On the Analysis of Human Mobility Model for Content Broadcasting in 5G Networks

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***Abstract*—Today's mobile service providers aim at ensuring end-to-end performance guarantees. Hence, ensuring an efficient content delivery to end users is highly required. Currently, transmitting popular contents in modern mobile networks rely on unicast transmission. This result into a huge underutilization of the wireless bandwidth. The urban scale mobility of users is beneficial for mobile networks to allocate radio resources spatially and temporally for broadcasting contents. In this paper, we conduct a comprehensive analysis on a human activity/mobility model and the content broadcasting system in 5G mobile networks. The objective of this work is to describe how human daily activities could improve the content broadcasting efficiency. We achieve the objective by analyzing the transition probabilities of a user traveling over several places according to the change of states of daily human activities. Using a real-life simulation, we demonstrate the relationship between the human mobility and the optimization objective of the content broadcasting system.**

I. Introduction

In the convention, random walk and random waypoint models are used in mobility modeling [1]. These models follow the stochastic approach in moving direction, velocity, and independent with the previous status. However, human mobility is far from being considered random. It is known that people exhibit a high degree of spatial and temporal regularity, following a simple and reproducible pattern such as traveling between home and work locations [2]. Xu *et al.* empirically studied human mobility from the big data of a mobile network in a metropolitan city with over 9600 cellular towers. The results reveal that the human mobility has strong correlations with the mobile traffic. Furthermore, the mobility and the mobile traffic have regular patterns and can be linked with social ecology [3]. Therefore, studying of human mobility models become crucial in data dissemination in various types of communication networks. For example, in opportunistic networks, there is no fix available end-to-end path for transmitting data from a source to the destination. Instead, the data are relayed by the mobile nodes in a hop-by-hop fashion [4].

In order to reproduce synthetic realistic mobility patterns close to reality, daily activities of the human schedule are considered in the mobility models. Ekman *et al.* proposed the working day movement model in [5] by presenting the everyday life of average people, such as sleeping at home, working in the office, and evening activities. Issacman *et al.* proposed WHERE which model large populations move with different metropolitan areas from real-world probability distributions [6]. This model primarily generates synthetic traces for the people moving between two places. It is scalable to more locations but with introducing extra complexity. Zheng *et al.* proposed the agenda driven mobility model in [7] emphasizing the social role of a human for making movement decisions.

The number of mobile subscribers has dramatically grown during the recent years. The bandwidth demand for popular media contents such as movies, TV shows, games, and software updates continue to increase. It poses a severe network congestion problem for content delivery in the mobile networks [8]. In the future fifth-generation (5G) networks, content providers would be able to deploy their distribution algorithms through the functionalities of software defined network (SDN) and network function visualization (NFV) onto the core network (CN) and the radio access network (RAN) [9]. In the SDN approach, a cloud-based software defined controller (SDC) receives high-level services policies from content providers and implements control signal in the CN and RAN for radio resources allocation, content distribution scheduling, and cooperated broadcasting and multicasting, such as researches in [10]–[12].

User mobility has been considered for caching and content delivery system. Poularakis *et al.* proposed a distributed approximation algorithm in [13] for delivering content in a femto-caching architecture. The femto-caching architecture was proposed in [14] for offloading the popular large size video contents onto femtocell-like base station (BS). Lee *et al.* analyze human mobility from traces of location-based social networks to develop a method to deliver video data by moving people to static kiosks [15]. Authors in [16] exploit the human mobility patterns and social tie for caching contents in the mobile devices for distribution through device-to-device communication. To summarize, mobile networks utilize these large-scale universal mobility patterns to schedule massive transmission to deliver popular contents in the crowded area and time for the best usage of radio resources. Although the mobility models are widely adopted in the content delivery

TABLE I
MODEL PARAMETERS

Symbols	Descriptions
$\mathbb{G} = \{g_1, ..., g_G\}$	A set of user groups
$\mathbb{V} = \{v_1, ..., v_V\}$	A set of mobility states
u	Index of a user
$A^u_{v_i}$	Activity of user u at state v_i
$L^u_{v_i}$	Location of user u at state v_i
$D^u_{v_i}$	Staying Duration of user u at state v_i
$t^{D_u}_{v_i}$	Upper bound of the duration D_{v_i}
$t^{D_l}_{v_i}$	Lower bound of the duration D_{v_i}
$S^u_{v_i}$	Starting time of user u being at state v_i
$t^{S_u}_{v_i}$	Upper bound of state starting range of v_i
$t^{S_l}_{v_i}$	Lower bound of state starting range of v_i
$E^u_{v_i}$	Ending time of user u finishing at state v_i
$m^u_{v_i,v_j}(t)$	Transition probability from state v_i to v_j at time t
$\mathbb{B} = \{b_1, ..., b_B\}$	A set of base stations
$\mathbb{C} = \{c_1, ..., c_C\}$	A set of contents
$N_{c,b,t}$	Number of subscribers of content c in BS b at time t
a^c_t	Number of active cells of content c at time t

systems, there is a lack of statistical analysis in this area.

