Energy Efficiency of Cooperative Base Station Sleep Scheduling for Vehicular Networks

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***Abstract*—This paper investigates the energy efficiency of base station sleep scheduling strategies in 1-D infrastructure-based wireless communication networks formed by vehicles traveling on a highway. In certain scenarios, vehicular speeds and locations can be measured with a high degree of accuracy, and this information can be exploited to reduce the energy consumption of base stations. This paper considers cooperative base station scheduling strategies where base stations can switch between sleep and active modes to reduce the average energy consumption, while guaranteeing the connectivity of every vehicle. Analytical results on the expected amount of energy saving for a base stations are derived, which reveals for the first time the existence of a threshold parameter, determined by both the vehicular density and mobility, below which base stations can switch off and save energy, but above which no energy saving can be achieved.** [1]

***Index Terms*—Energy Saving; Vehicular networks; Sleep mode**

I. Introduction

Vehicular data communication networks are receiving increasing attention recently, seeing a large number of applications such as improving safety and productivity of road transport [1]. In such networks, information (such as advertisement, news and traffic update) is delivered from base stations deployed along the road to vehicles traveling on the road. As improving energy efficiency has become an important design goal for wireless communication networks [2], this paper focuses on the energy efficiency of base stations for infrastructure-based vehicular networks.

In many infrastructure-based wireless communication networks, such as cellular networks, base stations are usually the dominant components consuming the largest portion (e.g. 60-80% [3]) of the total energy used in wireless communications. Base station sleep scheduling strategies have been widely studied and considered to be efficient methods that can realize substantial energy saving [3], [4]. Specifically, when the number of users is smaller or when the traffic load is low, idle base stations can be switched off to save a considerable amount of energy. This feature is enabled by the sleep mode commonly available in base stations, where the sleep model mainly contains two types: the micro sleep mode, where base stations suspend transmission in the order of milliseconds, and the deep sleep mode, where base station transmitters are shut down for extended periods of time [5]. This paper focuses on the benefits of the deep sleep mode since it saves a significantly larger amount of energy compared with the micro sleep mode.

The design of base station sleep scheduling strategies in vehicular networks is challenging mainly due to the fact that the network topology of a vehicular network is *highly dynamic*. The dynamic network topology is caused by vehicular mobility, which is random in nature and can only be characterized stochastically [6]. In addition, the dynamic network topology is also attributable to that fact that the vehicle densities can also be very different depending on different time-of-day or different day-of-week [7]. Consequently, base station sleep scheduling strategies need to take both vehicular density and mobility into account in order to identify the scenarios that are suitable to operate.

In this context, our main contributions are as follows: 1) we develop a statistic energy saving model for 1-D Infrastructure-based vehicular networks; 2) analytical results on the expected energy saving are obtained, for both an online and an offline scheduling strategy, where the offline case considers an ideal scenario and gives an upper bound on the energy saving and the online strategy takes practical constrains into account; 3) we show the existence of a threshold parameter, determined by vehicular density and mobility, below which base stations can switch off and can save energy, but above which no energy saving can be achieved; 4) the analysis is validated using simulations.

The rest of this paper is organized as follows: Section II reviews related work. Section III describes the network model. The analysis on the energy efficiency is presented in Section IV. Section V validates the analysis using simulations. Finally Section VI concludes this paper and proposes future work.

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II. Related work

A number of studies in this area focused on the connectivity between base station and vehicles [8]. In particular, in [3] Marsan et al. considered the both the network with random deployment of base stations and the network with regular deployment of base stations, by numerical results they showed that the regular deployment provided the highest level of connectivity for all densities of the nodes and base stations. Motivated by this, this paper considers a regular deployment of base stations, which is described in Section III.

