamma} - 1\right].$$

Using the Refined Campbell Theorem [5],

$$\bar{R}_{\Phi_b}(\lambda_b, \lambda_u, P, \sigma^2) = \int\limits_{\gamma=0}^{\infty}\int\limits_{r>0}\mathbb{P}^0\left(SINR_0 > e^{\gamma} - 1\right)\Lambda_b\left(dr\right).$$

Here, $\mathbb{P}^0$ is the Palm distribution of $SINR_0$ and Λ_b is the intensity measure of the BS Poisson process. By the Theorem of Slivnyak [5], the spatially average rate ($\bar{R}_{\Phi_b}(\lambda_b, \lambda_u, P, \sigma^2)$) is

$$= \int_0^{\infty}\int_0^{\infty} 2\pi\lambda_b r\exp\left(-\pi\lambda_b r^2\right)\mathbb{P}\left(SINR_0 > e^{\gamma} - 1\right)dr d\gamma.$$

From [4], the probability of coverage or the probability that a point $y \in \mathbb{R}^2$ is covered by its nearest transmitter (for some threshold t) can be defined as

$$\begin{aligned}p_c\left(\lambda_b, \lambda_u, t, P, \sigma^2\right) &= \int_0^{\infty} 2\pi\lambda_b r\exp\left(-\pi\lambda_b r^2\right)\times \\ &\quad\mathbb{P}\left(SINR_0 > t\right)dr \\ &= \int_0^{\infty} 2\pi\lambda_b r\exp\left(-\pi\lambda_b r^2\right)\mathcal{L}_W\left(\mu t r^{\beta}\right)\mathcal{L}_{I_{\Phi_b}}\left(\mu t r^{\beta}\right)dr\end{aligned}$$

where $\mathcal{L}_{I_{\Phi_b}}\left(\mu t r^{\beta}\right)$ is the Laplace transform of the interference, $\mathcal{L}_W\left(\mu t r^{\beta}\right)$ is the Laplace transform of the noise and μ is the fading mean. It's assumed that the constant 'A' in the omni-directional path loss function $l\left(r\right) = \left(Ar\right)^{\beta}$ is equal to 1 for the rest of this proof. The above equation implies that the spatially averaged rate can then be written as

$$\bar{R}_{\Phi_b}(\lambda_b, \lambda_u, P, \sigma^2) = \int_0^{\infty} p_c\left(\lambda_b, \lambda_u, \left(e^{\gamma} - 1\right), P, \sigma^2\right)d\gamma. \quad (3)$$

The probability of coverage can be written as

$$\begin{aligned}&p_c\left(\lambda_b, \lambda_u, t, P, \sigma^2\right) = \int_0^{\infty} 2\pi\lambda_b r\exp\left(-\pi\lambda_b r^2\right)\times \\ &e^{\left(-\mu t r^{\beta}\sigma^2\right)}\exp\left(-2\pi\lambda_b\int\limits_{u>r} u\left(1 - \mathcal{L}_P\left(\frac{\mu t u^{\beta}}{r^{\beta}}\right)\right)du\right)dr\end{aligned}$$

where $\mathcal{L}_P\left(\mu t u^{\beta}/r^{\beta}\right)$ is the Laplace transform of the power received at a point y. The probability of coverage for $2 < \beta < 4$ can be found by numerical integration but $\beta = 4$ gives a closed form. Assuming $\beta = 4$ implies

$$\begin{aligned}&p_c\left(\lambda_b, \lambda_u, t, P, \sigma^2\right) = \int_0^{\infty} 2\pi\lambda_b r\exp\left(-\pi\lambda_b r^2\right)\times \\ &\exp\left(-\frac{t r^4\lambda_b\sigma^2}{\lambda_u P}\right)\exp\left(-2\pi\lambda_b\int_r^{\infty}\frac{u}{1 + \frac{\lambda_b}{\lambda_u}\left(\frac{u^4}{t r^4}\right)}du\right)dr.\end{aligned}$$

