Energy Efficient Ultra-Dense Network Using Long Short-Term Memory

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Abstract—The energy consumption of cellular systems is becoming a matter of grave concern in both economic and environmental perspectives. Recently, in order to reduce the energy consumption of base stations (BSs), which takes the largest portion, turning off under-loaded BSs has been suggested. However, determining the on/off mode of BSs is a non-convex optimization problem. Also, the problem must be solved in accordance with the time-varying environment since the transition overhead in the future may outrun the power saving at the moment. In this paper, we propose Long Short-Term Memory (LSTM) based framework to make far-sighted control decisions maximizing energy efficiency from a long-term perspective. The LSTM-based network can intelligently determine the on/off modes, utilizing the time-correlated property of the channel and approximating complex mapping between channel state and desired power control coefficient. Lastly, through the convex optimization technique, the optimal power allocation for the active BSs can be found. Simulation results show that the proposed technique outperforms the conventional techniques by a large margin.

I. INTRODUCTION

In recent years, an ultra-dense network (UDN) where a large number of small cells (i.e., pico cell and femto cell) are densely deployed (more than $10^3$ cells/km$^2$) on top of the macro cells has received a great deal of attention as a means to improve the network capacity of future wireless communication system [1], [2]. UDN shortens the physical distance between the base station (BS) and the mobile device, resulting in a reduction of the path loss caused by wireless transmission, in particular for the millimeter wave (mmWave) band. Further, it enables aggressive reuse of frequency resources, thereby achieving a significant improvement in the quality of service (QoS) of wireless networks [3].

Despite a variety of benefits, intensive deployment of small cells in UDN may pose a serious concern in energy efficiency [4]. In fact, a surge of energy consumption due to the use of a large number of small and macro cells is a heavy burden for the network operators since it increases the operational expense (OPEX) to a large extent [5]. Pursuing an enhancement in the energy efficiency is, therefore, an inevitable direction to ensure the sustainability of wireless network [6], [7].

Among several factors contributing to the energy consumption of the cellular systems, by far the most dominant one is the BS. To reduce the energy consumption of BS, a technique so-called sleep mode technique that turns off the lightly loaded BSs has been proposed over the years. The basic idea of this approach is to switch off the power amplifier (PA) of underutilized BS. There have been some works proposing strategies to turn off underutilized BSs [8]. In [9], an approach to randomly shut off the BSs while guaranteeing the coverage of a network has been proposed. In [10], an approach that iteratively turns off the BSs one by one until the traffic-load of remaining BSs reaches the limit has been proposed. However, these approaches are computationally inefficient in UDN since it requires exploring decision set that increases exponentially with respect to the size of the network.

The primary purpose of this paper is to propose an entirely new approach based on deep neural network (DNN) to achieve the reduction of energy consumption in UDN. Among various DNN techniques, long short-term memory (LSTM) is perhaps most effective in handling the sequential data and extracting its features [11]. In our context, this means that LSTM extracts time-correlated features from the channel state information (CSI) to a make fast yet accurate prediction of the time-varying channel. Based on the prediction, LSTM can decide the on/off mode of BSs minimizing the long-term energy consumption of UDN. While the conventional approaches aim to minimize the instantaneous energy consumption, and hence incurs a significant waste of energy due to frequent mode transition (on to off and off to on), the proposed LSTM-based power control technique pursue minimization of the total energy consumption over long-term operational period. Since we turn off BSs without having active users in its coverage, the baseband processing block, as well as the analog block (i.e., PA, RF filter), can be switched off.

From the simulation results, we demonstrate that the proposed LSTM-based power control technique achieves a significant reduction of the energy consumption against the conventional approaches. For example, the proposed method saves almost 40% of energy compared to the full-association scenario where all the BSs are turned on.

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II. ULTRA-DENSE NETWORK SYSTEM