Seeing that base stations are the dominant components of energy consumption in wireless communication networks, there have been a large number of efforts in reducing the amount of energy consumption (as well as the CO2 emission) of base stations [9]. Joo et al. in [10] introduced a GSM BTS power saving mechanism. Specifically, from a power-consumption point of view, a GSM transmitter can be split into three parts: digital signal processing, radio power amplifier (PA) and active timeslots (TS). In [10], the authors assumed that there are more than one TCH transceiver (TX) in a radio cell, and the power used for calls (active TS) varies with data traffic load. When data traffic is light, the TX might not have any active timeslots at all, in which case only the "digital" and "PA" parts of the transceiver consumes power. The power-savings mode reduces or shuts off power to all but the "digital" part of the transceiver. When traffic in a cell increases and the amount of idle timeslots falls below a given threshold, the idle TX is immediately put back into service. This feature enables operators to manage Base Transceiver station (BTS) in a vastly more energy efficient way which on average yields a 15% to 25% reduction in BTS power consumption.

A recent work of Hammad et al. [11] provided a timeslot-based base station scheduling strategy. Specifically, when a vehicle first enters the coverage range area of a road side unit (SU), it transmits its current position and speed to the SU. The SU minimizes the downlink infrastructure-to-vehicle energy communication by delaying the information transmission until the vehicle come closer to the SU, because the power consumption needed when the SU communicates to a nearby vehicle can be significantly lower than when it communicates with a more distant vehicle. Differently, this paper considers a base station sleep scheduling strategy which only switches off idle base stations without affecting QoS, i.e. without delaying the information dissemination or affecting connectivity.

III. Network model

This paper considers a 1-D infrastructure-based wireless communication network formed by vehicles on a highway. The spatial distribution of vehicles follows a homogeneous Poisson process with intensity ρ [8]. Speed of each vehicle is considered to be independently and identically distributed following a common uniform distribution [12]. Specifically, denote by V the vehicle speed, whose probability density function (pdf) is $f(v) = \frac{1}{b-a}$ where $b > a > 0$. Though we only consider that vehicles travel in one direction, the analysis can be straightforwardly extended to the case

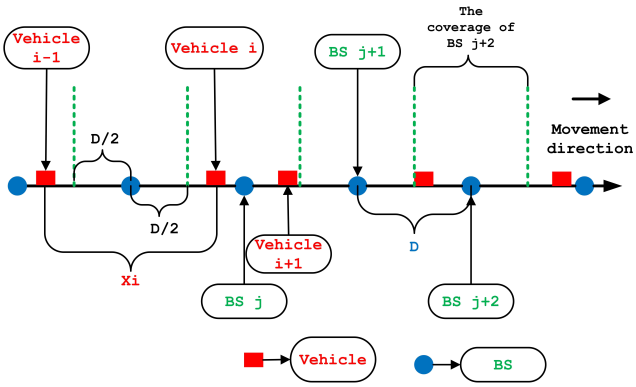

Figure 1. Illustration of the network topology, where D is the distance between BSs, X_i is the distance between vehicle $i+1$ and vehicle i. Details about the notations are introduced in Section IV.

involving traffics in both directions. Further, as commonly done in this field, we consider that vehicular speed remains constant over time [13].

A set of base stations (BSs) are regularly deployed with distance D between adjacent BSs [8], as illustrated in Fig. 1. Typical values of D can be found in [14], depending on practical implementations. Further, it is considered that each vehicle is served by its closest BS. Consequently, the *coverage* of a BS, as illustrated in Fig. 1, is the road segment wherein all vehicles are served by the BS. As shown in Fig. 1, vehicle i is served by BS j and vehicle $i+1$ is served by BS $j+1$.

Further, it is assumed that each BS can detect the position and speed of vehicles in its coverage [15] and then transmit the information to other BSs via wired connections. This paper focuses on the energy efficiency of base stations that is not at the beginning of a road segment, which is a special case because it does not receive information about incoming vehicles. As introduced in Section I, a BS can be in either of the active mode or the sleep mode. In the active mode, a BS operates as normal; while in the sleep mode, a BS switches off the transmitter and amplifier to save energy. Therefore, a BS cannot transmit or receive when it is in the sleep model. This paper considers sleep scheduling strategy that switches BSs between the active mode and the sleep mode without affecting the QoS such as delay and connectivity. That is, the nearest BS to every vehicle is in the active mode at any time instant. The detailed sleep strategies are described later in Section IV.

