LiFi-based D2D Communication in Industrial IoT

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***Abstract*—This paper analyses the performance of LiFi-based device-to-device (D2D) communication in industrial internet-of-things (IIoT). We present a comprehensive analysis of mobility management of D2D communication in industrial LiFi networks. Using the semiangle at half illuminance of the AP and D2D transmitting IIoT, a coverage model for the D2D communication range is derived. By adopting stochastic geometry, closed-form expressions for mode selection rate and residence time are derived as functions of the AP density, IIoT density, and velocity. The results have shown that high velocity and denser deployment cause a decrease in the average D2D residence time and an increase in the average D2D transition rate or vice versa. The proposed analytical models are then verified with Monte Carlo simulation results. The results provide system-level design insights.**

Index Terms*—Device-to-device communication, industrial internet-of-things, LiFi, optical wireless communication, visible light communication.

I. INTRODUCTION

At the end of 2025, it is estimated that short-range internet-of-things (IoT) connections could reach close to 21 million connections by increasing 13 percent annually [1]. In recent years, new use cases for conventional IoT networks have been introduced such as sensing and recording data, smart metering, logistic management, and monitoring for industrial applications, which are known as the industrial IoT (IIoT) networks [2].

IIoT networks are expected to cope with the continuous increase in the amount of transmitted data and a suitable solution can be device-to-device (D2D) communication. In D2D communications, IoT devices transmit and receive data directly among themselves without the need for relaying through a base station (BS) or an access point (AP). Thus, D2D offers improvements in resource usage, energy efficiency and latency [3]. However, the problem in D2D communication is that the majority of the licensed spectrum is occupied and crowded. Also, the interference among D2D pairs creates a huge problem. In order to deal with the RF-based D2D communication challenges and meet the data transmission demands, LiFi networks (a light-based wireless networks) have been proposed as a promising solution. Due to the accurate indoor positioning, high throughput, high reliability, and low latency requirements of the IIoT, LiFi is a potential D2D communication technology for enabling IIoT networks [4]. Mobility management in such as a light-based IIoT network is investigated in this paper.

Previous D2D studies in VLC/LiFi can be categorized into two approaches:

- The first approach combines radio frequency (RF) and visible light bands to maximize efficiency of the system. The existing D2D studies mostly focus on the hybrid RF-VLC networks. In this type of studies, authors propose to use VLC for D2D communication and RF for cellular communication, namely connection between IoTs and BSs. Hybrid networks usually need a much longer processing time than conventional networks due to the change of air interfaces [5]. In addition, it is clear that the RF system provides lower system capacity than the VLC network, and a very large number of RF users will significantly reduce efficiency. Due to these reasons, previous studies have investigated mode selection, resource allocation, and some optimizations in hybrid D2D schemes have been investigated previously [6]–[13]. Zhang *et al.* propose a hierarchical game framework for resource allocation in heterogeneous network with VLC and D2D individual [6], [7]. In the game, the data packet size, the price of licensed spectrum and data rates are determined with equilibrium solutions, and each VLC transmitter (VLCT) determines the optimal data transmission route. Najla *et al.* focus on a multi-objective optimization problem which is the selection between RF and VLC bands for D2D [8], [9]. In these studies, they propose low-complexity heuristic algorithm and deep neural network for solving the problem. The studies reported in [10]–[12] suggest dynamic dynamic dwell timer and graph theory-based algorithms, tailored for D2D communication, in deciding whether or not it is beneficial for a user equipment to switch from VLC to RF or vice versa. Finally, [13] proposes a reinforcement learning (RL)-based approach to determine data transmission routes in an indoor VLC-D2D heterogeneous network.
- The second approach relates to the use visible light band for both direct and D2D communication. In this approach, the direct communication is defined as the link between IoTs and APs, not IoTs to IoTs. Little has been reported on this model, which is more beneficial than hybrid networks because of the aforementioned reasons. Proposed and analyzed in [14] are ways to understand how increasing distance between IoT devices affects efficient D2D communication. In the same model, optical repeaters are also suggested for enhancing the performance of D2D communications. In [15], the paper proposes a game theory–based solution for the mode selection mechanism between direct and D2D communication. This work uses system capacity as the utility function to optimize system performance and selects the optimal