In this paper, we focus on analyzing the synthetic human activity-based mobility models and demonstrate how the future 5G mobile network could utilize this information for massive content delivery. We describe a typical model of human activity and mobility model and the optimization objective function for a content broadcasting system. The contribution of this work is first to statistically evaluate the human activity mobility model. We begin by deriving the probability of a user starting an activity. Followed by the probability of a user to end an activity. Then, connecting the probability of a user being in a location at a given time to derived probabilities. It followed by deriving the total expected number of users within a location. Then, the content delivery system exploits this information for the decision marking to achieve the optimization goal which is disseminating a content to all of the subscribers with the least amount of radio resources in an optimal timing. We support our study by conducting a real-life simulation incorporated with a real geographical location and realistic schedules to demonstrate the human movement and the proper timing for content distribution.

The rest of this paper is organized as follows. Section II presents human mobility model and the content broadcasting system in 5G mobile networks. The statistical modeling is explained in Section III. Section IV describes the details of the simulation setup and result. Finally, the paper is concluded in Section V.

II. SYSTEM MODELS

In this section, the human mobility model is described followed by the efficient content broadcasting system.

A. Human Activity Mobility Model

The mobile users are categorized into different sets of user groups $\mathbb{G} = \{g_1, ..., g_G\}$ according to their occupation, living habit, and behavior for generating individual mobility traces with a degree of randomness, while representing the realistic environment. The human states mobility model makes use of the human daily life routine for each user group which is composed of a set of states $\mathbb{V} = \{v_1, ..., v_V\}$. The users within the same user group have similar daily routines from the same set of states with same activity stages and state starting range, but different staying locations and durations.

Each state v_i consists of the following components for each user u, an activity stage $A^u_{v_i}$, a staying location $L^u_{v_i}$, a staying duration $D^u_{v_i}$, a state starting range and a set of transition probabilities.

1) Activity Stage: An activity stage $A^u_{v_i}$ is the name of a daily activity such as 'Sleeping' and 'Working'. A series of activity stage forms a life routine for a user group. Each user group has different sets of activity stages in their corresponded mobility model. For example, a group of office staff has a 'Working in office' stage while a group of students has a stage 'At school'.

2) Staying Location: A staying location $L^u_{v_i}$ is randomly chosen from a various set of places, depends on the activity and the user group. There is static and dynamic spatial information for a mobile user in different states. For instance, home and work locations are static. These places remained unchanged for a mobile user in this model. On the other hand, the dining and recreation locations are dynamic. The mobile user may visit different places for dining and leisure on various days. These locations are randomly chosen from a set $\mathbb{L}^u_{v_i}$ of related locations within a reasonable distance. The selection process of the location is independent of the other state parameters.

3) Staying Duration: The staying duration $D^u_{v_i}$ of each state v_i is a random variable which following a truncated normal distribution with a lower bound $t^{D_l}_{v_i}$ and an upper bound $t^{D_u}_{v_i}$. Each state has individual mean $\mu_{D_{v_i}}$, variance $\sigma_{D_{v_i}}$, and truncation boundary for the staying duration according to the activity stage and user group. For example, the staying duration of a 'Sleeping' state of an adult may have a mean of 7 hours with a larger variance whereas 10 hours for a child with a smaller variance.

4) State Starting Range: The state starting range consists of a pair of lower bound $t^{S_l}_{v_i}$ and upper bound $t^{S_u}_{v_i}$ for controlling the start of a state. It is independent of the staying duration. A state starts if and only if the starting time $S^u_{v_i}$ of the user u of a state i is within this range.

In addition to the components mentioned above, the starting time and the ending time of a state for a user are introduced. The ending time of a state is defined as the sum of the starting time and the staying duration. Let $E^u_{v_i}$ is the ending time of user u staying at the state v_i, and it is formulated as,

$$E^u_{v_i} = S^u_{v_i} + D^u_{v_i}, \tag{1}$$

where $S^u_{v_i}$ is the starting time of state v_i of user u. We assume, the starting time of initial state $S^u_{v_1}$ is a constant at $t = t_0$.