We next describe the energy consumption model. Let E_a be the energy consumption per unit time of an active base station and let E_s be the energy consumption per unit time of a sleeping base station, as illustrated in Fig. 2. Further, consider that the energy cost of turning a BS off and then back on is E_{c1} and E_{c2} respectively, where typical values of them can be found in [16]. Then the total energy cost of turning a BS off and later back on is $E_c = E_{c1} + E_{c2}$. This extra energy cost can have a significant impact on the design of the base station sleep strategies as can be seen in the next section.

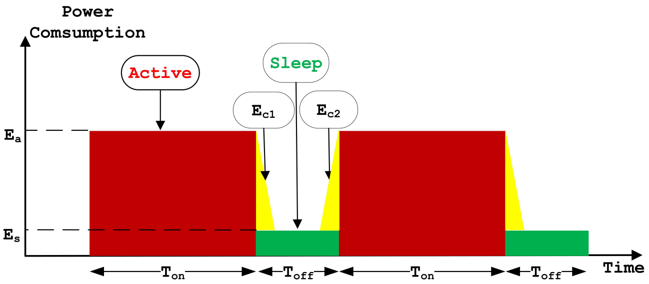

Figure 2. Illustration of two base station duty cycles: each cycle consists of an active period (T_{on}) followed by a sleep period (T_{off}).

IV. Analysis of the Energy Efficiency

This section presents analysis of the energy efficiency of both online and offline base station sleep strategies. An offline sleeping strategy assumes a complete knowledge of the network topology, which gives an upper bound on the energy saving; while an online sleeping strategy is designed according to practical scenarios and results in a less amount of energy saving compared with that of the offline counterpart.

A. Offline sleep strategy

As introduced in Section III, when a BS is sleeping instead of active, the amount of energy saving per unit time interval is $E_0 \triangleq E_a - E_s$. Further, the energy cost of turning a BS off and then later back on is E_c. Denote by T_{th} a threshold time interval, longer than which a BS sleeps resulting in a positive value of $E_0 T_{th} - E_c$, but if a BS sleeps shorter than the threshold cannot save energy (i.e. has a negative value of $E_0 T_{th} - E_c$). It is straightforward that the threshold time interval is given by

$$T_{th} = \frac{E_c}{E_a - E_s}. \tag{1}$$

Denote by X the Euclidean distance between two adjacent vehicles (say vehicle i and vehicle $i+1$ as illustrated in Fig. 1 at a randomly chosen time instant. Due to Poisson distribution of vehicles, X follows an exponential distribution with pdf $\Pr(X = x) = \rho \exp(-\rho x)$. Denote by T_g the *time gap of vehicles*, which is defined as the time period from the time when a vehicle $i+1$ leaves the coverage of a BS j but next vehicle i has not enter the coverage of the BS j, to the time when the next vehicle i enters the coverage of the BS j. Then T_g is the time period when BS j is idle and can be switched off to save energy. Recall that V is the speed of a randomly-chosen vehicle. It can be shown that $T_g = \frac{X-D}{V}$.

We first consider an ideal scenario where BSs have a complete knowledge of the network topology. If each BS knows exactly the distance X between adjacent vehicles at any time, then a BS can power off to save energy during the period where the time gap of vehicles is larger than the threshold T_{th} given by Eq. 1. Specifically, the offline base station sleep strategy is described as follows

Definition 1 (Offline Sleep Strategy)**.** Suppose at time t a vehicle leaves the coverage of a BS and there is no other vehicle in its coverage range. Suppose that the BS knows that the next vehicle will enter its coverage at time $t + T_g$, then the BS powers off to save energy from time t to $t + T_g$ if and only if $T_g > T_{th}$, where T_{th} is given by Eq. 1.