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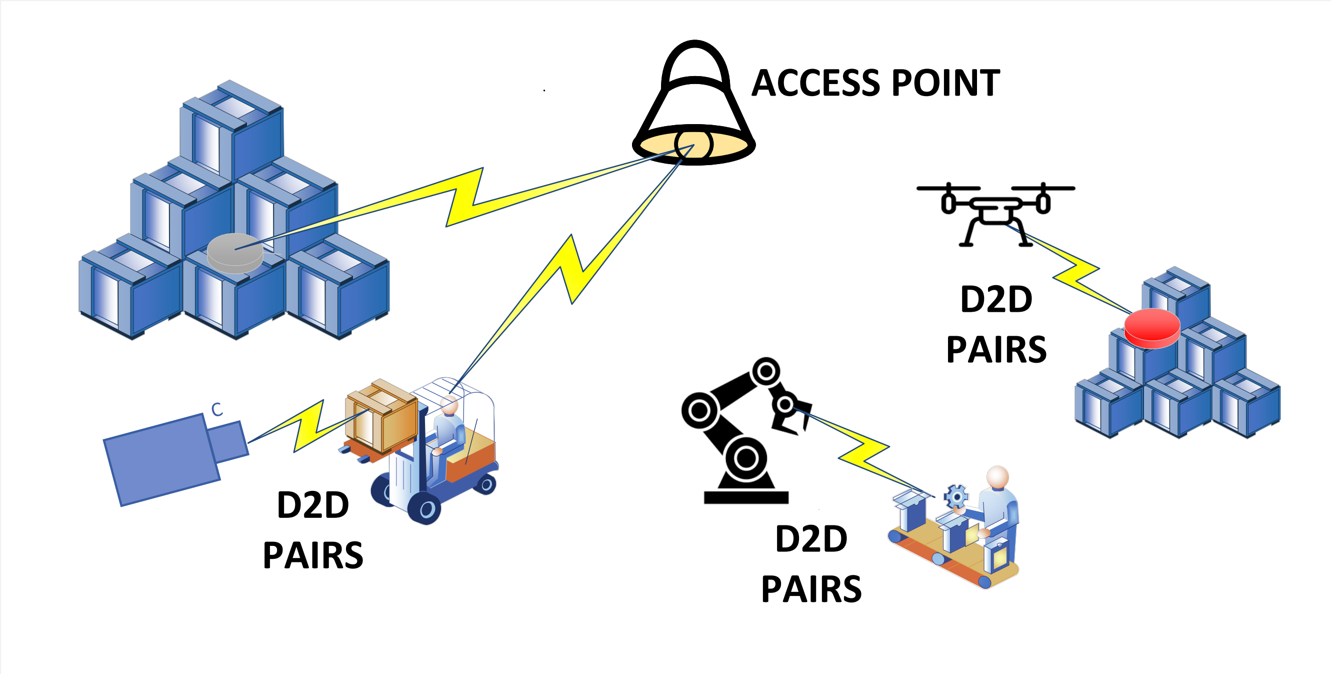

Figure 1: Industrial LiFi network with the access point and IIoT devices.

communication mode. Chaleshtori *et al.* investigate D2D communications using smart phones' display pixels and their built-in cameras [16], [17]. The impact of the receiver orientation on the channel characteristics is also investigated, where two static users face each other and the receiver is intentionally oriented towards the transmitter. Finally, in [18], the challenges and applications of LiFi in D2D communication are given briefly and LiFi is compared with other D2D communication options such as WiFi and Zigbee.

All the previous studies as detailed above focus on algorithms for mode selection, resource allocation, and some optimizations in hybrid networks. None of them consider the crucial impact of device mobility properly. In [6]–[9], [13], there is no explanation about user movements and assume that device positions are fixed. At least, in [10], [11], it is said that this is initial work in this field, they do not consider the mobility of the users and they leave these aspects for further research. On the other hand, in [12], it is assigned a constant speed as $v = 1$ m/s. As a similar concept to the previous one, in [16], [17], the fixed distance between D2D devices is defined. However, it should be highlighted that, especially for [12], [16], [17], current studies are simulation-based with no analytical results to back up.

To the authors' best knowledge, the D2D communication with mobile IIoT devices in LiFi networks has not been studied in any previous work. This paper investigates the role of mobile IIoT devices for D2D communication in ultra-dense industrial LiFi networks using stochastic geometry. This work is based on a realistic scenario as contained in 'Scenario 4: Manufacturing Cell' in LiFi standards, produced by the IEEE 802.11bb Task Group on Light Communication [19]. The major contributions of this paper are summarized as follows:

- We present an analytical modelling of LiFi-based D2D communication range for IIoT devices based on the half-angle of the AP and D2D transmitting IIoT.
- Closed-form expression are derived for the D2D mode transition rate and D2D mode residence time in terms of AP density, IIoT density, semi-angle at half illuminance of the transmitters and device velocity.
- Extensive Monte-Carlo based simulations presented to validate the analytical model.
- The impact of system parameters, such as user velocities on the communication performance is investigated and inferences drawn. This is vital towards the design of a practical industrial LiFi network.

The remainder of the work is organized as follows. The next section introduces the network model, LiFi channel model, and mobility model as parts of the system model. In Section III and IV, the D2D communication range, D2D mode transition rate and D2D mode residence time with closed-form expressions are proposed. Simulation assessment to verify of the analytical results are shared in Section V. Section VI, finally, presents the concluding remarks and future research directions.

II. SYSTEM MODEL

This section provides the D2D network model for mobile IIoT devices which is used in the study. First, Poisson Point Process (PPP) model with the Poisson-Voronoi tessellation (PVT) is used to distribute the IIoT devices and APs. Then, the details of the LiFi channel model used in the study are given. Mobility model of the IIoT devices is also presented.

