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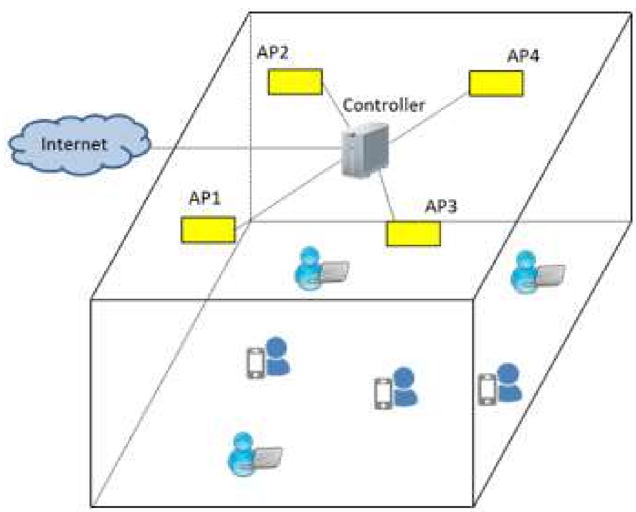

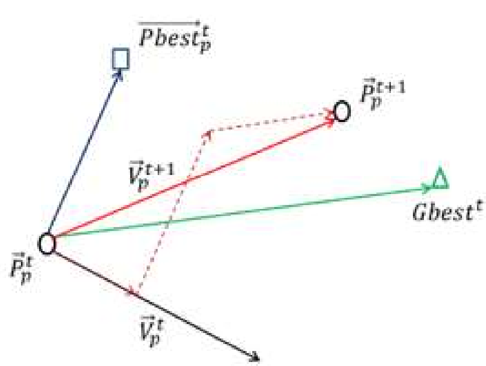

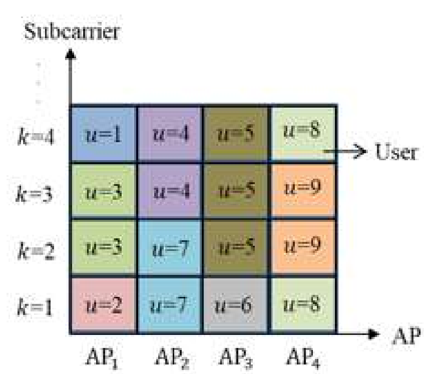

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Unified Resource Allocation and Mobility Management Technique Using Particle Swarm Optimization for VLC Networks

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Abstract: In this paper, we present a unified resource allocation and mobility management algorithm based on particle swarm optimization (PSO) for indoor visible light communication (VLC) networks. We consider a VLC network where multiple LEDs serve as access points (APs). A centralized controller collects channel state information, quality of service requirements of the users and the overload status of the APs. Based on the available information, in each time interval, the controller decides which user is served by which AP and assigns subcarriers to the users with the objective of maximizing both the system throughput and user satisfaction. We formulate the resource allocation problem as a constrained nonlinear integer programming problem and solve it using meta-heuristic PSO. Through an extensive simulation study, the superiority of the proposed algorithm in terms of system throughput and user satisfaction over Round Robin, Best Channel Quality Information and Genetic algorithms is demonstrated.

Index Terms: Visible light communications, resource allocation, particle swarm optimization, mobility management, DCO-OFDM.

1. Introduction

The demand for high-speed and ubiquitous broadband wireless access has spurred an immense growth in mobile data traffic. Due to limited available bandwidths in the radio frequency (RF) band, current wireless systems have hard time to cope with this demand. Visible light communication (VLC) has emerged as a complementary short-range wireless access technique based on the dual use of light emitting diodes (LEDs) [1]. In VLC systems, light from LEDs is modulated at high speeds not noticeable to the human eye without any adverse effects on illumination levels. Therefore, wireless access is provided as an add-on service to the primary task of illumination of LEDs [2].

In recent years, there has been a growing attention on VLC and the literature on point-to-point VLC systems is already rich and well established [3]. While the existing works with a particular emphasis on physical layer aspects are important to demonstrate the potential of VLC, significant further efforts on upper layer issues are required to transform VLC into a multi-user, scalable, and fully networked wireless technology to meet the needs of future wireless networks. Towards this purpose, some studies on handover and resource management [4]-[16] were reported in the context of VLC networks. In [4], a handover method based on received signal intensity is investigated for indoor VLC scenarios. In [5], a handover method is proposed that uses predictive received signal strength to reduce the number of handovers and associated delays. In [6], cell coverage areas are dynamically changed to make handover while maintaining desired illuminance in the environment. The work in [7] investigates handover hysteresis regions for VLC systems under illumination constraints.