It is straightforward that the probability that a randomly-chosen BS can turn off to save energy is

$$\begin{aligned}
\Pr(T_g \geq T_{th}) &= \int_{T_{th}}^{\infty} \Pr(T_g = t) dt \\
&= \int_a^b \int_{D+vT_{th}}^{\infty} \Pr(X = x) \Pr(V = v) dx dv \\
&= \int_a^b \int_{D+vT_{th}}^{\infty} \rho \exp(-\rho x) \Pr(V = v) dx dv \\
&= \int_a^b \exp(-\rho(D + T_{th} v)) \frac{1}{b-a} dv \\
&= \frac{\exp(-\rho D)(-\exp(-\rho b T_{th}) + \exp(-\rho a T_{th}))}{(b-a)\rho T_{th}}.
\end{aligned} \tag{2}$$

Denote by $\mathbb{E}[T_{off}]$ the expected length of the sleep time interval of a randomly-chosen BS. Then there is

$$\begin{aligned}
\mathbb{E}[T_{off}] &= \frac{\int_{T_{th}}^{\infty} t \Pr(T_g = t) dt}{\Pr(T_g \geq T_{th})} \\
&= \frac{\int_a^b \int_{D+vT_{th}}^{\infty} \frac{x-D}{v} \Pr(X = x) \Pr(V = v) dx dv}{\frac{\exp(-\rho D)(-\exp(-\rho b T_{th}) + \exp(-\rho a T_{th}))}{(b-a)\rho T_{th}}} \\
&= \frac{\int_a^b (T_{th} + \frac{1}{\rho v}) \exp(-\rho(D + T_{th} v)) \frac{1}{b-a} dv}{\frac{\exp(-\rho D)(-\exp(-\rho b T_{th}) + \exp(-\rho a T_{th}))}{(b-a)\rho T_{th}}} \\
&= \frac{\frac{-\exp(-\rho b T_{th}) + \exp(-\rho a T_{ths}) + Ei(-b\rho T_{th}) - Ei(-a\rho T_{th})}{(b-a)\rho}}{\frac{-\exp(-\rho b T_{th}) + \exp(-\rho a T_{th})}{(b-a)\rho T_{th}}} \\
&= T_{th}\left(1 + \frac{-Ei(-b\rho T_{th}) + Ei(-a\rho T_{th})}{\exp(-b\rho T_{th}) - \exp(-a\rho T_{th})}\right),
\end{aligned} \tag{3}$$

where $Ei(.)$ is the exponential integral function.

As shown in Fig. 2, each sleep period T_{off} is followed by an active period T_{on}. We next study T_{on}. A BS needs to keep active if the time gap T_g between vehicles is smaller than T_{th}, which happens with probability $p_{on} = 1 - \Pr(T_g \geq T_{th})$. Further, denote by K_{on} the number of consecutive time gaps that are smaller than T_{th}. Because of the Poisson distribution of vehicles and independence of vehicle mobility, it can be shown that K_{on} follows a geometric distribution $\Pr(K_{on} = k) = p_{on}^{k-1}(1 - p_{on})$. Consequently, there is $\mathbb{E}[K_{on}] = \frac{1}{1-p_{on}}$. Denote by $\mathbb{E}[T_{on}]$ the expected length of the active period. There is

$$\begin{aligned}
\mathbb{E}[T_{on}] &\approx \mathbb{E}[K_{on}] \frac{\int_{-\infty}^{T_{thres}} (t + \frac{D}{v}) \Pr(T_g = t) dt}{1 - \Pr(T_g \geq T_{th})} \\
&= \frac{1}{1 - p_{on}} \frac{\int_{-\infty}^{T_{thres}} (t + \frac{D}{v}) \Pr(T_g = t) dt}{1 - \Pr(T_g \geq T_{th})} \\
&= \frac{\int_{-\infty}^{T_{th}} (t + \frac{D}{v}) \Pr(T_g = t) dt}{\Pr(T_g \geq T_{th})(1 - \Pr(T_g \geq T_{th}))},
\end{aligned} \tag{4}$$

