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Markov chain-based on path selection in the heterogenous Internet of Things model

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***Abstract*—The Internet of Things (IoT) is a new heterogeneous system integrated by various end-users with different technologies. However, the limiting factor is bandwidth in the IoT due to exploding the end-users and the network bandwidth requirement. A novel IoT model, which integrates the Power Line Carrier (PLC) and the Wireless Network (WN), is proposed to solve the bandwidth problem from the architecture, especially in the areas lacking network facilities. In addition, we exploit an effective virtual layer (EVL) which allows the different end-users access to the model seamlessly. Then, the attractor selection algorithm based on Markov chain (ASMA) is employed to select an optimal path among the PLC or the WN. Simulation results demonstrate that the proposed model has the smaller delay than other algorithms and makes the model more stable.**

I. Introduction

The internet of things (IoT) is a new heterogeneous system integrated by a variety of technologies. It is based on the internet and expands to the interaction and connection between people and objects, objects and objects at any time and any place. The IoT technology can be used in many important fields such as smart grid, smart home, city management, urban intelligent transportation, health care, precision agriculture, ecological environment, resources monitoring, etc. The wide applications of the IoT technologies can improve resource utilization, production levels, the relationship between man and nature with more meticulous and dynamic management of production and life. In 2016, the global mobile devices and connections grew to 8.0 billion, up from 7.6 billion in 2015 [1]. Looking to the future, Cisco Internet Business Solutions Group (IBSG) predicts that there will be 50 billion devices connected to the internet by 2020 [2]. The flourishing development of the IoT is closely related to communication connection technology which is the one of the bottlenecks of the development of the IoT. Because of the rich and varied business scenarios and the diversity of the end-users in the IoT, the ways of the communication connection technology of the IoT are varied. On the other hand, the number of end-users is growing rapidly, and bandwidth demand for users continues to increase. Thus, the coverage area and bandwidth of the existing network cannot satisfy the user's transmission requirements. The shortage of network bandwidth not only reduces the data transmission of the IoT, but also affects the quality and experience of the communication. Therefore, connecting the end-users seamlessly and allocating dynamically the appropriate network resources are the inevitable problems of the IoT.

With the explosion of devices, there is an imminent need for network which allows all end-users to be connected seamlessly. The access wireless network technologies mainly contain WiFi, Bluetooth Low-Energy (BLE), Radio-frequency identification (RFID), Near-field communication (NFC), Long Term Evolution-Advanced (LTE-A), etc. At present, the main structure forms of the heterogeneous wireless network are WLAN - worldwide interoperability for microwave acces (WiMax), WiMax - WiFi, WLAN - universal mobile telecommunications system (UMTS), WiMax - 3G (3rd generation), etc. [3]-[5]. However, these heterogeneous networks are deployed on wireless network (WN) with some challenges, such as the blind areas, deployment of additional network infrastructure and shortage of spectrum resources, etc. These challenges are becoming more and more prominent with the increase of the end-users. On the other hand, power line communication (PLC) is applied in the smart metering and smart grid widely with the characteristics of economic benefit, stability and reliabiltiy, which improves the degree of smart city [6][7]. It is a kind of high speed information transmission technology through the power line and a basic communication way of power system, has wider coverage areas without deployment of additional infrastructure. Those features are important and cost-effective for users in the IoT to coverage the blind areas, for example, the countryside, mountain area, no-human-zone, etc. In summary, PLC can provide network connection with high-speed, wide coverage, large-capacity and low-cost for the IoT. Thus, PLC and WN can be complementation and coexistence in the heterogeneous network.

One of the key technologies in the heterogeneous network is the path selection. The IoT also need the path selection technology. Following, we focus on the network selection algorithm which consists of network selection decision criteria and network decision selection algorithm. Some network selection decision criteria have been proposed in the literatures. Common decision criteria are received signal strength (RSS), which is important for the mobile equipment to keep seamless connection. The mobile equipment decides whether or not to select a new network according to RSS of current serving network [8]-[10]. Available bandwidth is also a main criterion for the network selection. Paper [11] proposed a handover algorithm based on a general bandwidth which can

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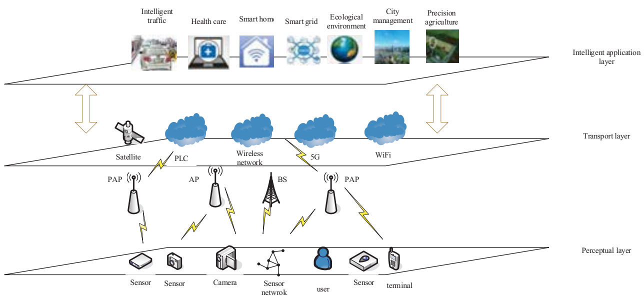