A. Network Model

In most previous studies about LiFi networks, cell shapes are modeled as either hexagonal or square. However, a huge number of 'statistically random' APs and IIoT devices, such as sensors, robotic arms, drones, surveying and inspection machines, and even automatic guided vehicles (AGV) are parts of the ultra-dense industrial LiFi networks [20], [21]. Thus, using a perfectly defined deterministic/regular model for the positioning of these IIoT devices and APs is impractical. Stochastic geometry is therefore considered to provide a more accurate and tractable model for the distribution of nodes in an industrial LiFi network. The principal idea underlying the research on the stochastic geometry models, also known as random spatial models, is that it is best to assume that the locations of nodes and the other quantities are random in nature due to the size and unpredictability of users in wireless networks. Therefore, in most practical scenarios, a thinning process needs to be applied to the locations of of modeling LiFi APs. Such a thinning process is stochastic because it depends on the user locations as well as their mobility profile, both of which are random in nature [22]. Most of the existing literature has used computer simulations due to the analytical intractability of the non-stochastic models. However, the analytical framework is necessary as it helps understand the impact of different network parameters on the network performance, which is cumbersome otherwise. Thus, this work is based on stochastic geometry due to mathematical tractability and its predictive power for the performance of actual LiFi networks [23]. A PPP consists of randomly located points on a mathematical space with parameter λ (means intensity) [24]. The number of points in any compact cluster $B \subset R^d$ is a Poisson random variable if and only if a point process $\Phi = \{x_{(i)} : i = 1, 2, \dots\} \subset R^d$ is a PPP . In the real plane, the R^d is called d dimensional space. The number of points in discrete sets are independent and have a Poisson distribution:

$$P\{t \text{ points in set } B\} = P\{\Phi(B) = t\} = \frac{\Lambda^t}{t!} \exp(-\Lambda), \tag{1}$$

where the Poisson random variable of density $\lambda(x)$ is the intensity measure of $\Lambda = \int_B \lambda(x) \mathrm{d}x$. It can be said that the PPP is uniform or homogeneous PPP (HPPP), if $\lambda(x)$ is constant ($\lambda(x) = \lambda$) [25]. Especially, the expected number of points in a set B is an intensity measure which as described below [26]:

$$\Lambda(B) \triangleq E[N(B)], \forall B \in R^d. \tag{2}$$

If $|.|$ is the Lebesgue measure of set B, $N(B)$ has a Poisson distribution with mean $\lambda|B|$ for every compact cluster B. Then, the equation (1) turns into:

$$P\{\Phi(B) = t\} = \frac{(\lambda(B))^t}{t!} \exp(-\lambda(B)). \tag{3}$$

The IIoT devices and APs are deployed on the Voronoi tessellation according to the PPP indicated with Φ and density λ and the cluster B is regarded as a two-dimensional Euclidean space [27]. The partition of the plane into n convex polytopes is named as the Voronoi tessellation. The APs in the system are deployed following an independent PPP with density λ_p. In addition, the IIoT devices are modeled into two categories: D2D transmitting IIoT and D2D receiving IIoT. Also, they are deployed following and independent PPP with densities λ_t and λ_r, respectively. Through this approach, the industrial LiFi network model is more convenient for the optimization processes including studying mobility management. Also, it contributes to designing more realistic scenarios. Figure 1 presents an exemplar ultra-dense industrial LiFi network deployment which includes various IIoT devices.

B. LiFi Channel Model

Industrial LiFi deployments constitute challenging environments where moving IoT machines may produce high-definition video and other heavy sensor data during surveying and inspection operations. Mobility management process for D2D communication in ultra-dense industrial LiFi networks is connected with the Received Optical Intensity (ROI). In other words, the initiation of the connection process from an IIoT device to another IIoT device is based on measured ROIs. The effect of multiple reflections from the objects and human shadowing are neglected. This means that only line-of-sight (LOS) is taken into account for the LiFi channel model in this study. The insignificance effect of the reflection paths on the ROIs is presented in [28]. According to this assumption, the ROI of the D2D receiving IIoTs from the APs and the D2D transmitting IIoTs can be expressed as [29]:

$$\mathrm{ROI}_i(d_{i,u}) = P_i \frac{(m_i + 1) A_r}{2\pi d_{i,u}^2} \cos^{m_i}(\varphi_i) T_s g(\psi_i) \cos(\psi_i), \tag{4}$$

where represent the direct link ($i = k$) and D2D link ($i = n$), respectively. In addition, $d_{i,u}$ shows the distance from the D2D receiving IIoT to an transmitter point i, A_r is the receiver effective area, P_i is the transmitted power, ψ_i is the angle of incidence with respect to the axis normal to the receiver surface, φ_i is the angle of irradiance with respect to the axis normal to the transmitter surface, ψ_{con} and $g(\psi_i)$ and are the field-of-view (FOV) and concentrator gain, T_s is the filter transmission, respectively, and m_i is the Lambertian index described as [29]:

$$m_i = -\frac{\ln(2)}{\ln[\cos(\varphi_{1/2})]}, \tag{5}$$

where $\varphi_{1/2}$ is the semi-angle at half illuminance of the transmitter. Further, the gain of the optical concentrator at the receiver is expressed by [29]:

$$g(\psi) = \begin{cases} \eta^2/\sin^2(\psi_{con}), & \text{if } 0 < \psi \leq \psi_{con} \\ 0, & \text{if } \psi_{con} \leq 0, \end{cases} \tag{6}$$

where η is the refractive index.

C. Mobility Model

The Random Way Point (RWP) mobility model is preferred in this work due to its practicality for modeling movement patterns of the D2D communication in ultra-dense industrial LiFi networks [30].