Therefore, equation (1) is obtained by a straightforward simplification and solution of the integral above. Substituting equation (1) in equation (3) with $t = e^{\gamma} - 1$ and then changing the limits of integration by the substitution $\frac{\lambda_u}{\lambda_b}\left(e^{\gamma} - 1\right) = \tan^2 z$ results in

$$\bar{R}_{\Phi_b}(\lambda_b, \lambda_u, P, \sigma^2) = \int_0^{\pi/2} \frac{\pi^{3/2}\lambda_u \sec^2 z}{\left(\tan^2 z + \frac{\lambda_u}{\lambda_b}\right)} \sqrt{\frac{P}{\sigma^2}} \times \mathrm{Erfc}\left[\frac{\pi\lambda_u \left\{1 + z\tan z\right\}}{2\tan z}\sqrt{\frac{P}{\sigma^2}}\right] \times \exp\left[\frac{\pi^2\lambda_u^2 P \left\{1 + z\tan z\right\}^2}{4\sigma^2 \tan^2 z}\right] dz.$$

Changing the limits back to 0 to ∞ with the substitution $\tan z = y$, yields

$$\bar{R}_{\Phi_b}(\lambda_b, \lambda_u, P, \sigma^2) = \int_0^{\infty} \frac{\pi^{3/2}\lambda_u}{\left(y^2 + \frac{\lambda_u}{\lambda_b}\right)} \sqrt{\frac{P}{\sigma^2}} \times \mathrm{Erfc}\left[\frac{\pi\lambda_u \left\{1 + y\tan^{-1} y\right\}}{2y}\sqrt{\frac{P}{\sigma^2}}\right] \times \exp\left[\frac{\pi^2\lambda_u^2 P \left\{1 + y\tan^{-1} y\right\}^2}{4\sigma^2 y^2}\right] dy. \tag{4}$$

The equation above gives the exact formulation for spatially averaged rate. Integration after using the series expansion of the inverse trigonometric function to the second order gives a closed form expression for spatially averaged rate, $\bar{R}_{\Phi_b}(\lambda_b, \lambda_u, P, \sigma^2)$

$$= \frac{\pi^{5/2}}{2}\sqrt{\frac{\lambda_u\lambda_b P}{\sigma^2}}\, \mathrm{Erfc}\left[\frac{\pi^2\lambda_u}{4}\sqrt{\frac{P}{\sigma^2}}\right] \exp\left[\frac{\pi^4\lambda_u^2 P}{16\sigma^2}\right],$$

that approximates equation (4) quite closely. ∎

A. Examination of Results

The following inferences can be made from the equation above:

1) The exponential term in equation (2) usually dominates the other terms. If, however, $\lambda_u\sqrt{\frac{P}{\sigma^2}} >> \frac{4}{\pi^2}$ then spatially averaged rate is given by

$$\bar{R}_{\Phi_b}(\lambda_b, \lambda_u) \approx 2\sqrt{\frac{\lambda_b}{\lambda_u}}. \tag{5}$$

This is because the complementary error function can be represented as

$$\mathrm{Erfc}[z] \approx \frac{e^{-z^2}}{\sqrt{\pi}z}, \qquad \forall z >> 1.$$

Making this substitution in equation (2) results in equation (5). Given $\lambda_u > 1$ and the fact that thermal noise power at room temperature is extremely small, it is highly probable that $\lambda_u\sqrt{\frac{P}{\sigma^2}} >> \frac{4}{\pi^2}$. Therefore, equation (5) gives a *good rule of thumb* for calculating the average rate a system can provide for a large $\lambda_u\sqrt{\frac{P}{\sigma^2}}$. Equation (5) also makes it obvious that the spatially averaged rate is not a function of transmit power and noise power. In such cases, assuming an interference limited system and using results obtained in [1] would provide greater accuracy. $\lambda_u\sqrt{\frac{P}{\sigma^2}}$ being much larger than 1 can also be interpreted as $\sigma^2 \to 0$, which means that the SINR model converges to the SIR model (as expected). Therefore, the approximation found above validates the system model used in this paper.