A. System Model of Ultra-Dense Network

In this section, we discuss the UDN system model. We consider the network where $M$ BSs cooperatively serve $K$ users equipped with a single antenna. Nevertheless, the proposed approach can be easily extended to multiple-input multiple-output (MIMO) scenarios. The transmit signal $x_m^l$ of the BS $m$ at time slot $l$ is

$$x_m^l = \sum_{k=1}^{K} \sqrt{\epsilon_m} s_m^l, \quad (1)$$

where $s_k^l$ is the data symbol and $s_m^l$ is the transmit power of the BS $m$ to the user $k$ at time slot $l$. The received signal $y_k^l$ of the user $k$ at time slot $l$ is

$$y_k^l = \sum_{m=1}^{M} h_{m,k}^l x_m^l + n_k^l = \sum_{m=1}^{M} \sqrt{\epsilon_m} h_{m,k}^l s_m^l + \sum_{j \neq k} \sum_{m=1}^{M} \sqrt{\epsilon_m} h_{j,m,k}^l s_j^l + n_k^l, \quad (2)$$

where $h_{m,k}^l$ is the channel coefficient and $n_k^l \sim \mathcal{CN}(0, \sigma_n^2)$ is the additive Gaussian noise at time slot $l$. The corresponding rate of the user $k$ at time slot $l$ is

$$R_k^l = \log_2 \left(1 + \frac{\sum_{m=1}^{M} \epsilon_m h_{m,k}^l |s_m^l|^2}{\sum_{j \neq k} \sum_{m=1}^{M} \epsilon_m g_{j,m,k} |h_{j,m,k}^l|^2 + \sigma_n^2} \right). \quad (3)$$

B. Power Consumption Model and Problem Formulation

The power consumption of the BS consists of three parts: 1) transmission power $p_{tx}^{m,l}$ consumed by the power amplifier and RF circuitry, 2) maintenance power $P_{m}^{on}$ consumed by the power supply and air conditioning, and 3) mode transition power $p_{m}^{trans,l}$ consumed when the BS is switched on and off. Thus, the total power consumption $P_{m}^{tot,l}$ of the BS $m$ at time slot $l$ is given by

$$P_{m}^{tot,l} = P_{m}^{tx} + P_{m}^{on} + p_{m}^{trans,l}. \quad (4)$$

The transmission power of the BS $m$ at time slot $l$ is

$$p_{m}^{tx,l} = \alpha_m^l \sum_{k=1}^{K} \sum_{l} \gamma_{m,k}^l, \quad (5)$$

where $\alpha_m^l = [\alpha_m^1, \ldots, \alpha_m^L]^T$ is the binary vector indicating the on/off mode of the BSs at time slot $l$ ($\alpha_m^l = 0$ and $1$ indicate that the BS $m$ is turned on and off, respectively) and $\epsilon_m$ is the amplifier efficiency of the BS $m$ (generally, around 40% $\sim$ 50% [12]). Note that the amplifier efficiency quantifies the portion of the transmission power being transmitted. Typically, in micro cells, nearly 50% of the total power is consumed as transmission power [13].

The maintenance power, consumed at the BS for the air conditioning and power supply, is expressed as

$$P_{m}^{on} = \alpha_m^l \rho_{m}^{on}, \quad (6)$$

where $\alpha_m^{on}$ is the power consumption when the BS $m$ is turned on. Commonly, almost 35% of the total power is consumed for the maintenance power [13].

The mode transition power, consumed to switch on/off the BS $m$ at time slot $l$, is

$$p_{m}^{trans,l} = |\alpha_m^l - \alpha_{m}^{l-1}| \rho_{m}^{trans}, \quad (7)$$

where $\rho_{m}^{trans}$ is the power consumed for the mode transition at the BS $m$. In general, about 15% of the total power is consumed for the mode transition [14].

While many of the conventional works focused on the reduction of the instantaneous power consumption [8], we pursue a reduction of the total energy consumption over a long-term period. To be specific, we define the total energy consumption $E_{tot}$ as the sum of power consumption of every BS during $L$ time slots. That is,

$$E_{tot} = \sum_{l=1}^{L} \sum_{m=1}^{M} P_{m}^{tot,l}. \quad (8)$$

The energy consumption minimization problem is formally expressed as

$$\mathcal{P}_1 : \min_{\{\alpha^1, \cdots, \gamma^1\}} E_{tot}$$

s.t. $R_k^l \geq R_{k,min}, \forall k, \forall l$ \quad (9a)

$P_{m}^{tx,l} \leq P_{m,max}, \forall m, \forall l$ \quad (9b)

$P_{m}^{on} = 0, \forall m, \forall l$ \quad (9c)

where $R_k^l$ is the required rate of the user $k$ at time slot $l$ and $P_{m,max}$ is the maximum transmission power of the BS $m$. Since $\alpha^l$ is an integer, $\mathcal{P}_1$ is a mixed-integer programming problem. In solving the problem, basically, we need to explore humongous decision set. For example, if there are 20 coordinated BSs, the size of decision set would be $2^{20} \approx 10^6$ so that the computational overhead to find out the solution would be prohibitive. Note also that the optimal solution of $\mathcal{P}_1$ can be found only when the CSI for the entire $L$ time slots are known at once, which is clearly not possible for the causality issue.
III. Long Short-Term Memory-based Energy Efficient Ultra-Dense Network