The mobile IIoT devices act in a limited area such as $\mathcal{A}$ in the RWP mobility model. The next steps (referred to as waypoint) are determined as uniformly distributed in $\mathcal{A}$. After that, the IIoT devices follow a straightway between the initial point to the newly determined waypoint at the chosen constant speed. It is possible that the IIoT can prefer an optional random pause duration. Following all of this, the mechanism repeats at each destination point. In this mobility model, at each waypoint the mobile IIoT device chooses three different parameters. First, a random direction which is uniformly distributed on [0, 2π]. Then, a transition longness that follows uniform distribution. Finally, a mobile IIoT device with a speed that is based on uniform distribution. After selecting these three different parameters, the mobile IIoT device moves to the next waypoint (determined by choice 1 and 2) at the determined speed. The mobile machines and people together have very complex movement patterns in terms of time and space; thus, they cannot be perfectly modeled [31], [32]. The existence of physical objects in the area impacts humans and mobile intelligent machines. Modeling their movement is extremely complicated and will depend on the given scenario and environment. This work will not focus on improving such a movement model. Instead, it is assumed that the movement of the IIoT devices is random and pursues the RWP mobility model. The D2D communication with mobile IIoT devices in ultra-dense LiFi networks can be modeled in a tractable way and provides a basis to evaluate mobility management with the RWP mobility model. By preferring this model, analyzing the impact of IIoT devices on LiFi networks and providing deeper insight for designing reliable industrial networks is possible. The framework presented in our work can however be extended to other mobility models.

Infinite sequence of quadruples $\{(\mathbf{X}_{k-1}, \mathbf{X}_k, V_k, S_k)\}_{k\in K}$, where k denotes the k-th movement period is used to explain the RWP mobility model. Along the k-th movement, $\mathbf{X}_{k-1}$ shows the beginning waypoint, $\mathbf{X}_k$ shows the target waypoint, V_k shows the velocity, and S_k shows the pause time at the waypoint $\mathbf{X}_k$. Given the beginning waypoint $\mathbf{X}_{k-1}$, a homogeneous PPP $\Phi_u(k)$ with density λ_u is independently generated and then the nearest point in $\Phi_u(k)$ is selected as the target waypoint. That is:

$$\mathbf{X}_k = \arg\min_{\mathbf{x}\in\Phi_u(k)} |\mathbf{x} - \mathbf{X}_{k-1}|. \tag{7}$$

Thus, $L_k = |\mathbf{X}_{k-1} - \mathbf{X}_k|$ shows the transition length of the kth movement. The cumulative distribution function (CDF) of L_k can be expressed as [33]:

$$P_{L_k}(L_k \le l) = 1 - \exp(-\lambda_u \pi l^2), \quad l > 0 \tag{8}$$

Velocity V_k and pause time S_k are independent, identically distributed (i.i.d.) with distributions $P_V(.)$ and $P_S(.)$, respectively. In addition, the transition lengths are Rayleigh distributed [34].

III. Analytical Model in Moving IIoT Devices Scenario

Generally, an industrial network consists of multiple cells that are neighbor to each other. The cell coverage area is delimited by the neighbor cells. That is, ROI in LiFi is the principal criteria for shaping the cell borders [30]. In this work, the transmitters and receivers positions are based on the 'Scenario 4: Manufacturing Cell' in LiFi standards, produced by the IEEE 802.11bb Task Group on Light communications [19]. This standard considers multiple robots as IIoT devices in a factory environment. Faces of IIoT devices look upward. Besides, it is assumed that IIoT devices in industrial LiFi networks move in a two-dimensional space.

When the D2D communication mobility pattern is considered, IIoT devices are initially distributed under the coverage

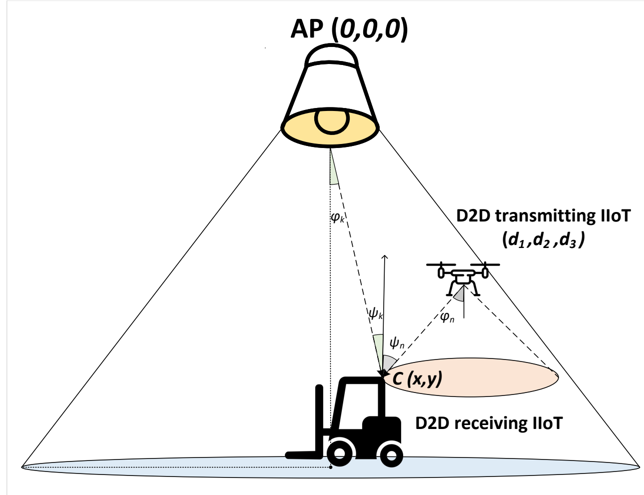

Figure 2: The LiFi network with the access point , the D2D transmitting IIoT and the D2D receiving IIoT.

of APs such as in Figure 2. It is assumed that the APs serve as an umbrella tier and IIoT devices are deployed under this umbrella. That is, each IIoT devices are under the coverage of an AP. In this work, IIoT devices initiate the mode selection process when they move inside or outside of the coverage of the D2D communication. Without loss of generality, the position $\mathbf{x_t}(d_1, d_2, d_3)$ is the location of an IIoT device and a typical AP is located at the origin. Using the ROI metric, the coverage boundary of the D2D transmitting IIoT can be determined as,

$$C = \{(x, y) \in \mathbb{R}^2 \mid \mathrm{ROI}_k(d_{k,u}) = \mathrm{ROI}_n(d_{n,u})\}. \tag{9}$$