5) Transition Probability: The transition probability $m^u_{v_i,v_j}(t)$ is the probability of transiting from state v_i to v_j at time t. It is a function of time depends on the ending time of the current state i, the starting range of state j, and a state selection probability $\rho_{i,j}$.

The transition from a state i to a future state j can be triggered when the ending time of the current state i is within the range of the starting time in state j.

B. Content Broadcasting System in 5G Mobile Networks

We consider a mobile network that has a set of BS $\mathbb{B} = \{b_1, ..., b_B\}$ deployed in a certain region. Let t be the time segment. A set of contents $\mathbb{C} = \{c_1, ..., c_C\}$ arrive at the system as a Poisson process. In the region, there is a set of mobile users $\mathbb{U} = \{u_1, ..., u_U\}$. A *subscriber* is a mobile user who subscribes to content which has not yet been delivered. Let $q_{u,c}$ be a binary variable where $q_{u,c} = 1$ if a mobile user u is a subscriber of a content c. Let $q_{u,c,b,t}$ be a binary variable where $q_{u,c,b,t} = 1$ if a subscriber of a content c is associated with BS b at time segment t. The total number of subscribers of content c in BS b at time t is equal to,

$$N_{c,b,t} = \sum_{u \in \mathbb{U}} q_{u,c,b,t}. \tag{2}$$

An *active cell* for a content is defined as a BS that has at least a single active subscriber. The number of active cells of content c at time t is denoted as a_t^c as,

$$a_t^c = \sum_{b \in \mathbb{B}} [N_{c,b,t} > 0], \tag{3}$$

where the notation [.] is the Iverson bracket. If the condition in the square bracket is fulfilled, the number is 1, while 0 otherwise.

An active cell a_t^c implies that there is at least one active subscriber of a content c within the cell coverage area at time t. This definition can be changed as per the network engineering demands. The constraint can be relaxed through replacing the 0 on the right side of the inequality in (3) by a threshold. From the BS point of view, if the radio reception levels of the mobile users are good, broadcasting content in a cell to all subscribers yield the most efficiency. It requires only a single radio transmission instead of multiple duplicated transmission comparing to unicast transmissions. From the network point of view, perceiving a time with the minimum number of broadcasting transmissions will be the most efficient way to deliver a content, i.e., using the minimum amount of radio resource for transmitting to all of the subscribers. Therefore, our objective is to search for a time segment t that minimizes the number of *active cells* a_t^c for delivering the content c. The original problem is formulated as follows,

$$\min_{t} \quad a_t^c \tag{4a}$$

$$\text{subject to} \quad t_a^c < t < t_e^c, \tag{4b}$$

where t is the time segment, which is an integer. The variables t_a^c and t_e^c are the arrival and expiry time of content c. The model parameters are summarized in Table I. We model this problem by considering the human activity states as random events; then we used conditional probability theorems to find an expression for the minimum number of active cell. This analysis is provided in the next section.

III. Statistical Modeling

The primary objective of the aforementioned delivery system is to broadcast the content to all users with the minimum number of transmissions, i.e., the minimum number of active cells. For this purpose, we need to find a time and optimal locations that have the maximum number of subscribers for a content. Therefore, we calculate the expected number of users at a time t in location L.

The building blocks of these calculations start with finding the probability of a user starting the state j at time t, which can be calculated based on the staying duration and starting time of that user at previous states.

We then find the probability of ending a state j at time t. It follows that we incorporate the selection of location l in the starting and ending time probabilities. Then, we calculate these probabilities for all users, at all possible time segments. Followed by finding the optimal time which guarantees a minimum number of active cells.

A. Probability of starting a state at a given time segment

In order to calculate the probability of a user u starting a state j at time t, we have recognized five events which contribute to the starting point, described as follows,

- R: The ending time of previous state i is in between time t and $t-1$.
- Z: The ending time $E_{v_i}^u$ of previous state i must be larger than the lower bound of the starting time $t_{v_j}^{S_l}$ of the current state j and lower than the upper bound of starting time $t_{v_j}^{S_u}$.
- X: For every previous state i, the staying duration $D_{v_i}^u$ is lower and upper bounded by $t_{v_i}^{D_l}$ and $t_{v_i}^{D_u}$, respectively.
- Y: The current searching time t, must be lower than the maximum staying duration in the previous state i.
- W: There is a positive transition probability from state i to state j.