Furthermore, some resource management studies including resource allocation, scheduling and interference management were reported in [8]-[14]. In [8], the scheduling problem for indoor multiuser VLC systems is investigated to minimize inter-user interference. In [9], resource allocation problem for a VLC system is formulated to achieve proportional fairness under delay requirements. In [10], a centralized resource allocation scheme is proposed to assign the visible light multicolor logical channels to different users to minimize the co-channel interference. In [11], a location-based proportional fair scheduling algorithm for VLC is introduced. An underlying assumption in [10] and [11] is that the users are always connected to the access point (AP) with the best channel information, therefore this does not guarantee that each user gets the best service. In [12], a centralized resource allocation method for orthogonal frequency division multiple access (OFDMA) VLC system is proposed

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based on genetic algorithms to maximize system throughput. In [13], based on collision monitoring, a decentralized resource allocation method is introduced for OFDMA VLC systems. In the proposed system of [13], each AP is required to broadcast the information of utilized resources. Unlike the aforementioned studies [8]-[13] where traffic type and data rate requirements of the users are not considered, the work in [14] considers user satisfaction and addresses both resource allocation and load balancing for an orthogonal frequency division multiplexing (OFDM) VLC system, however, the proposed method does not consider the mobility of the user. Furthermore, there are some other studies THAT investigated resource allocation and load balancing in hybrid VLC – radio frequency (RF) networks [15]–[18].

In this paper, we propose a unified resource allocation and mobility management algorithm for indoor VLC networks. A centralized controller collects channel state information, quality of service (QoS) requirements of the users and the overload status of the APs. Based on the available information, in each time interval, the controller first decides which user is served by which AP and then assigns subcarriers to the users in order to maximize the system throughput and user satisfaction. We formulate the resource allocation problem as a constrained nonlinear integer programming problem and solve it using the meta-heuristic particle swarm optimization (PSO). The performance of the proposed scheme is compared with Round Robin, Best Channel Quality Information (CQI) and Genetic algorithms in terms of system throughput and user satisfaction.

The remainder of this paper is organized as follows. In Section 2, we describe the system model. In Section 3, we present our proposed unified resource allocation and mobility management algorithm. In Section 4, we present simulation results to demonstrate its performance. Finally, we conclude in Section 5.

2. System Model

As illustrated in Fig.1.a, we assume a centralized light access network (C-LiAN) [19] where multiple LEDs serve as APs. There is a centralized controller responsible for mobility management and resource allocation. This controller is a gateway that connects VLC network to the Internet. It is assumed to have channel state information (CSI) of the links between users and the APs. Users are assumed to be randomly located in the indoor environment and the Random Waypoint Model (RWP) in [20] is used to model the user mobility.