Thus, the coverage boundary of the D2D communication range forms a cluster of equal ROI points in (9). Using these points, the mobility management parameters can be derived for an industrial LiFi network. For a D2D receiving IIoT located at $(x, y) \in \mathbb{R}^2$ and the height from the ground is h, the distance from the D2D receiving IIoT to the AP, and the D2D transmitting IIoT are given, respectively, by [35],

$$d_{k,u} = \sqrt{x^2 + y^2 + h^2}, \tag{10}$$

$$d_{n,u} = \sqrt{(x - d_1)^2 + (y - d_2)^2 + (h - d_3)^2}. \tag{11}$$

In addition, $\cos(\varphi_k) = \cos(\psi_k) = \frac{h}{\sqrt{x^2+y^2+h^2}}$ and $\cos(\varphi_n) = \cos(\psi_n) = \frac{h-d_3}{\sqrt{(x-d_1)^2+(y-d_2)^2+(h-d_3)^2}}$ because IIoT device faces are directed upward. By substituting (10) and (11) into (9), we obtain,

$$W.(x^2 + y^2 + h^2)^{\widehat{m}} - [(x - d_1)^2 + (y - d_2)^2 + (h - d_3)^2] = 0 \tag{12}$$

where, $W = \left(\frac{\mathrm{P_n}(m_n+1)(h-\mathrm{d_3})^{m_n+1}}{\mathrm{P_k}(m_k+1)h^{m_k+1}}\right)^{\frac{2}{m_n+3}}$, $\widehat{m} = \frac{m_k+3}{m_n+3}$. At this point, it is assumed that the Lambertian indices of the transmitters in the system are identical. Thus, both the AP and the D2D transmitting IIoT share an equal Lambertian index ($m_k = m_n$), $\widehat{m}$ equals 1. Thus, expression (12) defines the geometry of a circle. The corresponding center, $\mathbf{x_c} =$

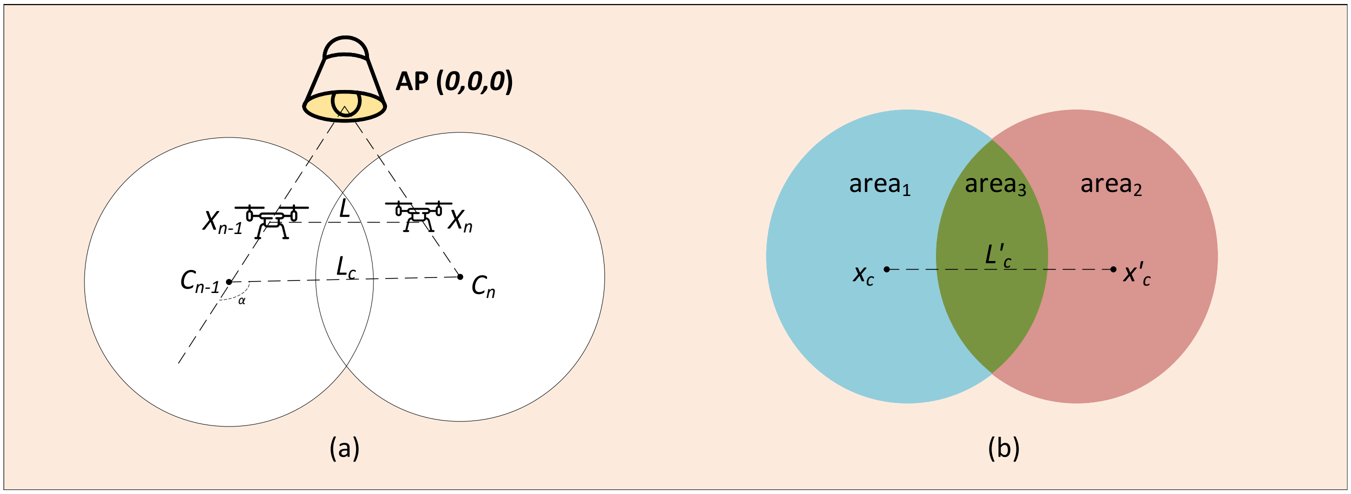

Figure 3: (a) Changing of D2D communication range; (b) Relative movement analytical framework.

(x_c, y_c) as well as the radius, R_c is calculated as:

$$\mathbf{x_c} = \left(\frac{d_1}{1-W}, \frac{d_2}{1-W}\right) \tag{13}$$

$$R_c = \sqrt{\frac{W({d_1}^2 + {d_2}^2)}{(1-W)^2} + \frac{Wh^2 - (h-d_3)^2}{(1-W)}}. \tag{14}$$

Based on stochastic geometry and the proposed coverage boundary of the D2D communication, it is possible to propose an analytical model for mode selection in moving D2D scenarios. Thus, the scenario can be simplified to only one D2D receiving IIoT device together with distributed multiple D2D transmitting IIoT devices using the character of PPP. From equation (14), it is understood that the position of the D2D transmitting IIoT device is relevant to the D2D communication range. On the other side, the relative distance of the IIoTs to one another determines the mode of the D2D receiving IIoT. For clear presentation, subscript 'c' is used to indicate the transition length of the D2D communication range center and superscript '′' to denote the relative movement transition length.