2) The complementary error function can be bounded by

$$\frac{2}{\sqrt{\pi}}\frac{e^{-z^2}}{z + \sqrt{z^2+2}} < \mathrm{Erfc}\left[z\right] \le \frac{2}{\sqrt{\pi}}\frac{e^{-z^2}}{z + \sqrt{z^2 + \frac{4}{\pi}}},$$

$\forall z > 0$. Therefore, for a given user density (λ_u), BS density (λ_b), transmit power (P), and noise power (σ^2), this enables the spatially averaged rate to be bounded as

$$\frac{\pi^2\sqrt{\frac{\lambda_u\lambda_b P}{\sigma^2}}}{\frac{\pi^2\lambda_u}{4}\sqrt{\frac{P}{\sigma^2}} + \sqrt{\frac{\pi^4\lambda_u^2 P}{16\sigma^2} + 2}} < \bar{R}_{\Phi_b}(\lambda_b, \lambda_u, P, \sigma^2) \le \frac{\pi^2\sqrt{\frac{\lambda_u\lambda_b P}{\sigma^2}}}{\frac{\pi^2\lambda_u}{4}\sqrt{\frac{P}{\sigma^2}} + \sqrt{\frac{\pi^4\lambda_u^2 P}{16\sigma^2} + \frac{4}{\pi}}}.$$

3) A finer approximation can be obtained from [6],

$$\exp\left(z^2\right)\mathrm{Erfc}\left[z\right] \approx \frac{1}{\frac{377}{324}z + \sqrt{1 + \frac{314}{847}z^2}},$$

where the maximum relative error is < 0.0033 for $z \ge 0$. The spatially averaged rate can then be approximated as

$$\bar{R}_{\Phi_b}(\lambda_b, \lambda_u, P, \sigma^2) \approx \frac{\frac{\pi^{5/2}}{2}\sqrt{\frac{\lambda_b\lambda_u P}{\sigma^2}}}{\frac{377}{324}\left(\frac{\pi^2\lambda_u}{4}\sqrt{\frac{P}{\sigma^2}}\right) + \sqrt{1 + \frac{314}{847}\left(\frac{\pi^4\lambda_u^2 P}{16\sigma^2}\right)}}. \tag{6}$$

Equation (6) (approximating the SINR model) shall be used for numerical computations required in the forthcoming sections.

III. Energy Consumption Model

The linear power model for a BS, as described in [7], is as follows:

$$P_c = \begin{cases} \Delta_p P_{T_x} + P_0 & \text{if the BS is active} \\ P_S & \text{if the BS is in sleep mode} \end{cases} \tag{7}$$

where P_{T_x} is the transmit power, P_0 is the power consumed by the BS at the lowest possible output power, and Δ_p is the slope of the load dependent power consumption. The power density which is "power consumed per square kilometer (W/km^2)", (without sleep modes) can be defined as

$$D_P = \lambda_b P_c = \lambda_b\left(\Delta_p P_{T_x} + P_0\right), \tag{8}$$

and forms a basis for the comparisions made in this paper. Considering a homogeneous Poisson point process to represent

BSs implies that all BSs in the network are of the same type and we consider them to be macro BSs. The spatially averaged rate (from equation (6)) can be used to estimate the power that is required by the lowest possible BS density that can cater to a given user demand as follows:

1) The user density (users/km^2) is found using
$$\lambda_u = \frac{U\eta(t)}{D}, \tag{9}$$
for a given user demand D Mbps, daily load/ traffic density profile $\eta(t)$, and the maximum rate density per unit area U Mbps/km^2.
2) The spatially averaged rate (in bps/Hz) a system provides is given by
$$\bar{R}_{\Phi_b}(\lambda_b, \lambda_u, P_{T_x}, \sigma^2) = \frac{\bar{R}}{B}, \tag{10}$$
where B is the effective bandwidth in MHz, and the average rate a system provides ($\bar{R}$ in Mbps) is always assumed to be greater than or equal to user demand D.
3) The user density found using equation (9) and the spatially averaged rate found in equation (10) along with suitable values for transmit power P_{T_x}, and noise power σ^2 are used in equation (6) to find the BS density λ_b that satisfies the requirements given above.

Step (3) provides the BS densities – required to satisfy a given user demand when the user densities change throughout the day depending on a traffic or load profile – which shall be utilized in the subsequent sections.

A. Sleep Modes Vs. BW Variation

Power saved can be calculated in different ways depending on the power saving method chosen. This subsection and the next shall focus on a comparison of the amount of savings that can be achieved using sleep modes and BW variation. Power saving using sleep modes is achieved by utilizing only those BSs which help satiate user demands and turning off the other BSs. Whereas, power saving using BW variation is achieved by decreasing the BW while ensuring that user demands are satisfied. An important observation is made in the theorem below and it is corroborated by numerical evidence in the following section.