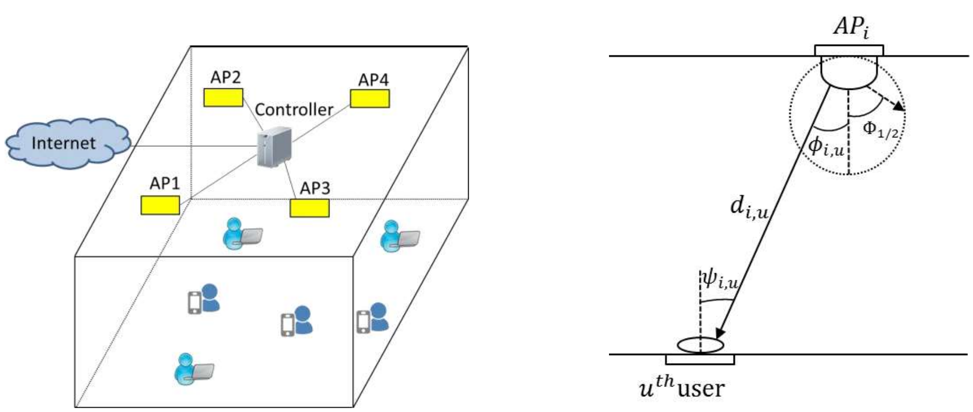

Fig. 1 a) Indoor VLC network **b)** Channel model

The physical layer builds upon direct current biased optical orthogonal frequency division multiplexing (DCO-OFDM). Either phase shift keying (PSK) or quadrature amplitude modulation (QAM) can be used in conjunction with DCO-OFDM system. We assume that there are N_{AP} APs serving a total of N users and an individual user can be served by only one AP. Each AP has K transmission channels (subcarriers) that are shared by a number of users. One or more subcarriers of an AP can be assigned to a specific user in each signaling interval. At the transmitter AP, the input bit stream is first mapped to the complex PSK/QAM modulation symbols, i.e., $s_1\ s_2\ \dots\ s_{(K/2)-1}$, where K is the number of subcarriers. Hermitian symmetry is further imposed on the data vector to ensure that the output of inverse discrete Fourier transform (IDFT) block is real. The resulting data vector for the i^{th} AP has the form of $\mathbf{X}_i = [0 \ s_1 \ s_2 \ \dots \ s_{(K/2)-1} \ \dots \ 0 \ s^*_{(K/2)-1} \ \dots \ s^*_2 \ s^*_1]$. After *K*-point IDFT operation and adding DC bias, the transmitted waveform from the AP_i is written as [21]

$$x_i(t) = \sum_{k=0}^{K-1} \underbrace{\frac{1}{\sqrt{K}} X_i(k) e^{j\frac{2\pi k}{K}t}}_{x_{i,k}(t)} + x_{DC}, \qquad t = 0,1,\dots,K-1 \tag{1}$$

where $X_i(k)$ is the k^{th} element of $\mathbf{X}_i$, $x_{i,k}(t)$ is the corresponding signal component on subcarrier k and x_{DC} is the DC bias. At the receiver, the received signal by the u^{th} user, $1 < u \le N$, on subcarrier k can be expressed

$$y_{u,k}(t) = RH_{0,u}x_{0,k}(t) + R\sum_{i\in U} H_{i,u}x_{i,k}(t) + n_k(t) \tag{2}$$

where R is the responsivity of the photodetector and $n_k(t)$ denotes the noise signal with zero mean and variance of $\sigma_k^2 = N_0W/K$. Here, N_0 is the noise power spectral density (PSD) and W is the total modulation bandwidth. In (2), $x_{i,k}(t)$ denotes the transmitted signal from the i^{th} AP on the k^{th} subcarrier. U denotes the set of interfering APs. Therefore, the first term of (2) represents the desired transmitted signal from AP serving the user and the second term denotes the received interference signal. Based on the line-of-sight channel (LOS) model, see Fig.1.b, the channel coefficient between the i^{th} AP and the u^{th} user is expressed as

$$H_{i,u} = \begin{cases} \frac{(m+1)AR}{2\pi {d_{i,u}}^2} cos^m(\phi_{i,u})\, cos(\psi_{i,u}), & 0 \le \psi_{i,u} < \Psi_{1/2} \\ 0, & \psi_{i,u} > \Psi_{1/2} \end{cases} \quad , i = 0,1,\dots,N_{AP}-1 \tag{3}$$

where A denotes the photodetector area, and $d_{i,u}$ denotes the distance between the i^{th} AP and the u^{th} user. The angle of irradiance and the angle of incidence between the i^{th} AP and the u^{th} user are denoted by $\phi_{i,u}$ and $\psi_{i,u}$, respectively and $\Psi_{1/2}$ is the field-of-view (FOV) semi-angle of the photodetector. In (3), $m = -1/log_2(cos(\Phi_{1/2}))$ is the order of Lambertian emission where $\Phi_{1/2}$ denotes the semi-angle of the LED.

3. PSO Based Resource Allocation

In this section, we formulate a subcarrier allocation problem to maximize the user satisfaction index. In wireless networking, users have different types of data traffic (i.e., high-quality video, voice, delay sensitive data, etc) and therefore their data rate requirements vary. According to Jain's fairness index [22], satisfaction index for the overall network is defined as

$$\xi = \frac{(\sum_{u=1}^{N}\theta_u)^2}{N\sum_{u=1}^{N}\theta_u^2} \tag{4}$$

Here, θ_u denotes the satisfaction degree of the u^{th} user and is given by [14]

$$\theta_u = \begin{cases} \frac{C_u}{R_u} & \text{if } C_u \le R_u \\ 1 & \text{otherwise} \end{cases} \tag{5}$$

where R_u denotes the required data rate and C_{u} represents the achievable data rate. Based on the ergodic channel capacity definition, C_{u} can be calculated as

$$C_u = \sum_{k=0}^{K-1}\sum_{i=0}^{N_{AP}-1} \alpha_{i,u}^k \frac{W}{K} log_2(1+\gamma_{u,k}) \tag{6}$$