As shown in Figure 3a, the D2D transmitting IIoT is located at the waypoint $\mathbf{X}_{n-1}$ and moves to waypoint $\mathbf{X}_n$ at the next step when the AP is located at the origin. Based on the parallel relationship between line $\mathbf{X}_{n-1}\mathbf{X}_n$ and line $\mathbf{C}_{n-1}\mathbf{C}_n$, the transition length of the center of the coverage boundary can be obtained as $L_c = L \times \sqrt{\frac{\left(\frac{d_1}{1-W}\right)^2 + \left(\frac{d_2}{1-W}\right)^2 + h^2}{{d_1}^2 + {d_2}^2 + {d_3}^2}}$.

If the D2D receiving IIoT is taken as a reference point, then the D2D transmitting IIoT could be treated as moving towards the reference point, i.e, the receiving IIoT. Thus, the relative movement scenario could simplify the complex multiple object movements scenario to single object movement, which simplifies the analysis while still keeping the realistic features. As shown in Figure 3b, the coverage boundary of the D2D transmitter IIoT can be represented before and after the relative movement. If we assume that the D2D receiving IIoT has a fixed location, three different scenarios are possible according to the relative movement of the D2D transmitter IIoT:

1) When the D2D receiving IIoT is located in area$_1$ (the blue area), the D2D receiving IIoT will perform mode transition from D2D mode to direct mode because the D2D transmitting IIoT moves from area$_1$ to area$_2$ (the red area).
2) When the D2D receiving IIoT is located in area$_2$, the D2D receiving IIoT will change its communication mode from direct mode to D2D mode because the D2D transmitting IIoT moves from area$_1$ to area$_2$.
3) When the D2D receiving IIoT is located in area$_3$ (the green area), the D2D receiving IIoT will maintain its communication mode.

IV. D2D MOBILITY ANALYSES FOR RESILIENT INDUSTRIAL LIFI NETWORK

A. Mode Transition Rate

With the next-generation industrial LiFi systems being a part of wireless communication, network densification through D2D communication will be an inescapable phenomenon. This densification brings with it smaller and denser cell deployment which causes higher transition rate. The network signaling overhead is directly related to mode transition rate. The movement trace of the IIoT devices can be divided into infinite parts according to the RWP mobility model. Thus, the D2D mode transition rate, H, is expressed as the expected number of D2D mode transition, $E[N]$, along one movement period divided by the expected period of time, $E[T]$. That is [36], [37]:

$$H = \frac{E[N]}{E[T]}. \tag{15}$$

Considering n-th movement, the expected number of D2D mode transition is given by:

$$E[N] = \lambda_t |\mathcal{A}| E_t[N] \tag{16}$$

where λ_t, $|\mathcal{A}|$ and $E_t[N]$ are the D2D transmitter IIoT density, entire probability space and the expected D2D mode transition number for the typical transmitting IIoT, respectively. Based on the proposed model in the Figure 3b, the probability of performing D2D mode transition during the

k-th movement period is denoted as the probability of the receiving IIoT located at area$_1$ and area$_2$, that is $\frac{S_{area_1}+S_{area_2}}{|\mathcal{A}|}$ for a typical D2D transmitting IIoT. The expected D2D mode transition number for the D2D transmitting IIoT is derived:

$$E_t[N] = \int\int \frac{S_{area_1}+S_{area_2}}{|\mathcal{A}|} f_{L_c'}(l) f_{R_c}(r) dl dr \quad (17)$$

where $f_{L_c'}(l)$ is the probability density function (PDF) of the circle center relative movement transition length L_c' and $f_{R_c}(r)$ is the PDF of the D2D coverage radius.

According to Figure 3, $S = S_{area_1} + S_{area_2}$ can be obtained. Note that the D2D communication range before and after the movement is almost unchanged because the value of W and the expression in (14) are much smaller than 1. It means that the circle radius is almost unchanged. Therefore, two circles with the same radius ($R_c = R_c'$) fit quite well for the analytical framework. The expression of S is given by:

$$S = \begin{cases} 2\pi R_c^2 - 4R_c^2 \arccos\frac{L_c'}{2R_c} + 2L_c'\sqrt{R_c^2 - \frac{L_c'^2}{4}}, & L_c' < 2R_c \\ 2\pi R_c^2, & L_c' \geq 2R_c \end{cases} \quad (18)$$

If we regard S as a function of $\frac{L_c'}{2R_c}$, we can approximate it by using the Taylor series expansion and get the expected D2D mode transition number for a typical transmitting IIoT as:

$$\begin{aligned} E_t[N] &= \int\int \frac{4lr}{|\mathcal{A}|} f_{L_c'}(l) f_{R_c}(r) dl dr \\ &= \frac{4}{|\mathcal{A}|} E[L_c'] E[R_c] \end{aligned} \quad (19)$$

As a result, the D2D mode transition rate can be expressed as closed-form as:

$$\begin{aligned} H &= 4\lambda_t v E[R_c] \sqrt{\frac{\left(\frac{d_1}{1-W}\right)^2 + \left(\frac{d_2}{1-W}\right)^2 + h^2}{{d_1}^2 + {d_2}^2 + {d_3}^2}} \\ &= 4\lambda_t v \sqrt{\frac{W E[X_{p2t}]^2}{(1-W)^2} + \frac{Wh^2 - (h-d_3)^2}{(1-W)}} \\ &\times \sqrt{\frac{\left(\frac{d_1}{1-W}\right)^2 + \left(\frac{d_2}{1-W}\right)^2 + h^2}{{d_1}^2 + {d_2}^2 + {d_3}^2}} \\ &= 4\lambda_t v \sqrt{\frac{W}{4\lambda_p(1-W)^2} + \frac{Wh^2 - (h-d_3)^2}{(1-W)}} \\ &\times \sqrt{\frac{\left(\frac{d_1}{1-W}\right)^2 + \left(\frac{d_2}{1-W}\right)^2 + h^2}{{d_1}^2 + {d_2}^2 + {d_3}^2}} \end{aligned} \quad (20)$$

where the expected value of distance between the AP and the D2D transmitting IIoT is given as $E[X_{p2t}] = \frac{1}{2\sqrt{\lambda_p}}$ based on stochastic geometry [38], [39].