As mentioned, one of the main tasks in the energy efficient UDN is to decide on/off mode of all the BSs. In this work, we use LSTM to perform this task. By feeding the training data into the properly designed LSTM network and using the training process, the proposed LSTM-based framework learns the nonlinear mapping $f$ between the input (i.e., the CSI $h^l = [h^l_1, \ldots, h^l_M]^T$ and required user rate $r^l_{\text{min}} = [R^l_{1,\text{min}}, \ldots, R^l_{K,\text{min}}]^T$) and BSs on/off indication vector $\alpha^l$. The corresponding on/off decision problem can be expressed as

$$\alpha^l = f(h^l, \ldots, h^l_{1}, r^l_{\text{min}}, \ldots, r^l_{\text{min}}; \theta),$$

where $\theta$ is the set of internal parameters. The primary goal of the LSTM-based framework is to find out $f$ parameterized by $\theta$, closest to the optimal mapping function $f^*$. 

A. Basics of the LSTM

In this subsection, we briefly explain the LSTM network. The key ingredients of LSTM network are the cell state which can be seen as memory and three gates that read, write, and remove the information in the cell state. The LSTM network is composed of multiple LSTM blocks. Basically, in the $l$-th LSTM block, the output vector denoted as $z^l$ is a composite of the input vector $x^l$, the cell state $c^l$, and previous output vector $z^{l-1}$. When generating the output vector $z^l$, forget gate, input gate, and output gate are used to determine each contribution of $x^l$, $c^{l-1}$, and $z^{l-1}$. To be specific, the forget gate determines which information of the previous cell state $c^{l-1}$ to remain in $c^l$. Similarly, the input gate decides whether $x^l$ and $z^{l-1}$ is delivered to $c^l$ or not. Let $f^l$ and $i^l$ be a forget gate vector and input gate vector, respectively, then $c^l$ can be expressed as

$$c^l = f^l \circ c^{l-1} + i^l \circ \text{tanh} \left(W_c x^l + U_c z^{l-1} + b_c \right),$$

where $\circ$ is the element-wise multiplication, $W_c$ and $U_c$ are the weights, and $b_c$ is the bias. After obtaining $c^l$, the output vector $z^l$ is determined based on $c^l$ and output gate vector $o^l$ as

$$z^l = o^l \circ \text{tanh} \left(c^l \right).$$

Note that forget gate vector $f^l$, input gate vector $i^l$, and output gate vector $o^l$ are the internal network parameters obtained from the training process and given by

$$f^l = \sigma_g \left(W_f x^l + U_f z^{l-1} + b_f \right),$$

$$i^l = \sigma_g \left(W_i x^l + U_i z^{l-1} + b_i \right),$$

$$o^l = \sigma_g \left(W_o x^l + U_o z^{l-1} + b_o \right),$$

where $W_f$, $W_i$, and $W_o$ are the weights associated with $x^l$, $U_f$, $U_i$, and $U_o$ are the weights corresponding to $z^{l-1}$, $b_f$, $b_i$, and $b_o$ are the biases, and $\sigma_g(x) = f_{\text{sig}}(x) = \frac{1}{1+e^{-x}}$ is a sigmoid activation function. It is worth pointing out that LSTM can dynamically control the cell state $c^l$ according to the input vector $x^l$ and the previous output vector $z^{l-1}$ since $f^l$ and $i^l$ depend heavily on $x^l$ and $z^l$.

B. LSTM-based On/Off Mode Decision

In this subsection, we introduce the LSTM-based on/off mode decision in UDN. The proposed scheme consists of LSTM layer, fully-connected (FC) layer, rectified linear unit (ReLU) layer, and sigmoid layer. In the LSTM layer, the input vector $x^l$ is a composite of the CSI $h^l$ and user rate requirement $r^l_{\text{min}}$. That is,

$$x^l = \left[ h^l \right]_{r^l_{\text{min}}}. $$

From the $x^l$ and information in the previous cell state $c^{l-1}$, the LSTM layer extracts the time-correlated feature of channels and user demand. Then, the extracted features are encoded into output vector $z^l$ by using (12).