Event R limits the ending time of previous state i is within the time segment t as follows,

$$R : t - 1 \leq S_{v_i}^u + D_{v_i}^u \leq t. \tag{5}$$

Event Z ensures that the ending time of the previous state i is within the range of starting time of the current state j. It is formulated as,

$$Z : t_{v_j}^{S_l} \leq S_{v_i}^u + D_{v_i}^u \leq t_{v_j}^{S_u}. \tag{6}$$

Event X describes that the staying duration $D_{v_i}^u$ is a truncated random variable which is upper bounded by $t_{v_i}^{D_u}$ and lower bounded by $t_{v_i}^{D_l}$, which is,

$$X : t_{v_i}^{D_l} \leq D_{v_i}^u \leq t_{v_i}^{D_u}. \tag{7}$$

Event Y indicates the current time t, should be less than the maximum staying duration of previous state i in order to have a valid transition from state i to current state j, which is formulated as,

$$Y : t \leq t_{v_i}^{S_u} + t_{v_i}^{D_u}. \tag{8}$$

Finally, event W is a positive transition probability from state i to state j. This probability excludes all of the possibilities for transiting from previous state i to k other than the current state j.

$$W : m_{v_i,v_j}(t) = 1 - \left(\sum_{\substack{k>i,k\neq j\\ i,j,k\in\{1,\ldots,V\}}} m_{v_i,v_k}(t) \right). \quad (9)$$

The probability of a user u starting a state j at time t is a combination of the aforementioned events, and it is formulated as follows,

$$\Pr\{S^u_{v_j} = t\} = \Pr\{R, Z, X, Y, W\}. \quad (10)$$

The probability $\Pr\{S^u_{v_j} = t\}$ is the probability of intersection between all events, X, Y, Z, W. Hence, we can reformulated using conditional probability facts to the following expression,

$$\Pr\{S^u_{v_j} = t\} = \sum_{\substack{i<j\\ j\in\{1,\ldots,V\}}} \Pr\{R, Z|X, Y\}\Pr\{X\}\mathbb{I}\{Y\}m_{v_i,v_j}(t). \quad (11)$$

Note that event Y does not contain any random variable, hence, we express the intersection with event Y as an indicator function, $\mathbb{I}(Y) = 1$ when Y is true and $\mathbb{I}(Y) = 0$ when Y is false. It follows that using (6)-(9), expression (11) is expanded as in (12).[1]

B. Probability of ending a state at a given time segment

We calculate the probability of the ending time of state v_j at time t since it is necessary to obtain the next state probabilities. The ending probability of state v_j is formulated as follows,

$$\begin{aligned}
&\Pr\{E^u_{v_j} = t\} = \Pr\left\{S^u_{v_j} + D^u_{v_j} = t\right\}\\
&= \sum_{d^u_{v_j}\in\mathbb{D}_{v_j}} \Pr\left\{ S^u_{v_j} + d^u_{v_j} = t \,\middle|\, D^u_{v_j} = d^u_{v_j}\right\} \Pr\left\{D^u_{v_j} = d^u_{v_j}\right\}\\
&= \sum_{d^u_{v_j}\in\mathbb{D}_{v_j}} \Pr\left\{ S^u_{v_j} = t - d^u_{v_j} \,\middle|\, D^u_{v_j} = d^u_{v_j}\right\} \Pr\left\{D^u_{v_j} = d^u_{v_j}\right\}.
\end{aligned} \quad (13)$$

Then, we let $n_{v_j} = t - d^u_{v_j}$ and $\delta_{v_j} = \Pr\left\{D^u_{v_j} = d^u_{v_j}\right\}$[2]. Expression (13) is reformulated as,

$$\Pr\{E^u_{v_j} = t\} = \sum_{d^u_{v_j}\in\mathbb{D}_{v_j}} \Pr\left\{ S^u_{v_j} = n_{v_j} \,\middle|\, D^u_{v_j} = d^u_{v_j}\right\} \delta_{v_j}. \quad (14)$$

Recall that the staying duration $D^u_{v_j}$ at v_j is independent from the starting time $S^u_{v_j}$ of v_j. It follows that the value of $\Pr\left\{ S^u_{v_j} = n_{v_j} \,\middle|\, D^u_{v_j} = d^u_{v_j}\right\}$ is in similar form of (12).

[1] Note that we convert the event Z from its original definition in (6) to $Z : t^{S_l}_{v_j} \leq t \leq t^{S_u}_{v_j}$. because we already bound $S^u_{v_i} + D^u_{v_i}$ by $t-1$ and t.