B. D2D Residence Time

The expected IIoT dwell time interval in a D2D communication range can be described as residence time [40]. With determined mode changes areas, it is easy to obtain the expected D2D mode residence time. The probability of receiving IIoT which operates in D2D communication mode is relevant with the proportion of the coverage areas, $\frac{\pi R_c^2}{|\mathcal{A}|}$. Also, the probability that the receiving IIoT changes its communication mode from D2D mode to direct mode after the relative movement is $\frac{S_{area1}}{|\mathcal{A}|}$. Thus, the probability of $L_t < l$ can be obtained as:

$$P(L_t \leq l) = \frac{S_{area1}}{\pi R_c^2} = 1 - \frac{2}{\pi}\arccos\frac{l}{2R_c} + \frac{l}{\pi R_c^2}\sqrt{R_c^2 - \frac{l^2}{4}} \quad (21)$$

In addition, the PDF of the trajectory length L_t is derived as:

$$f_{L_t} = \frac{1}{\pi R_c}\left(\frac{4\pi R_c^3 - l^2}{4\pi R_c^3\sqrt{1-(l/2R_c)^2}} + \sqrt{1-(l/2R_c)^2}\right). \quad (22)$$

As a last step, the expected trajectory length inside a D2D communication range and D2D mode residence time is given respectively by:

$$\begin{aligned} E[L] &= \int\int_0^{2r} l f_{L_t(l)} f_{R_c(r)} dl dr \\ &= \frac{\pi}{2}\sqrt{\frac{W}{4\lambda_p(1-W)^2} + \frac{Wh^2 - (h-d_3)^2}{(1-W)}} \end{aligned} \quad (23)$$

$$T = \frac{E[L]}{E[V]} = \frac{\pi}{2v}\sqrt{\frac{W}{4\lambda_p(1-W)^2} + \frac{Wh^2 - (h-d_3)^2}{(1-W)}}. \quad (24)$$

V. NUMERICAL RESULTS AND DISCUSSIONS

In this section, we discuss the performance metrics of the D2D communication for industrial LiFi networks with mobile IIoT devices. The closed-form analytical expressions are compared with the Monte Carlo simulation results in MATLAB. Monte Carlo simulation is a technique used to study how a model responds to randomly generated inputs. Unless otherwise stated, the simulation environment considered has dimensions: $30 \times 30 \times 5\ \mathrm{m}^3$, the semiangle at half illuminance of the transmitters are selected as equal to $60°$, and λ_t / $\lambda_p = 3$. Moreover, the relationship among transmit powers are set as $P_k = 25P_n$ for this illustration environment. The height of the D2D receiving IIoTs and the D2D transmitting IIoTs from the ground is taken as 2 m and 3 m, respectively.

In Figs 4 and 5, the analytical results of the D2D communication performance metrics are shown to fit well with the simulation results. The movement of IIoT devices is also modelled according to the RWP mobility model whose details are given in Section II. The D2D receiving IIoTs and the D2D transmitting IIoTs are deployed using two independent homogenous PPPs, Φ_r, Φ_t, with densities λ_r and λ_t, respectively. Additionally, three different velocity values, $v = \{0.2, 0.5, 1.4\}$ m/s, are assigned to the IIoT devices to account for different devices such as robotic arms, drones, automated guided vehicles among others. In line with related work in literature [38], [41], the default velocity is assumed to be $v = 1.4$ m/s. This represents the velocity of a human.

Figure 4 shows the relationship between D2D mode transition rate and different access point density λ_p. The figure shows that as the AP density increases so does the D2D transition rate. This is because the AP deployment gets denser as λ_p increases, which means that transition between the AP and the D2D transmitting IIoT is initiated more.

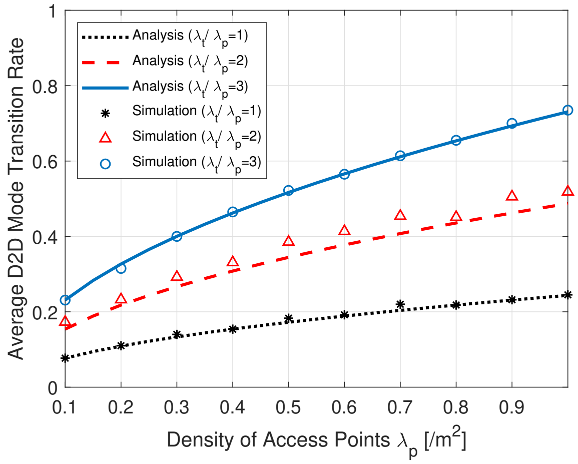

Figure 4: Average D2D mode transition rate by analyses and simulation.