Fig. 1. The instance of HIoT

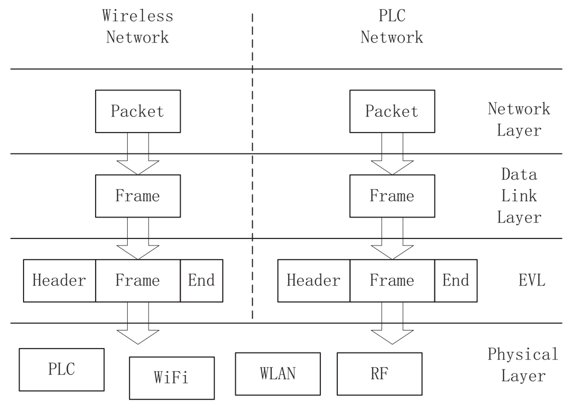


Fig. 2. The process of protocol conversion

be used as criteria to evaluate handover algorithm. Paper [12] proposed a network condition detection algorithm which is further estimated when the calculated result is larger than the pre-described threshold. Network load is also one of the criteria to be considered. In [13], the author develops a vertical hanoff decision algorithm which balances the network load among all attachment points (e.g, base stations and access points). Considering the variety of constraints, there are some studies considering united decision criterion. In [14], a united-decision criterion is approached including network metrics, device relation, application requirements and user preferences. [15] proposes a novel fuzzy-logic(FL)-based decision-making algorithm based on network handoff cost, delay, available bandwidth as the network selection decision criteria. On the other hand, the network decision selection algorithm is based on the network selection criteria. One of the most widely used algorithm is multiple attribute decision making (MADM) which contains four steps, selection of the decision criteria, collection of values for the selected criteria, criteria weights and ranking of the alternatives [16]. Based on MADM, [17] proposed a Markov decision process of the network decision selection algorithm which decreases long handoff delays and connection latency. In conclusion, the network selection in current works is limitation with decision criteria. Because the decision criteria have a fixed threshold, the network selection works when the threshold conditions to be triggered.

In this paper, a novel heterogeneous IoT (HIoT) model integrated the PLC and WN is proposed. The HIoT model not only can solve the problem of the deficient bandwidth and coverage in the IoT, but also increase the stability and robustness of the HIoT model. In order to transmit the data seamlessly, we apply an effective virtual layer (EVL) to convert the protocol of the data packet. Moreover, we propose an adaptive network selection algorithm based on the attractor selection algorithm combining the Markov chain (ASMC) to provide better allocation of the network resources. The ASMC has the ability to adaptively select an optimal path which applies the Markov chain to get the queue length. In order to decrease the handoff number of path selection, we contrast the results of different threshold of the handoff. The simulation results show that ASMC can select the optimal path dynamically. Considering the HIoT with delivery delay and handoff time, ASMC is the best algorithm compared with greedy algorithm (GA), Ad hoc On-demand Distance Vector Routing (AODV) and the original attractor selection algorithm (OASA). The rest of the paper is organized as follows. We first introduce the system model consists of network model, queuing model and extended attractor selection model in section II. In section III, we introduce how to calculate the optimal path based on the Markov chain. Then we show results of numerical evaluation and comparison with some typical network selection algorithm in section IV. Finally, we conclude the paper and describe future directions in section V.

II. System Model

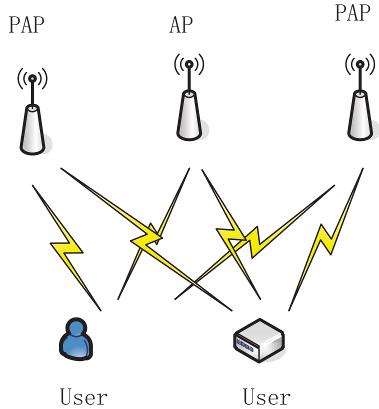
In this section, we propose the system model of the HIoT as shown in Fig. 1. Then, the path selection algorithm exploited in the proposed is also investigated.