where

$$\begin{aligned}
&\int_{-\infty}^{T_{th}} (t + \frac{D}{v}) \Pr(T_g = t) dt \\
&= \int_a^b \int_0^{D+vT_{th}} \frac{x}{v} \Pr(X = x) \Pr(V = v) dx dv
\end{aligned} \tag{5}$$

$$= \int_a^b (\frac{1-\exp(-\rho(D+vT_{th}))}{\rho v}$$
$$\frac{-\rho(D+vT_{th})\exp(-\rho(D+vT_{th}))}{\rho v}) \Pr(V=v)dv$$
$$= \frac{\ln(b)-\ln(a)}{\rho(b-a)}$$
$$-\frac{(1+\rho D)(Ei(-b\rho T_{th})-Ei(-a\rho T_{th}))\exp(-\rho D)}{\rho(b-a)}$$
$$\frac{(\exp(-b\rho T_{th})-\exp(-a\rho T_{th}))\exp(-\rho D)}{\rho(b-a)},$$

where $Ei(.)$ is the exponential integral function.

Finally, because the vehicles follow a Poisson distribution and move independently, the operation of a typical BS can be modeled by a renewal reward process, where each cycle consists of an active period followed by a sleep period and the reward is the energy saving. Recall that the amount of energy saved as a BS is given by $E_{off} = T_{off}E_0 - E_c$. Then the expected energy saving per unit time for a typical BS can be calculated by

$$E_{save} \approx \frac{\mathbb{E}[E_{off}]}{\mathbb{E}[T_{off}+T_{on}]} = \frac{\mathbb{E}[T_{off}]E_0 - E_c}{\mathbb{E}[T_{off}]+\mathbb{E}[T_{on}]}, \quad (6)$$

where $\mathbb{E}[T_{off}]$ and $\mathbb{E}[T_{on}]$ are given by Eq. 3 and Eq. 4 respectively.

B. Online sleep strategy

In practical, there may not be a perfect information about the distance X between vehicles. Consequently, a BS may not know whether or not the next time gap will satisfy $T_g \geq T_{th}$. Consider the following online sleep strategy.

Definition 2 (Online Sleep Strategy)**.** A BS switches to sleep mode as soon as there is no vehicle in its coverage, and the BS switches to active mode as soon as the next vehicle enters its coverage.

Note that though a BS does not know the exact distance X between vehicles, the adjacent BSs can work cooperatively to inform the event of incoming vehicles, allowing enough time for a BS to be prepared to switch to the active mode in time.

This scenario is different from that in Section IV-A. Specifically, if the time gap between vehicles is small, then a BS may need to turn on and off frequently, which may cost even more energy consumption.

Denote by $\mathbb{E}[\hat{T}_{off}]$ the expected length of the sleep time interval of a randomly-chosen BS under this scheme. Then there is

$$\begin{aligned}
\mathbb{E}[\hat{T}_{off}] &= \frac{\int_0^\infty t\Pr(T_g=t)dt}{\Pr(T_g\geq 0)} \\
&= \frac{\int_a^b\int_D^\infty \frac{x-D}{v}\Pr(X=x)\Pr(V=v)dxdv}{\int_0^\infty \Pr(T_g=t)dt} \\
&= \frac{\int_a^b \frac{1}{\rho v}\exp(-\rho D)\frac{1}{b-a}dv}{\int_a^b\int_D^\infty \Pr(X=x)\Pr(V=v)dxdv} \\
&= \frac{\ln b - \ln a}{\rho(b-a)}. \quad (7)
\end{aligned}$$

Based on the above result, we have the following Theorem.