[2] Recall that $D^u_{v_j}$ is a Normal distributed random variable, with mean and variance $\mu_{D_{v_j}}$ and $\sigma_{D_{v_j}}$, hence, the probability of $\delta_{v_j} = \Pr\left\{D^u_{v_j} = d^u_{v_j}\right\}$ is known.

C. Probability of a user staying in a specific location within a period of state

The joint probability of ending a state v_j with the possibility of being at different locations is expressed as,

$$\Pr\left\{E^u_{v_j} = t, L^u_{v_j}\right\} = \sum_{l\in\mathbb{L}^u_{v_j}} \Pr\left\{ E^u_{v_j} = t \,\middle|\, L^u_{v_j} = l\right\} \Pr\{L^u_{v_j} = l\}, \quad (15)$$

where $L^u_{v_j}$ is the random variable that spans all possible locations for the same state, i.e., $\mathbb{L}^u_{v_j}$. Recall our assumption that the user selects the location of the activity in state v_j independent from the starting and ending time of that activity. Hence, the probability in (15) is calculated as follows,

$$\begin{aligned}
&\Pr\left\{E^u_{v_j} = t, L^u_{v_j}\right\} = \sum_{l\in\mathbb{L}_{v_j}} \Pr\left\{ E^u_{v_j} = t \,\middle|\, L^u_{v_j} = l\right\} \Pr\{L^u_{v_j} = l\}\\
&= \sum_{l\in\mathbb{L}^u_{v_j}} \sum_{d^u_{v_j}\in\mathbb{D}^u_{v_j}} \Pr\left\{ S^u_{v_j} = n_{v_j} \,\middle|\, D^u_{v_j} = d^u_{v_j}\right\} \Pr\{L^u_{v_j} = l\}\delta_{v_j}.
\end{aligned} \quad (16)$$

In similar lines, we link the probability of starting a state v_j at a time t with the set of locations $\mathbb{L}^u_{v_j}$, from (12), as in (17).

D. Expected number of users at each time t in each base stations

In this subsection, we calculate the expected value of a number of users at specific time and location. We begin by finding the probability of a single user u being in location l at time t, using the probabilities found in (16)-(17), as follows,

$$\begin{aligned}
&\Pr\left\{u_{v_j}|t, L^u_{v_j} = l\right\} = \Pr\left\{S^u_{v_j} \leq t, E^u_{v_j} \geq t | L^u_{v_j} = l\right\}\\
&= \sum_{s^u\in\{0,\ldots,t\}} \sum_{e^u\in\{0,\ldots,t\}} \Pr\left\{S^u_{v_j} = s^u | E^u_{v_j} = e^u, L^u_{v_j} = l\right\}\\
&\qquad \Pr\left\{E^u_{v_j} = e^u | L^u_{v_j} = l\right\},
\end{aligned} \quad (18)$$

where s^u and e^u are the starting and ending time deterministic values of the random variables $S^u_{v_j}$ and $E^u_{v_j}$, respectively, and in notation they are replaced by t at (12) and (13).

Utilizing the probability of each user being in location l at time t, expressed in (18), the expected numbers of users is obtained as,

$$\mathcal{E}\{N_U(t, l)\} = \sum_{u\in\mathbb{U}} \sum_{v_j(u):j\in\mathbb{J}} \Pr\left\{u_{v_j}|t, L^u_{v_j} = l\right\}. \quad (19)$$

E. Search minimum number of active cells at a time t in a time range

The time segment t^* at which the minimum number of active cells is enough to serve all subscribed users for a content can be found by solving the following optimization problem,

$$t^* = \arg\min_t \sum_{l\in\mathbb{BS}} \mathbb{I}\left(\mathcal{E}\{N_U(t, l)\} > m_u\right), \quad (20)$$

where m_u is the threshold of the minimum number of user to declare that a BS l is active.