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where $\alpha_{i,u}^{k}$ represents a binary variable defined as

$$\alpha_{i,u}^{k}=\begin{cases}1 & \text{if } k^{th} \text{ subcarrier of } i^{th} \text{ AP is assigned to the } u^{th} \text{ user} \\ 0 & \text{otherwise}\end{cases} \tag{7}$$

In (6), $\gamma_{u,k}$ denotes the signal-to-interference-noise-ratio (SINR) for the u^{th} user for the k^{th} subcarrier. Based on the signal model given by (2), it can be expressed as

$$\gamma_{u,k} = \frac{R^2 H_{0,u}^2 E_{0,k}}{R^2 \sum_{i\in U} H_{i,u}^2 E_{i,k} + \sigma_k^2} \tag{8}$$

where $E_{i,k}$ denotes the transmitted electrical signal power from the i^{th} AP on subcarrier k. Noting that only $K-2$ subcarriers carry data and η denotes the DC-bias factor which determines the level of DC-bias depth [23], $E_{i,k}$ can be written as $E_{i,k} = \left(E\left[x_{i,k}(t)\right]\right)^2/\eta^2(K-2)$.

We formulate a subcarrier allocation problem to maximize the user satisfaction index. Mathematically speaking, we can express this optimization problem as

$$\max \quad \xi = \frac{\left(\sum_{u=1}^{N}\theta_u\right)^2}{N\sum_{u=1}^{N}\theta_u^2} \tag{9}$$

$$\text{s.t.} \quad \sum_{u=1}^{N} n_{i,u} \le (K-2)/2, \qquad 0 < i < N_{AP}-1 \tag{10}$$

$$\sum_{i=0}^{N_{AP}-1} \alpha_{i,u}^{k} \le 1, \qquad 0 < k < K-1 \tag{11}$$

where $n_{i,u}$ shows the number of assigned subcarriers of the i^{th} AP to the u^{th} user. The first constraint is imposed to guarantee that the sum of allocated subcarriers is smaller than the total number of available subcarriers. The second constraint guarantees that each user is served by only one AP.

This is a complicated constrained nonlinear integer programming problem. For such complicated optimization problems, an effective and accurate optimization method is needed; however, for nonlinear integer programming problems there is no known polynomial time algorithm to find the optimal solution [24]. PSO method proposed by Kennedy et al. [25] has drawn attention as one of the promising optimization methods with high speed and accuracy [26], [27]. PSO is a bio-inspired optimization algorithm motivated from the social dynamics of birds and fishes where group of birds and fishes flock, change direction and move together in synchronization. Individuals called "particles" benefit from their own experiences and those of the other members of the swarm during the movement.

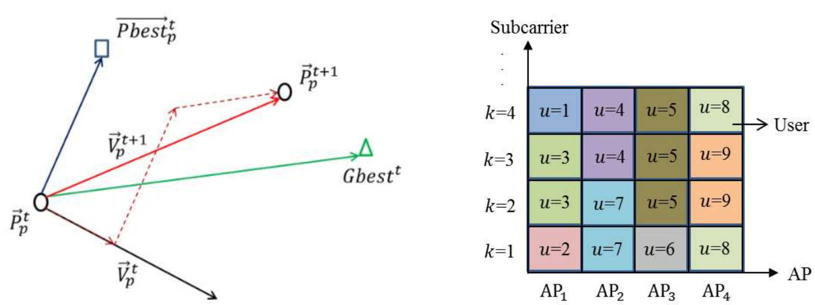

Fig. 2 a) Movement of a particle in PSO algorithm, **b)** Sample allocation map

As illustrated in Fig.2.a, in PSO, every particle has a velocity and a position which represents a candidate solution for a given optimization problem. At each iteration, a fitness function (i.e., objective function of optimization problem) is used to evaluate the solutions and each particle in the swarm moves toward to the historical personal best position and the global best position according to the set of equations given by [24]

$$V_p^{t+1} = wV_p^t + c_1\left(Pbest_p^t - P_p^t\right) + c_2\left(Gbest^t - P_p^t\right) \quad (12)$$