In the wireless communication environment, extracting the time-correlated feature might be difficult since it varies fast over time depending on the mobility and traffic pattern of the user. To address this issue, LSTM network adaptively adjust its internal parameters according to the time-correlation. Specifically, the values of the gate vectors $f^l$ and $i^l$ change to control the flow of the previous cell state $c^{l-1}$ and the input vector $x^l$. For example, when the time-correlation of channel is small due to the high mobility of the user, the forget gate vector $f^l$ will have a small value suppressing the impact of $c^{l-1}$ on the output vector $z^l$. In contrast, when the time-correlation of channel is large due to the low mobility of the user, the input gate vector $i^l$ would have a large value so that the impact of current input on $z^l$ will also be large. Thus, $z^l$ can contain the time-correlated feature even when the channel state changes rapidly.

After the LSTM layer, the output vector $z^l$ passes through the FC layer, ReLU layer, and sigmoid layer. The output of the FC layer $\hat{z}^l$ is given by

$$\hat{z}^l = W_d z^l + b_d, $$

where $W_d$ and $b_d$ are the weight and bias, respectively. It is well-known from the universal approximation theorem [15], a FC layer with the trained internal parameters can approximate a desired nonlinear function. In our context, this means that
the FC layer, together with ReLU and sigmoid layer, can approximate the mapping between the encoded vector $z^l$ and the desired BSs on/off mode.

Following the FC layer, a nonlinear activation function is applied to $z^l$ to determine whether the information is activated (delivered to the next layer) or not. To this end, we employ the ReLU function $f_{\text{ReLU}}(x) = \max(0, x)$ and thus the output of the ReLU layer $\hat{z}^l$ is

$$
\hat{z}^l = f_{\text{ReLU}}(z^l).
$$

Then, $\hat{z}^l$ passes through the sigmoid layer. In sigmoid layer, the sigmoid function generates the final output $\hat{\alpha}^l$ whose dimension is matched with the number of BSs $M$. The output $\hat{\alpha}^l = [\hat{\alpha}_1^l, \cdots, \hat{\alpha}_M^l]^T$ is

$$
\hat{\alpha}^l = f_{\text{sig}}(\hat{z}^l).
$$

Note that each element of $\hat{\alpha}^l$ ranges from 0 to 1. If $\hat{\alpha}_m^l$ is bigger than a given threshold value $\tau$, then $\hat{\alpha}_m^l = 1$ (the BS $m$ is turned on). Otherwise, $\hat{\alpha}_m^l = 0$ and the BS $m$ is turned off.

In order to use the LSTM network in real scenario, we need a training process finding out proper parameters $\theta = \{W, U, b\}$. For the training process, a loss function is defined to quantify the discrepancy between the current output and the desired one. Then, we find out $\theta$ that minimizes the loss function. In designing the loss function, a supervised learning strategy using a large number of pairs of the input vectors and desired output vectors is often used. However, as mentioned, since the optimization problem $\mathcal{P}_1$ belongs to the mixed-integer programming, finding out the optimal solution requires an exploration of all the cases, which is computationally infeasible. In this work, we instead train the LSTM network by unsupervised learning strategy.

To this end, we design the loss function to quantify both the power consumption and the violation of the constraints. Basically, the loss function $J(\theta)$ is a weighted sum of five terms. $C^{\text{on}}$, $C^{\text{trans}}$ and $C^{\text{txs}}$ are related to the minimization of the power consumption $P^{\text{on}}$, $P^{\text{trans}}$ and $P^{\text{txs}}$, respectively. $C^{\text{rate}}$ and $C^{\text{power}}$ are introduced to satisfy the rate constraint and maximum transmission power constraint, respectively. The corresponding loss function is

$$
J(\theta) = \frac{C^{\text{on}} + C^{\text{trans}}}{\text{loss for power consumption}} + \lambda_{\text{rate}} C^{\text{rate}} + \lambda_{\text{power}} C^{\text{power}},
$$

where $\lambda_{\text{rate}}$ and $\lambda_{\text{power}}$ are the weights determining the ratio among the terms of the loss function.