Theorem 3. *In a network with density ρ and vehicular speed uniformly distributed in $[a,b]$, let $\alpha(\rho,a,b) \triangleq \frac{\rho(b-a)}{\ln b - \ln a}$. Then using the online sleep strategy described in Definition 2, a positive value of energy saving can be achieved if $\alpha(\rho,a,b) < \frac{E_0}{E_c}$, otherwise no energy saving can be achieved.*

Proof: Note a BS is in either the active mode or the sleep mode. In active mode, no matter how long a BS keeps active, the energy saving is 0. In a sleep period with length T_{off}, the amount of energy saved is $E_{off} = \hat{T}_{off}E_0 - E_c$. According to Eq. 7, the expected energy saving in each sleep period is $E_{off} = \frac{\ln b - \ln a}{\rho(b-a)}E_0 - E_c$. It is straightforward that $E_{off} > 0$ if and only if $\frac{\ln b-\ln a}{\rho(b-a)} > \frac{E_c}{E_0}$. ∎

To characterize the expected amount of energy saving over a long run, we next study the length of the active period. Similarly as Section IV-A, let $\hat{p}_{on} = 1-\Pr(T_g \geq 0)$. Denote by $\mathbb{E}[\hat{T}_{on}]$ the expected length of the active period. There is

$$\begin{aligned}
&\int_{-\infty}^0 (t+\frac{D}{v})\Pr(T_g=t)dt \quad (8)\\
&= \int_a^b\int_0^D \frac{x}{v}\Pr(X=x)\Pr(V=v)dxdv \\
&= \int_a^b \frac{1-\exp(-\rho D)-\rho D\exp(-\rho D)}{\rho v}\Pr(V=v)dv \\
&= \frac{(\ln b-\ln a)(1-\exp(-\rho D)-\rho D\exp(-\rho D))}{\rho(b-a)}.
\end{aligned}$$

Then,

$$\begin{aligned}
\mathbb{E}[\hat{T}_{on}] &\approx \frac{1}{1-\hat{p}_{on}}\frac{\int_{-\infty}^0 t\Pr(T_g=t)dt}{1-\Pr(T_g\geq 0)} \quad (9)\\
&= \frac{\frac{(\ln b-\ln a)(1-\exp(-\rho D)-\rho D\exp(-\rho D))}{\rho(b-a)}}{\Pr(T_g\geq 0)(1-\Pr(T_g\geq 0))} \\
&= \frac{(\ln b-\ln a)(1-\exp(-\rho D)-\rho D\exp(-\rho D))}{\rho(b-a)\exp(-\rho D)(1-\exp(-\rho D))}.
\end{aligned}$$

Similarly as above, the expected energy saving per unit time for a typical BS can be calculated by

$$\hat{E}_{save} \approx \frac{\mathbb{E}[E_{off}]}{\mathbb{E}[\hat{T}_{off}+\hat{T}_{on}]} = \frac{E_0 - \frac{\rho(b-a)E_c}{\ln b-\ln a}}{1+\frac{1-\exp(-\rho D)-\rho D\exp(-\rho D)}{\exp(-\rho D)(1-\exp(-\rho D))}}. \quad (10)$$

V. Numerical evaluation

This section present numerical evaluation of the results presented in the previous section, followed by discussions and conclusions. The parameters are taking typical values reflecting certain practical scenarios. Specifically, the distance between base stations is $D = 0.8km$ [14]. The energy consumption model uses parameters $E_0 = 1kw$ and $E_c = 8J$ [8].

Fig. 3 shows the expected energy saving of a BS using the offline sleep strategy described in Section IV-A. It can be seen that the energy saving decreases as vehicle density increases. Because the scenario is ideal where BSs have a complete knowledge of the network topology, the energy saving is always non-negative and it is an upper bound on the energy saving using the online strategy shown in Fig. 3.