$$P_p^{t+1} = P_p^t + V_p^{t+1} \quad (13)$$

at the t^{th} iteration, $1 < t \leq t_n$ where t_n is the PSO iteration number. In (12) and (13), P_p^t represents the position of the p^{th} particle, $1 < p \leq p_n$, where p_n is the number of particles in the swarm. V_p^t shows the velocity of the p^{th} particle at the t^{th} iteration. $Pbest_p^t$ represents the personal best position and $Gbest^t$ is the swarm's best position at the t^{th} iteration. w is the inertia term and c_1 and c_2 are the acceleration coefficients. At the end of the last iteration, $Gbest^{t_n}$ becomes the final PSO solution. In our case, $Gbest^{t_n}$ is a $K \times N_{AP}$ matrix with each element denoted as $Gbest^{t_n}(k,i) = u$ indicating that the k^{th} subcarrier of the i^{th} AP is assigned to the u^{th} user, i.e., $\alpha_{i,u}^k = 1$ in (11). The pseudo code of proposed algorithm is described in Table 1. Fig.2.b. shows a sample algorithm solution,$Gbest^{t_n}$, which represents a resource allocation map. For instance, as shown in the figure, 2^{nd} and 3^{rd} subcarriers of the 4^{th} AP is assigned to the 9^{th} user.

Table 1 Pseudo-code of the proposed algorithm

```
for each particle (p = 1 to p_n) do
    initialize random position (P_p^0) and velocity (V_p^0);
    evaluate fitness function (Pbest_p^0);
end for
compute global best position (Gbest^0);
for each iteration (t = 1 to t_n)
    for each particle (p = 1 to p_n) do
            update position (P_p^t) and velocity (V_p^t);
            evaluate fitness function (Pbest_p^t);
    end for
    update global best position (Gbest^t);
end for
return global best position (Gbest^{t_n});
```

The proposed algorithm is executed in each time interval considering the location and the data rate requirements of the users and the overload status of the APs. In each time interval, the algorithm decides which AP will serve a specific user and which subcarriers of that AP will be assigned to that user. If there are overloaded APs, the controller performs load balancing and handovers to transfer the users to the neighboring available APs. It should be noted that this is imposed by the first constraint in (10). This constraint ensures that the algorithm does not allocate more subcarriers beyond the AP capacity. Furthermore, based on the channel condition (mainly determined by the location) of the user checked at every signaling interval on a regular basis, the controller handovers the user to available AP with a better channel state, if required.

4. Simulation Results and Discussions

In this paper, we consider an empty room with a size of 5m × 5m × 3m and assume 4 luminaries (each acting as an AP) on the ceiling with equidistant spacing of 2.5m in both x and y directions. The optical power for each luminary is 55 Watts and they have 40° half viewing angle. The height of the photodetectors are 0.75 m and they face upward towards the ceiling. The FOV and the area of the PDs are 85° and 1 cm^2, respectively. The number of users varies from 6 to 22 and the number of subcarriers for each AP is 16. As stated in Section II, RWP is used to model the user mobility. At the beginning of each trip, the mobile user chooses a random destination and a speed. Then, it travels toward the new destination at a constant speed of 3 km/h. Simulation parameters are summarized in Table 2.

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Table 2 Simulation parameters

Parameters	Values
Number of luminary	4
Power of each luminary	55 W
View angle of luminary	40°
Distance between luminaries	2.5 m
FOV of PD	85°
Area of PD	1 cm^2
Responsivity of PD	0.6 (A/W)
Vertical separation of Transmitter and receiver	2.25 m
Noise density	1×10^{-20} (A^2/Hz)
AP signal bandwidth	20 MHz
DC bias factor	3
Number of subcarrier	16
Average required data rate	53 Mbps