Specifically, we design the loss terms for power consumption from BS on/off mode as

$$
C^{\text{on}} = \sum_{l=1}^{L} \sum_{m=1}^{M} \hat{\alpha}_m^l \rho_m^l,
$$

(21a)

$$
C^{\text{trans}} = \sum_{l=1}^{L} \sum_{m=1}^{M} \left[ (1 - \hat{\alpha}_m^l) \hat{\gamma}_m^l + \hat{\alpha}_m^l (1 - \hat{\gamma}_m^l) \right] P_m^\text{trans}.
$$

(21b)

To calculate $C^{\text{txs}}$, we need an approximation of the transmission power. To this end, the proposed scheme has an internal variable $\Gamma^l$ obtained from $z^l$. $(m, k)$-th element of $\Gamma^l$ is an approximated transmission power $\hat{\gamma}_m^l \hat{\gamma}_m^k$ is multiplied by $P_{m, \text{max}}$ after being activated by sigmoid layer. Thus, the value of $\hat{\gamma}_m^l$ is bounded to be smaller than $P_{m, \text{max}}$. Using the approximated transmission power, we design the loss term for the transmission power as

$$
C^{\text{txs}} = \sum_{l=1}^{L} \sum_{m=1}^{M} \sum_{k=1}^{K} \hat{\gamma}_m^l \hat{\gamma}_m^k.
$$

(22)

Thus, minimization of the loss function will result in a reduction of power consumption including the transmission power.

To design the loss for rate constraint violation, we define approximated data rate as

$$
\hat{R}_k^l = \log_2 \left( 1 + \frac{\sum_{m=1}^{M} \hat{\gamma}_m^l \hat{\gamma}_m^k |h_{m,k}|^2}{\sum_{j \neq k}^{K} \sum_{m=1}^{M} \hat{\gamma}_m^j \hat{\gamma}_m^k |h_{m,k}|^2 + \sigma_n^2} \right).
$$

(23)

The difference between (3) and (23) is that $\hat{\gamma}_m^l \hat{\gamma}_m^k$ in (3) is replaced by $\hat{\alpha}_m^l \hat{\alpha}_m^k$ in (23). We design the loss for rate constraint and maximum transmit power constraint as

$$
C^{\text{rate}} = \sum_{l=1}^{L} \sum_{k=1}^{K} \left( f_{\text{ReLU}} \left( R_k^l - \hat{R}_k^l \right) \right)^2,
$$

(24a)

$$
C^{\text{power}} = \sum_{l=1}^{L} \sum_{m=1}^{M} \left( f_{\text{ReLU}}^2 \left( \sum_{k=1}^{K} \hat{\gamma}_m^l - P_{m, \text{max}} \right) \right)^2.
$$

(24b)

Note that the $C^{\text{rate}}$ quantifies how much the data rate constraint is violated. $C^{\text{rate}}$ will have a non-zero value if and only if $\hat{R}_k^l < R_k^l$ for any $k$ and $l$. Also, ReLU function in $C^{\text{rate}}$ takes squared value $\left( R_k^l - \hat{R}_k^l \right)^2$ instead of $R_k^l - \hat{R}_k^l$ so that the gradient be bigger when the constraint is strongly violated. Therefore, if the output does not satisfy the rate constraint in the training phase, gradient related to $C^{\text{rate}}$ will change the values of internal parameters so that the output satisfies the
constraint in next time. In other words, minimization of the loss function makes LSTM network ensure the QoS of the users by turning on more BSs. Likewise, \( C_{\text{power}} \) is introduced to make the output does not violate the maximum transmission power constraint. \( C_{\text{power}} \) has a non-zero value if and only if \( \sum_{k=1}^{K} l_{j_{m,k}} > P_{\text{max}} \) for any \( m \) and \( l \).

To find out proper parameters \( \theta = \{W, U, b\} \) that minimizes the loss function, stochastic gradient descent (SGD) method is widely used. SGD starts with some random initial values of \( \theta = \theta_0 \) and then simultaneously updates every parameter in \( \theta \) iteratively as

\[
\theta_{t+1} = \theta_t - \eta \nabla_{\theta} J(\theta_t),
\]

where \( \eta > 0 \) is the learning rate determining the step size at each iteration and \( \nabla_{\theta} \) is the gradient operator with respect to \( \theta \). Although there are a large number of parameters whose gradient must be calculated, the backpropagation (BP) algorithm quickly does that by using the chain rule [16]. By minimizing the loss function using the SGD method, the LSTM-based network learns the mapping between the input vector \( x_t \) and the desired BSs on/off mode \( \alpha_t \).

After the BS on/off mode \( \alpha \) is determined by the LSTM-based network, the transmission power for the active mode BSs is decided. The transmission power allocation problem can be formulated as a linear programming (LP) problem. Instead of LSTM, we allocate the transmission power by the convex optimization technique which guarantees the optimality of the solution. By using various tools such as CVX [17], we can find out the optimal transmission power that minimizes the total transmission power of the BSs.