Theorem 2. *For a system with an affine power model, operating at less than full load and all other parameters considered to be the same, networks using sleep modes are always more energy efficient than networks using bandwidth variation.*

Proof: Assume $P_0 > P_S$, then the power consumed at any given hour of the day for a network using sleep modes and a network using BW variation can be given by
$$D_{P_s} = \lambda_b\left(\Delta_p P_{T_x} + P_0\right) + \left(\lambda_{max(\eta(t))} - \lambda_b\right) P_S \tag{11}$$

$$D_{P_b} = \lambda_b\left(\Delta_p \eta(t) P_{T_x} + P_0\right) \tag{12}$$

where D_{P_s} is the power density while using sleep modes, D_{P_b} is the power density while using BW variation, $\eta(t)$ is the time varying load represented as a percentage, and $\lambda_{max(\eta(t))}$ is the BS density required to satisfy user demands at the maximum load. It's important to note that $\lambda_{max(\eta(t))}$ isn't always equal to $\max[\lambda_b]$. Actual deployments are usually designed to satisfy user demands at full load. Hence the BS density used for deployment is $\lambda_{max(\eta(t))}$,
$$\implies D_{P_b} = \lambda_{max(\eta(t))}\left(\Delta_p \eta(t) P_{T_x} + P_0\right). \tag{13}$$
While using sleep modes, BS density $\lambda_b \propto \eta(t)$ and can be written as $\lambda_b = \lambda_{max(\eta(t))}\eta(t)$,
$$\begin{aligned}\implies D_{P_s} &= \lambda_{max(\eta(t))}\eta(t)\left(\Delta_p P_{T_x} + P_0\right)\\ &+ \left(\lambda_{max(\eta(t))} - \lambda_{max(\eta(t))}\eta(t)\right) P_S.\end{aligned} \tag{14}$$
If the power consumed by using sleep modes is always greater than or equal to the power consumed while varying the bandwidth. Then,
$$D_{P_s} \geq D_{P_b}. \tag{15}$$
Simplification and grouping like terms after substituting equation (13) and equation (14) in equation (15) results in,
$$\eta(t) \geq \frac{P_0 - P_S}{P_0 - P_S}, \implies \eta(t) \geq 1.$$
However, the load as a percentage can never be greater than 1. Therefore, the power consumed by a network operating under 100% load at any given hour during the day using sleep modes is always less than a similar network using BW variation and is equal when the network operates at full load. Therefore,
$$D_{P_s} \leq D_{P_b}.$$
Hence, networks with sleep modes are more energy efficient than networks utilizing BW variation. ■

B. Numerical Validation

To bolster the case for using sleep modes over BW variation, the load profile shown in Fig. 1 is considered. All values

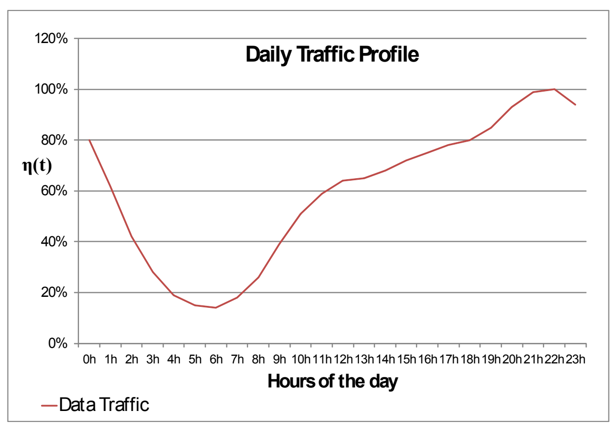

Fig. 1. Daily traffic/ load profile

assumed in this section are taken from [7], and are as follows:

1) The user demand D is set to 2 Mbps, a dense urban traffic profile with a maximum rate density per unit area U is equal to 120 Mbps/km^2, and the effective bandwidth B is 6.39 MHz (obtained by considering a

10MHz LTE system - 600 sub-carriers, frequency spaced at 15 KHz, and a control overhead of 29%).

2) The slope dependent power consumption $\Delta_P = 5.32$, the fixed power consumption $P_0 = 118.7$ W, and a sleep power $P_S = 0.5$ W that corresponds to a deep sleep mode is chosen.