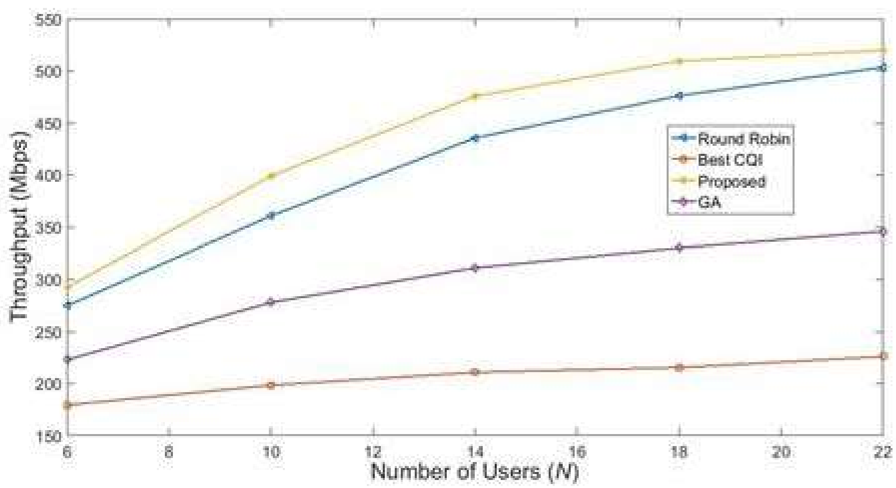

Fig. 3. System throughput vs the number of users

In Fig.3, we present the system throughput with respect to the number of users. The number of particles in the swarm p_n is 30, and the number of PSO iteration t_n is set to 70. Acceleration coefficients c_1 and c_2 are set to 2.5 and inertia term w is chosen as 0.5. As benchmarks, we include the performance of Round Robin (RR) algorithm [11], Best Channel Quality Information (CQI) [14] and Genetic Algorithm (GA) [12], [28]. RR aims to equally allocate the resources among users to provide fairness. CQI algorithm is designed to give priority to the user having strongest channel condition. GA is a population based iterative heuristic algorithm and aims to find an optimal solution for a defined problem. From Fig.3, we observe that our proposed algorithm outperforms RR, Best CQI and GA techniques. For example, when the number of users is set to 14, our algorithm provides a total system throughput of 476 Mbps while RR, GA and best CQI provide 436 Mbps, 311 Mbps and 210 Mbps, respectively. Best CQI algorithm tries to give all the resources to the user that has the best channel information and it does not consider the user's required data rate, therefore it has the worst throughput performance. GA approach has the second worst performance; in our simulation for a fair comparison, we set equal iteration numbers (i.e., 70) for both PSO and GA. It is observed that GA has poor performance, because it requires high iteration numbers to find an optimal solution. RR algorithm gives relatively better results compared to GA and best CQI. However, it does not consider the overload status of the APs, thus its throughput performance is worse than our proposed algorithm.

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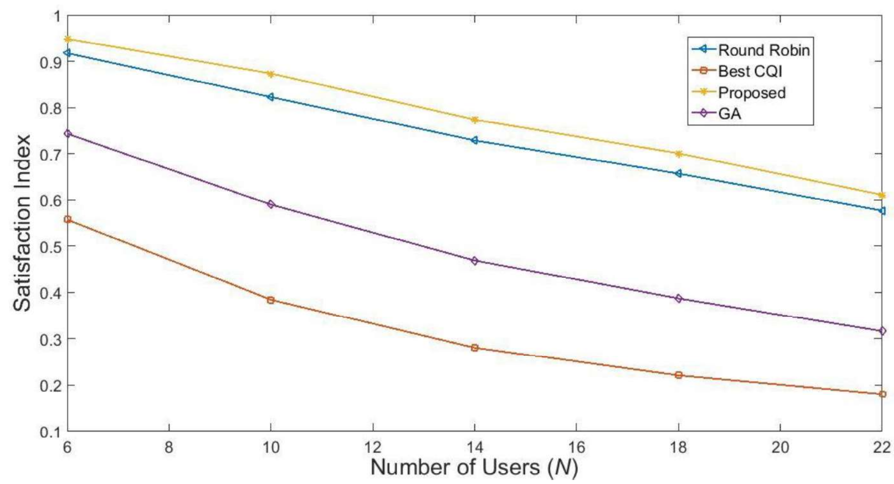

Fig. 4. Satisfaction index vs the number of users

Fig.4 presents the satisfaction index as a fairness indicator. Our algorithm achieves better performance in terms of fairness. For 14 users, our satisfaction index is 0.78 while RR, GA and best CQI have satisfaction index of 0.73, 0.47 and 0.28, respectively. RR algorithm equally allocates the subcarriers, however it does not consider the user's required data rate and therefore it ends up with worse fairness. As expected where there are limited resources, satisfaction index decreases when the number of user increases.