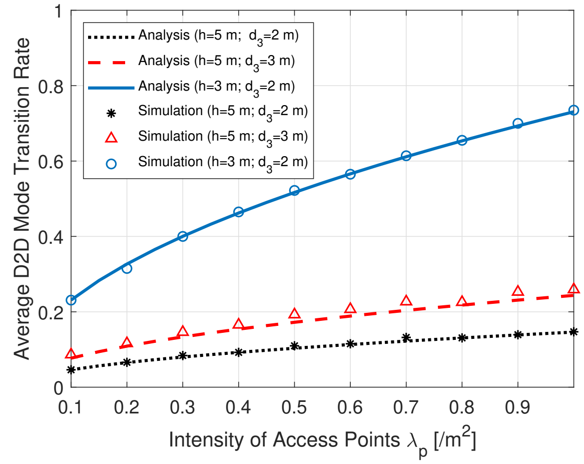

Figure 6: Average D2D mode transition rate for different heights from the ground.

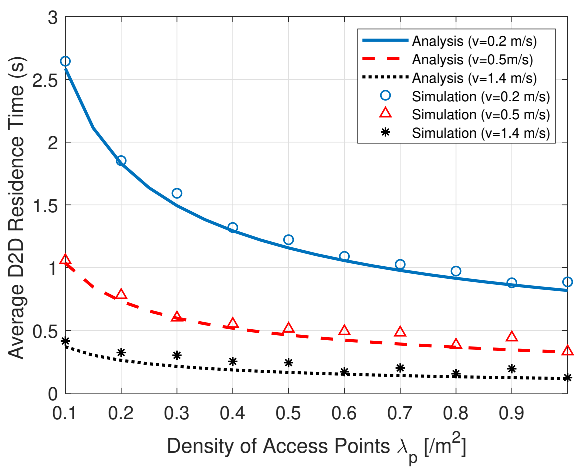

Figure 5: Average D2D residence time by analyses and simulation.

On the other hand, the decreasing density of transmitting IIoT is a reason for the decrease in D2D transition rate. Additionally, high velocity and denser deployment cause a decrease in the average D2D residence time in Figure 5. As expected, shorter residence time in a D2D communication range is directly related to higher IIoT velocity. The coverage area of the D2D transmitting IIoT communication also declines with high AP density.

Next, we studied the effect of different room sizes on communication performance. As can see from (20) and (24), the height from the ground of APs, h, and D2D transmitting IIoT devices, d_3, impacts the system performance. In Figure 6, three scenarios of different AP and D2D transmitting IIoT device heights are compared in terms of the average D2D mode transition rate. As the height of transmitters from the ground increases, it is expected that the coverage area on the ground of the transmitters also increases. Thus, an increase in height is a reason for less D2D transition rate. In this case, D2D receiving IIoTs spend more time connected to the transmitter rather than transitioning or vice versa. Because of this reason, scenario (h=3 m; d_3=2 m) which are the lowest values of the heights has the highest average D2D mode transition rate. Besides, using extensive Monte Carlo simulations, we generated a massive number of random user x-y trajectories in which the total distance of users is far beyond any network size. At this point, different lengths and widths of the room have an insignificant effect on system performance due to the total user trajectories exceedingly huge than room size.

With regards to comparison with other research results, in [35] and [41], the multi-tier LiFi concept is introduced and their key findings which is an increase in density of the access point is a reason for the high handover/transition rate is inline with our result. Also, another key result of this paper, which is the D2D residence time is inversely proportional to the device velocity, shows a similar relation to the result of [37].

The Monte Carlo simulation results match quite well with the analytical expression results. The simulation results not only verify the analytical results in Section IV, but also provide better system level design insight for the D2D communication in ultra-dense industrial LiFi networks. For example, the velocity of the IIoT can be estimated by using the analytical expression of the D2D transition rate when the value of the D2D transmitting IIoT density in a designed space is known. In addition, these analytical expressions are beneficial for increasing the positioning accuracy such as using the residence time when the results are not sufficient or the position error is very huge. In the event of a fixed deployment with known AP density, different types of strategies can be applied to indoor IIoT depending on the device velocities. For instance, the results have shown that increasing device velocity results in decreasing D2D residence time. Thus, highly mobile IIoT devices can be assigned to the APs rather that D2D transmitting IIoTs. This say, the high transition rate is reduced by avoiding D2D communication. Furthermore, it should be emphasized that this strategy envisages an in indoor industrial applications where the environment is controlled and carefully designed.

VI. CONCLUSION

In this work, the key performance metrics for the D2D communication in ultra-dense industrial LiFi networks are analyzed for mode transition from the AP to the D2D transmitting IIoT. Based on semiangle at half illuminance, the analytical model for the coverage areas of the D2D communication is presented. In addition, the D2D mode transition rate and the D2D residence time are obtained as closed-form expressions which are functions of the system parameters. From the closed-form expressions, it is clear that AP density, IIoT density, and velocity are crucial parameters of the D2D mobility management in ultra-dense industrial LiFi networks. In addition, simulation results that validate the analytical expressions are presented. The results are valuable in practical industrial LiFi design, deployment and mode selection.

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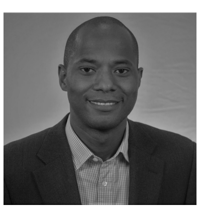

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