$$
\begin{aligned}
\Pr\{S^u_{v_j}=t\} = & \sum_{\substack{i<j\\ j\in\{1,\dots,V\}}} \Pr\left[t-1\le S^u_{v_i}+D^u_{v_i}\le t, t^{S_l}_{v_j}\le S^u_{v_i}+D^u_{v_i}\le t^{S_u}_{v_j} \middle| t^{D_l}_{v_i}\le D^u_{v_i}\le t^{D_u}_{v_i}, t\le t^{S_u}_{v_i}+t^{D_u}_{v_i}\right] \\
& \left[\mathrm{F}_{D^u_{v_i}}(t^{D_u}_{v_i})-\mathrm{F}_{D^u_{v_i}}(t^{D_l}_{v_i})\right]\mathbb{I}\left(t\le t^{S_u}_{v_i}+t^{D_u}_{v_i}\right) m_{v_i,v_j}(t), \quad \forall j\in[1,V]. \\
= & \sum_{\substack{i<j\\ j\in\{1,\dots,V\}}} \Pr\left[t-1\le S^u_{v_i}+D^u_{v_i}\le t \middle| t^{D_l}_{v_i}\le D^u_{v_i}\le t^{D_u}_{v_i}, t\le t^{S_u}_{v_i}+t^{D_u}_{v_i}\right] \\
& \left[\mathrm{F}_{D^u_{v_i}}(t^{D_u}_{v_i})-\mathrm{F}_{D^u_{v_i}}(t^{D_l}_{v_i})\right]\mathbb{I}\left(t^{S_l}_{v_j}\le t\le t^{S_u}_{v_j}\right)\mathbb{I}\left(t\le t^{S_u}_{v_i}+t^{D_u}_{v_i}\right) m_{v_i,v_j}(t), \quad \forall j\in[1,V].
\end{aligned}
\tag{12}
$$

$$
\begin{aligned}
\Pr\left\{S^u_{v_j}=t, L^u_{v_j}\right\} = & \sum_{l\in\mathbb{L}^u_{v_j}} \Pr\left\{S^u_{v_j}=t \middle| L^u_{v_j}=l\right\}\Pr\{L^u_{v_j}=l\} \\
= & \sum_{l\in\mathbb{L}^u_{v_j}} \sum_{\substack{i<j\\ i\in\mathbb{V}}} \Pr\left\{t-1\le S^u_{v_i}+D^u_{v_i}\le t \middle| L^u_{v_j}=l, t^{D_l}_{v_i}\le D^u_{v_i}\le t^{D_u}_{v_i}, t\le t^{S_u}_{v_i}+t^{D_u}_{v_i}\right\} \\
& \Pr\{L^u_{v_j}=l\}\left[\mathrm{F}_{D^u_{v_i}}(t^{D_u}_{v_i})-\mathrm{F}_{D^u_{v_i}}(t^{D_l}_{v_i})\right]\mathbb{I}\left(t^{S_l}_{v_j}\le t\le t^{S_u}_{v_j}\right)\mathbb{I}\left(t\le t^{S_u}_{v_i}+t^{D_u}_{v_i}\right) m_{v_i,v_j}(t), \quad \forall j\in[1,V].
\end{aligned}
\tag{17}
$$

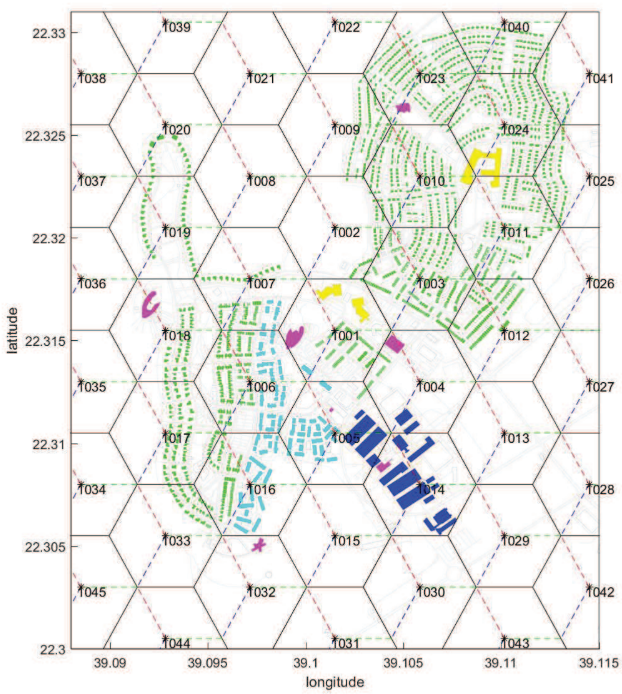


Fig. 1. The simulation area with buildings in the following coloring, green: townhouses, cyan: apartment buildings, blue: university campus, magenta: recreational and dining areas, yellow: primary and secondary schools. 45 base stations with their name and sectors are shown. The black straight and dotted color lines are the cell boundaries.