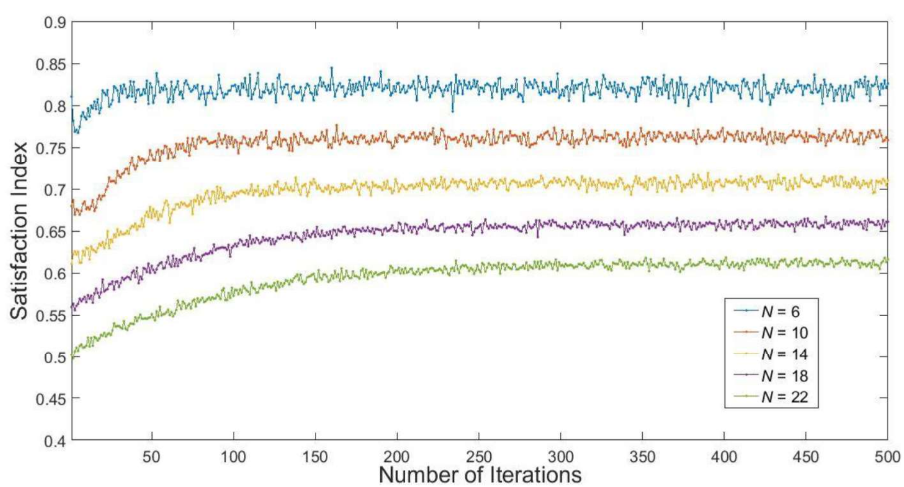

Fig. 5. Satisfaction index vs the number of iterations

Fig.5 shows the user satisfaction index of the proposed algorithm as a function of the number of iterations. For *N*=6 users, the proposed algorithm reaches a saturation point after about 50 iterations. The number of iterations required for convergence increases with the number of users. For example, it climbs to about 80, 130, 170 and 240 for *N*=10, 14, 18 and 22.

5. Conclusions

In this paper, we have considered a centralized DCO-OFDM based VLC network where multiple LEDs serve as APs for a number of mobile users. Taking into account that users have different data rate requirements, we have formulated a subcarrier resource allocation problem to maximize the user satisfaction index. For the solution of resulting constrained nonlinear integer programming problem, we used bio-inspired PSO method. In each time interval, based on the channel state information and the data rate requirements of the users as well as the overload status of the APs, the proposed algorithm decides which AP will serve a specific user and which subcarriers of that AP will be assigned to that user. If there are overloaded APs, the algorithm handovers the users to the neighbor available APs. If the mobile user experiences unfavorable channel conditions due to its location, the algorithm handovers the user to another available AP with better channel conditions. We have conducted a simulation study to investigate the system throughput and satisfaction index. Our numerical results have clearly demonstrated the superiority of the proposed algorithm over Round Robin, Best CQI and Genetic algorithms.