**IV. SIMULATION RESULTS**

We consider the UDN scenario where 9 micro BSs are deployed on top of a macro BS and 4 users move freely in a square of size \( D \times D \text{km}^2 \) at a constant speed \( v \). The users move randomly on the boundary. The channel models for the path loss and shadow fading are defined as

\[
H_{m,k}^{l} = P_{L_{m,k}}^{l} \cdot 10^{-\frac{\sigma_{sh} z_{m,k}}{10}},
\]

where \( P_{L_{m,k}}^{l} \) represents the path loss at time slot \( l \), and \( 10^{-\frac{\sigma_{sh} z_{m,k}}{10}} \) represents the shadow fading with the standard deviation \( \sigma_{sh} \), and \( z_{m,k} \sim \mathcal{N}(0,1) \). We use a three-slope model for the path loss [18]. To be specific, given distance \( d_{m,k}^{l} \) between the BS \( m \) and the user \( k \), the path loss in dB is

\[
P_{L_{m,k}}^{l} = \begin{cases} 
-L - 35 \log_{10}(d_{m,k}^{l}), & \text{if } d_{m,k}^{l} > d_1 \\
-L - 15 \log_{10}(d_{m,k}^{l}) - 20 \log_{10}(d_{m,k}^{l}), & \text{if } d_0 < d_{m,k}^{l} \leq d_1 \\
-L - 15 \log_{10}(d_{m,k}^{l}) - 20 \log_{10}(d_{0}), & \text{if } d_{m,k}^{l} \leq d_0 
\end{cases}
\]

where

\[
L = 46.3 + 33.9 \log_{10}(f) - 13.82 \log_{10}(h_B) - (1.1 \log_{10}(f) - 0.7) h_U + (1.56 \log_{10}(f) - 0.8),
\]

and where \( f \) is the carrier frequency (in MHz), \( h_B \) is the BS antenna height (in m), and \( h_U \) denotes the user antenna height (in m).

The proposed LSTM network consists of 3 LSTM layers followed by 7 DNN layers. Every layer has a width of 512 and we set the sequence length \( \tau \) and \( L \) as 5 and 0.01, respectively. The proposed LSTM network is trained and tested by synthetic data generated based on the channel model. For the fair evaluation, the training data set and testing data set are completely separated.

For performance evaluation, we compare 1) the proposed LSTM-based technique, 2) full association where all the BSs are turned on, 3) random on/off where each BS is turned off with probability \( p = 0.2 \) [9], and 4) analytic method where the BS which least impact the system is iteratively turned off one by one until the QoS can not be satisfied [10]. We assume that only the micro BSs can be turned off and the macro besestation is always turned on. In every simulation, we evaluate the total power consumption over 50 time slots.

In Fig. 4, we evaluate the average power consumption as a function of the background noise power. We observe that the proposed method outperforms the other methods across all the cases.
Fig. 5: Total power consumption vs. the required data rate. Here, $\sigma_n^2 = -84$ dBm

noise power regimes. For example, when the noise power $\sigma_n^2$ is -84 dBm, the proposed method saves about 11% of power over the analytic method and about 25% over the random on/off. While setting a higher probability for the random on/off will save more power, it may result in a severe coverage hole. Even though the analytic method has a meaningful gain over the full association and random on/off, it still has a performance gap to the analytic method. The performance improvement mainly comes from solving the problem from a long-term perspective.

In Fig. 5, we plot the average power consumption under the various required data rate. We observe the the proposed method saves a significant amount of power across the board. Here, we assume that the noise power $\sigma_n^2$ is -84 dBm. For example, when the required data rate is 0.15 bps/Hz, the proposed LSTM network saves about 15% power over the analytic method and about 32% over the random on/off. Note that the performance gain is obtained only from determining the BS on/off mode intelligently since the transmission power of all techniques are found by the same convex optimization tool. Especially when the user demand is small, the power saving of proposed technique is significant.

## V. Conclusion

In this paper, we presented the LSTM-based energy efficient UDN systems. To be specific, we proposed to improve the energy efficiency over a long operational period by determining the on/off mode of BSs with LSTM network. By dint of LSTM, the sequential property of the channel can be exploited and the on/off mode of BSs can be intelligently determined. From the simulation results, we showed that the proposed framework saves a considerable amount of power compared to the conventional techniques.

### REFERENCES