IV. Performance Evaluation

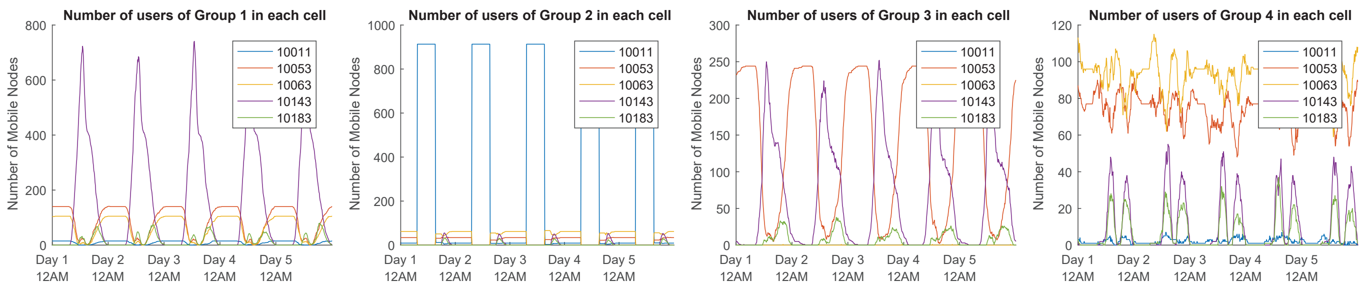
In this section, a real-life simulation is presented to illustrate the relationship between the human mobility and the optimization objective, which is searching for a time segment that having the minimum number of active cells.

A. Setup

1) Location: A small town located in Thuwal, Makkah Province, Saudi Arabia, is considered in the simulation. It is a moderate density living compound that facilitates both working and living environment. In the simulation, there are about 2000 townhouses and 80 two-story apartment buildings. Each townhouse populates a family or 3-8 people and an apartment building populates about 20-40 people. In the compound, the university campus is the major working area for the residents and three schools for primary and secondary school students. Furthermore, there are six buildings for recreation, dining, and shopping. For the mobile network, it is a typical hexagonal cell deployment with about 540 meters inter-BS distance. There are 45 BSs are deployed in the simulation area and named as a 4-digit number from 1001 to 1045. Each BS consists of three 120 degree sectors and each sector is considered as a cell with a 5-digit number name. The sector name is constructed by extended one more digit from the BS name to the right most digit, such as 10011(northeast), 10022(southeast), and 10033(west) for three sectors of BS 1001. In total, 135 cells are deployed in the $9.57\,\mathrm{km}^2$ simulation area. A map of the simulation with the BS deployment and cell boundaries is shown in Figure 1.

2) Mobility: In the simulation, a daily life of a user is modeled with random locations and durations. The model first randomly selects a home and a work location for certain user. These locations are static for a user throughout the simulation period. Then, the durations of staying are randomly generated following various truncated normal distributions. Furthermore, a user has a certain probability of visiting different recreational and dining places. Four groups of mobile users with different daily mobility patterns employed in the simulation are described in the following.

- Staff: A model for the movements of office staff is adopted for 2200 users. There are 75% of users live in townhouses and 25% of users live in apartment buildings. Their office locations are static and randomly chosen in university campus buildings. The daily mobility patterns start by staying at home at the midnight until morning.



(a) Staff (b) School Students (c) University Students (d) Dependents

Fig. 2. Number of users of each group in five selected cells

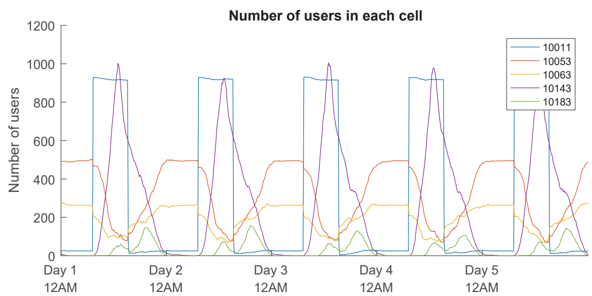


Fig. 3. Number of total users in five selected cells

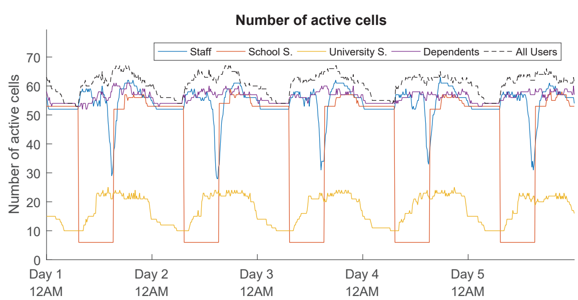


Fig. 4. Number of active cells

Then, users start moving to offices and stay until lunch hours. After an average one-hour lunch break, users go back to offices until evening. A percentage of people will go to the recreational and dining areas after work. Finally, most of the users return to home in the evening.