3) The transmit power (in dBm) is calculated using $P_{T_x} = -120 + 10\log_{10}(\text{No. of sub-carriers}) + 30$, and the noise power (in dBm) is calculated by $\sigma^2 = -174 + 10\log_{10}(B)$.

The average rate provided by the system is assumed to satisfy user demands in the area and is considered to be 2 Mbps (i.e. $\bar{R} = 2$ Mbps). Equation (10) then gives the spatially averaged rate required. Here's where the methods of calculating the power saved for sleep modes and BW variation differ. For sleep modes, all available sub-carriers (600) are used whereas the number of sub-carriers utilized in BW variation is a function of the traffic profile (i.e. no. of sub-carriers utilized = max. no. of sub-carriers $\times\eta(t)$). In the case of BW variation, this results in a transmit power that is a function of the load. The BS densities required at different user densities are found by substituting the values assumed above in equation (6). The BS density required to satisfy user demands at maximum load ($\lambda_{max(\eta(t))}$) – considered to be the BS density actually deployed – is found. The power density (at a given hour) while using sleep modes and BW variation are found using equation (11) and equation (12) respectively. The power saved while employing either method is calculated using

$$\text{Power Saved} = D_{P_{max}} - D_P,$$

where $D_{P_{max}}$ is the maximum power density utilized for the given traffic profile and D_P is the power density at a given hour of the day, which is found using equation (11) or equation (12) depending on the method being considered. Fig. 2 shows the variations in power saved throughout the day for both sleep modes and BW variation. From Fig. 2, it's abundantly clear

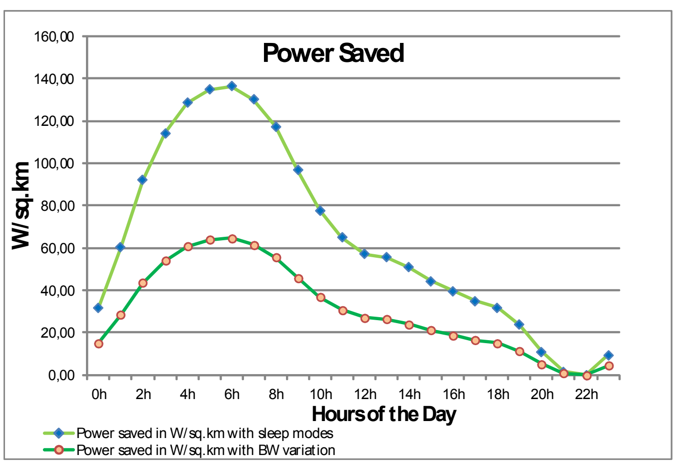

Fig. 2. Power saved using sleep modes vs. power saved using BW variation

that sleep modes save more power than BW variation at any given hour of the day if the load is less than full (i.e. load is less than 100%). At full load, employing either method saves the same amount of power as can be seen at hour 22 in Fig. 2. For the traffic profile considered, sleep modes save an average of approximately 64 W/km^2 (40% of $D_{P_{max}}$) through the day whereas BW variation saves an average of approximately 30 W/km^2 (18% of $D_{P_{max}}$). Similar conclusions can be drawn for evaluations with larger values of sleep mode power P_S as long as P_0 is not lesser than or equal to P_S. For example: sleep modes save an average of approximately 60 W/km^2 and 50 W/km^2 (37% and 31% of $D_{P_{max}}$) through the day for a P_S of 15 W and 50 W respectively. Therefore, the theorem holds for all scenarios of practical interest.

IV. Conclusion

An analytic expression for spatially averaged rate relating user density, BS density, transmit power, and noise power has been found. Various bounds and approximations for the expression have been detailed. This is utilized in an affine power model to examine the power saving potential of two energy management strategies – sleep modes and BW variation. A proof indicating that sleep modes always save more energy than BW variation under conditions of less than 100% load, for scenarios where the power consumed by a BS at the lowest possible output power is greater than the power consumed during sleep mode, has been given. Numerical evaluations that illustrate the assertion made have also been shown. The results obtained in this paper provide valuable insight into energy consumption of networks and affirms the benefits of using energy management strategies to reduce energy consumption in a network. Pitting the energy management strategies against each other (sleep modes versus BW variation) provides noteworthy consequences. Examining the energy consumption of a network with micro and macro BSs, analyzing the effects of incorporating more sophisticated power models within the current framework forms the foundation for future work of the authors.

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