Acknowledgements

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References

[1] S. Arnon, J. Barry, and G. Karagiannidis, Advanced optical wireless communication systems. Cambridge university press, 2012.
[2] M. Uysal, C. Capsoni, Z. Ghassemlooy, A. Boucouvalas, and E. Udvary, Optical wireless communications: an emerging technology. Springer, 2016.
[3] P. H. Pathak, X. Feng, P. Hu, and P. Mohapatra, “Visible light communication, networking, and sensing: A survey, potential and challenges,” IEEE communications surveys & tutorials, vol. 17, no. 4, pp. 2047–2077, 2015.
[4] A. M. Vegni and T. D. C. Little, “Handover in VLC systems with cooperating mobile devices,” in 2012 International Conference on Computing, Networking and Communications (ICNC). IEEE, 2012, pp. 126–130. [Online]. Available: https://doi.org/10.1109/iccnc.2012.6167395
[5] T. Nguyen, Y. M. Jang, and M. Z. Chowdhury, “A pre-scanning-based link switching scheme in visible light communication networks,” in Ubiquitous and Future Networks (ICUFN), 2013 Fifth International Conference on. IEEE, 2013, pp. 366–369.
[6] M. Rahaim and T. Little, “Sinr analysis and cell zooming with constant illumination for indoor vlc networks,” in Optical Wireless Communications (IWOW), 2013 2nd International Workshop on. IEEE, 2013, pp. 20–24.
[7] T.-C. Bui, S. Kiravittaya, N.-H. Nguyen, N.-T. Nguyen, and K. Spirinmanwat, “Leds configuration method for supporting handover in visible light communication,” in TENCON 2014-2014 IEEE Region 10 Conference. IEEE, 2014, pp. 1–6.
[8] Y. Tao, X. Liang, J. Wang, and C. Zhao, “Scheduling for indoor visible light communication based on graph theory,” Optics express, vol. 23, no. 3, pp. 2737–2752, 2015.
[9] F. Jin, X. Li, R. Zhang, C. Dong, and L. Hanzo, “Resource allocation under delay-guarantee constraints for visible-light communication,” IEEE Access, vol. 4, pp. 7301–7312, 2016.
[10] R. K. Mondal, M. Z. Chowdhury, N. Saha, and Y. M. Jang, “Interference-aware optical resource allocation in visible light communication,” in ICT Convergence (ICTC), 2012 International Conference on. IEEE, 2012, pp. 155–158.
[11] O. Babatundi, L. Qian, and J. Cheng, “Downlink scheduling in visible light communications,” in Wireless Communications and Signal Processing (WCSP), 2014 Sixth International Conference on. IEEE, 2014, pp. 1–6.
[12] M. S. Demir, O. F. Gemici, and M. Uysal, “Genetic algortihm based resource allocation technique for vlc networks,” in Signal Processing and Communications Applications Conference (SIU), 2017 25th. IEEE, 2017, pp. 1–4.
[13] B. Ghimire and H. Haas, “Resource allocation in optical wireless networks,” in Personal Indoor and Mobile Radio Communications (PIMRC), 2011 IEEE 22nd International Symposium on. IEEE, 2011, pp. 1061–1065.
[14] X. Wu, M. Safari, and H. Haas, “Bidirectional allocation game in visible light communications,” in Vehicular Technology Conference (VTC Spring), 2016 IEEE 83rd. IEEE, 2016, pp. 1–5.
[15] M. Kafafy, Y. Fahmy, M. Abdallah, and M. Khairy, “Power efficient downlink resource allocation for hybrid rf/vlc wireless networks,” in Wireless Communications and Networking Conference (WCNC), 2017 IEEE. IEEE, 2017, pp. 1–6.
[16] X. Li, R. Zhang, and L. Hanzo, “Cooperative load balancing in hybrid visible light communications and wifi,” IEEE Transactions on Communications, vol. 63, no. 4, pp. 1319–1329, 2015.
[17] W. Wu, F. Zhou, and Q. Yang, “Dynamic network resource optimization in hybrid vlc and radio frequency networks,” in Selected Topics in Mobile and Wireless Networking (MoWNeT), 2017 International Conference on. IEEE, 2017, pp. 1–7.
[18] Y. Wang, X. Wu, and H. Haas, “Load balancing game with shadowing effect for indoor hybrid lifi/rf networks,” IEEE Transactions on Wireless Communications, vol. 16, no. 4, pp. 2366–2378, 2017.
[19] R. C. Kizilirmak, O. Narmanlioglu, and M. Uysal, “Centralized light access network (c-lian): a novel paradigm for next generation indoor vlc networks,” IEEE Access, vol. 5, pp. 19 703–19 710, 2017.
[20] C. Bettstetter, G. Resta, and P. Santi, “The node distribution of the random waypoint mobility model for wireless adhoc networks,” IEEE Transactions on mobile computing, vol. 2, no. 3, pp. 257–269, 2003.
[21] J. Armstrong, “Ofdm for optical communications,” Journal of lightwave technology, vol. 27, no. 3, pp. 189–204, 2009.
[22] R. Jain, D.-M. Chiu, and W. R. Hawe, A quantitative measure of fairness and discrimination for resource allocation in shared computer system. Eastern Research Laboratory, Digital Equipment Corporation Hudson, MA, 1984, vol. 38.
[23] C. Chen, M. Ijaz, D. Tsonev, and H. Haas, “Analysis of downlink transmission in dco-ofdm-based optical attocell networks,” in Global Communications Conference (GLOBECOM), 2014 IEEE. IEEE, 2014, pp. 2072–2077.
[24] T. Matsui, K. Kato, M. Sakawa, T. Uno, and K. Matsumoto, “Particle swarm optimization for nonlinear integer programming problems,” in Proceedings of International MultiConference of Engineers and Computer Scientists 2008, pp. 1874–1877.
[25] J. Kennedy, “Particle swarm optimization,” in Encyclopedia of machine learning. Springer, 2011, pp. 760–766.
[26] A. Salman, I. Ahmad, and S. Al-Madani, “Particle swarm optimization for task assignment problem,” Microprocessors and Microsystems, vol. 26, no. 8, pp. 363–371, 2002.
[27] A. Basgumus, M. Namdar, G. Yilmaz, and A. Altuncu, “Performance comparison of the differential evolution and particle swarm optimization algorithms in free-space optical communications systems,” Advances in Electrical and Computer Engineering, vol. 15, no. 2, pp. 17–22, 2015.
[28] S. M. Sait and H. Youssef, Iterative Computer Algorithms with Applications in Engineering: Solving Combinatorial Optimization Problems, 1st ed. Los Alamitos, CA, USA: IEEE Computer Society Press, 1999.