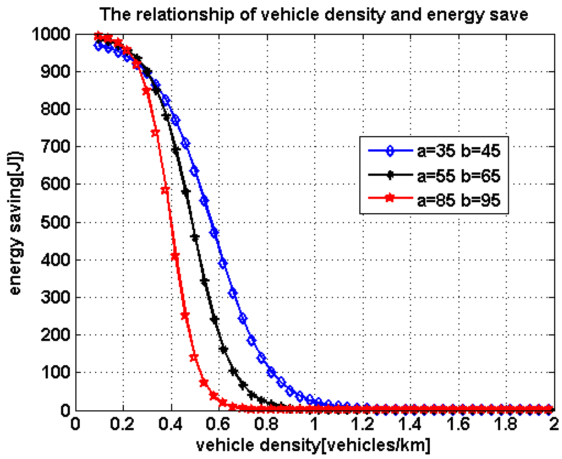

Figure 3. Energy saving using the offline sleep strategy

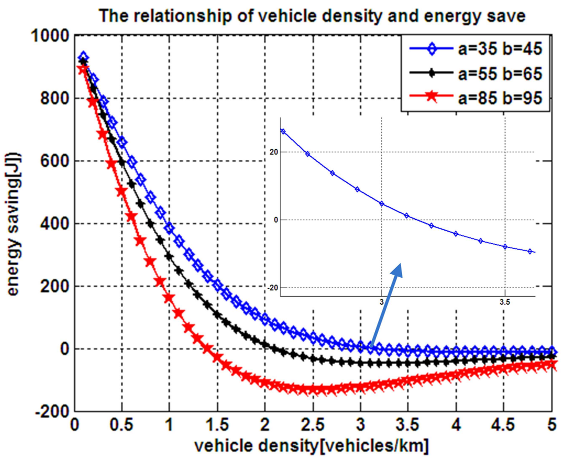

Figure 4. Energy saving using the online sleep strategy

Fig. 4 shows the expected energy saving of a BS using the online sleep strategy described in Section IV-B. It can be seen that the curves exhibit an interesting trend different from that in Fig. 3. When the vehicle density is low, a large amount of energy can be saved. Then the energy saving decreases as vehicle density increases, because the sleep time T_{off} becomes shorter and more energy is wasted in frequently switching the BS between sleep and active modes. As the vehicle density further increases, the energy waste of energy in switching between sleep and active modes becomes dominant and there is a negative energy saving. Moreover when the vehicle density is high, the distance between adjacent vehicles becomes so small that there is little opportunity to switch off a BS. In this case, the BS keeps active and the energy saving tends to 0. From the threshold $\alpha(\rho, a, b) \triangleq \frac{\rho(b-a)}{\ln b - \ln a}$ and $\alpha(\rho, a, b) < \frac{E_0}{E_c}$, we can calculate that when the vehicle speed is $a = 35, b = 45$, the energy saving is positive when $\rho < 3.2$; when the vehicle speed is $a = 55, b = 65$, the energy saving is positive when $\rho < 2.1$; when the vehicle speed is $a = 85, b = 95$, the energy saving is positive when $\rho < 1.39$. It is clear that the threshold is a key parameter in the implementation of online BS sleep strategies.

VI. Conclusion and Future Work

This paper analyzed the energy efficiency of base station sleep strategies in 1-D infrastructure-based wireless vehicular networks. Analytical results on the expected amount of energy saving for base stations were derived for both an offline and an online sleep strategy. We provided a threshold parameter, determined by vehicular density and mobility, below which base stations can switch off and save energy, but above which no energy saving can be achieved.

In a future work, we plan to verify our results in a network simulator driven by real world vehicular trace. To better reflect the real world scenario, the impact of time-varying vehicular speed on the sleep strategy needs to be evaluated. Moreover, multi-hop communication via ad-hoc connections between vehicles can be employed, which is expected to yield a more significant energy saving when combining with the strategies studied in this paper.

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