- School Students: This group includes 1400 primary and secondary school students who live in townhouses. Starting at midnight, the mobility of this user group is similar to the others, staying at home until morning. At 7am-7:30am, all of the school students go either to the primary or secondary school areas and stay until 3-3:30pm. After school, school students starts to travel around the community actively. In the evening, they return to home. This group of users has a significantly synchronized mobility pattern to travel and stay in the school period.
- University Students: There are 900 university students live in apartment buildings. The mobility patterns start from the midnight, while most of the university students stay in apartments until morning. In the morning and afternoon, university students move between the campus buildings and stay for classes and activities. In the evening, students may go to recreational and dining areas or go home. The major difference between adult staff and university students is that university students have the higher mobility to move inside the campus and a shorter average staying period.
- Dependents: There are 1700 dependents in the simulation. They have a fixed home location but without a fixed working location. Their staying locations and durations are more random and unpredictable than the other groups. In general, the mobility patterns start from midnight while users stay at home, until morning. Then users travel and stay randomly in the area.

B. Results

These four user groups have distinct mobility patterns. From the mobile network operator perspective, these movements generate various daily periodic patterns regarding the number of users in each cell. For instance, the cells covering the university campus area has a larger number of users in working hours. The cells covering primary and secondary schools have a significant decrease in users after the school hours. Figure 2 shows the number of users of each user group in the five selected cells over a five-days simulation period. Each cell covers a particular type of buildings. Cell 10011 covers two schools and some staff housing. Cell 10053 covers apartment buildings only, where mostly occupied by university students and a few staff. Cell 10063 covers staff housings only. Cell 10143 covers half of the university campus and the campus diner. Cell 10183 covers a recreational and dining building. In Figure 2a, the number of staff increases steadily in Cell 10143 starting in the morning and reaches the peak roughly at noon on a daily basis. Furthermore, Cell 10183 shows two peaks are observed daily. The first lower peak is the lunch hours and the second peak is the evening time before midnight when the people are seeking for recreation or dining. In Figure 2b, the Cell 10011, where the secondary school located, shows a significant sharp increase of school students from no users to over 900 users during the school hours. In Figure 2c, Cell 10143 and 10183 have similar patterns observed in the staff, but with a different number of users. In the Cell 10053, which cover one-fourth of the university student apartments, the peak numbers of university students appear in the night daily. In Figure 2d, the dependents have no static locations to travel or stay. Therefore, the numbers of users in Cell 10053 and 10063 are chaotic. However, the cells covering the dining area, Cell 10143 and 10183, have distinct daily patterns as described in Figure 2a. Figure 3 shows the aggregated number of users in these five selected cells. It clearly shows each cell has different periodic patterns and peak hours according to its coverage area.

Recall that the period of having the minimum number of active cells is the best timing for broadcasting contents to the user groups regarding using the minimum radio resources. In Figure 4, the numbers of active cells for each user group are illustrated. Three phenomena can be observed in this figure. First, in most of the time, the average number of active cells for staff, school students, and dependents are ranged from 55 to 62, but the university students have a lower number of active cells compare to the others. It is because those three groups of users are mainly living in the low-density housing area. When users go home in the evening, they spread evenly over a large area. For the university students, they live in the higher density apartment buildings and this area is located closely to the campus buildings. In general, they are more congregated in the evening and moves within a closer area than the other users. Therefore, the average number of active cells of university students is less than the others. Second, the periods of having the minimum number of active cells for the school students are longer than the other groups. School students arrive at the school on time and stay in the school for several hours every day. It is easier to look for a time segment for delivering contents to school students in the school area. However, although the minimum number of active cells for staff is relatively small compare to its average, it has only a short period in a day to achieve the minimum. In contrast, the university students have a longer period on maintaining the minimum number of active cells in the early morning when students are mainly in the apartments. Finally, since the mobility patterns of dependents group were mostly random, the minimum number of active cells of dependents are large comparing to other groups. In summary, among these four user groups, searching a time segment for broadcasting content to the school students are relatively easier than the other users, and consuming the minimum amount of radio resources in the transmission.

V. Conclusion

In this paper, we conduct a comprehensive analysis on the human activity mobility model tied with an efficient content broadcasting system in 5G networks. The analysis was conducted by using the concept of random events and associated conditional probabilities. It shows the relationship between the human mobility and the optimization objective of the content broadcasting system. A real-life simulation is presented to indicate the connection further. In the future, it is essential to evaluate the time complexity of the statistical analysis to investigate the cost of predicting an optimal solution for the delivery system.

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