A. Network Model

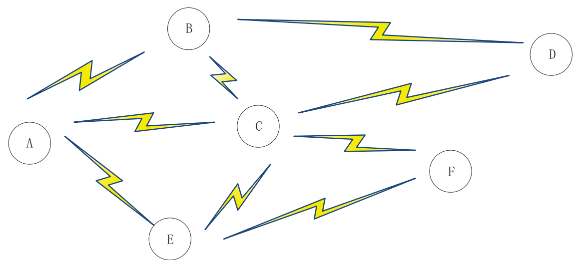
Because the protocols and the formats of the packets are different in different access technologies, we invent an effective virtual layer (EVL) to make sure that all packets come from different protocols having the same standard. Fig. 2 shows the protocol conversion in HIoT model. The header of the packet is added and resealed at the EVL which hides the diversity of transmission media without changing the existing path. Thus we assume the users can access to the HIoT through wired network or WN for ubiquitous and seamless connectivity. In order to make the model of HIoT more definite, we assume that there are two simplified models of the access network shown in Fig. 3. Fig. 3(a) shows a model of scenario that the end-users access to the HIoT. And Fig. 3(b) shows the other model of scenario which is a distributed multipath selection network in the HIoT. Without loss of generality, we make the following assumptions: 1)Both the end-users and the transmission nodes transmit the data through WiFi and PLC in the HIoT. They access to WiFi or PLC through access point (AP) or PLC access point (PAP), respectively. 2)Each end-user and transmission node has network interface of WiFi and PLC. 3)Each transmission node has the ability to update the path information by the path feedback. To facilitate the analysis of access network model, we simplify the HIoT model as shown in Fig. 4.

B. Queuing Model

When the users access to the HIoT model to transmit data, the nodes select an optimal path based on attractor selection



(a) End-users access to the HIoT



(b) Multipath selection network in the HIoT

Fig. 3. Simplified models of the access network

model which is presented in flowing section [18]. Then the data or packets are queuing up for better allocation of the network resource. The user data or packet queuing process is shown in Fig. 5. At the same time, the data flows obey the First Come First Served (FCFS) queuing discipline.

C. Extended Attractor Selection Model

The original attractor selection algorithm (OASA) is represented a mathematical model for network [19]-[21], which is ubiquitously used in biology and physics [18]. It has a nonlinear stochastic dynamics system consisting of two ordinary differential. But OASA has only two attractors which is not applicable to the dynamic HIoT environment with multiple users. Thus, we extend the OASA to the high dimension space which has M-th attractors as follows,

$$\frac{dm_i}{dt} = \frac{s(\alpha)}{1+m_u^2-m_i^2} - d(\alpha)\times m_i + \varepsilon_i \qquad i=1,\ldots.M \quad (1)$$

where $m_i(1 \le i \le M)$ are the state attractors which represent the path environment in this paper. This model has M attractors, and (1) can be calculated readily under the limited condition without noise,

$$\frac{dm_i}{dt} = 0 \qquad \forall i=1,\ldots.M \quad (2)$$

For the sake of simplicity, we denote

$$\Phi(\alpha) = \frac{s(\alpha)}{d(\alpha)} \quad (3)$$

where $\Phi(\alpha)$ is the increasing function of the activity α. Then,

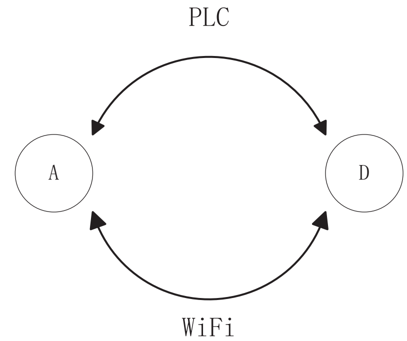


Fig. 4. The process of protocol conversion

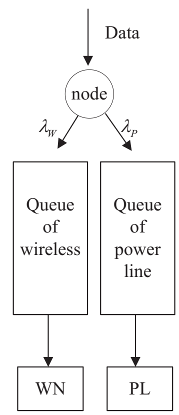


Fig. 5. Queuing model of the HIoT

we can get the solution set of (1),

$$\mathrm{M} = [m_1, \ldots, m_i, \ldots, m_M]^T \qquad i=1,\ldots M \quad (4)$$

where

$$m_i = \begin{cases} \Phi(\alpha) & high-value(i=\mathrm{u}) \\ \frac{1}{2}[\sqrt{4+\Phi(\alpha)^2}-\Phi(\alpha)] & low-value(i\neq \mathrm{u}) \end{cases} \quad (5)$$

Moreover, we use the following function given in [21],

$$\mathrm{S}(\alpha) = \alpha[5\alpha^3+1] \qquad \mathrm{D}(\alpha) = \alpha \quad (6)$$

In (2), when $m_u \gg m_i$, the network will select m_u to transmit the data, which has the high value and is the optimum solution in the solution sets. The other low values $(m_i \neq m_u)$ are abandoned. Because $m_u = \Phi(\alpha)$ is an increasing function, high activity indicates that the selection of (1) becomes more deterministic and the network state accommodates the environment well. On the other hand, when $m_u = m_i$, the activity α stays the very low value, then the selections of (1) are equal and (1) is controlled by the noise term. The network is in a bad condition which is unstable and selects a value randomly from the solution sets.

III. Optimal Path Selection

As explained above, the optimal selection algorithm defines the α and solves the value of (1). Hence, we calculate the queue length in the HIoT model and map the queue length to

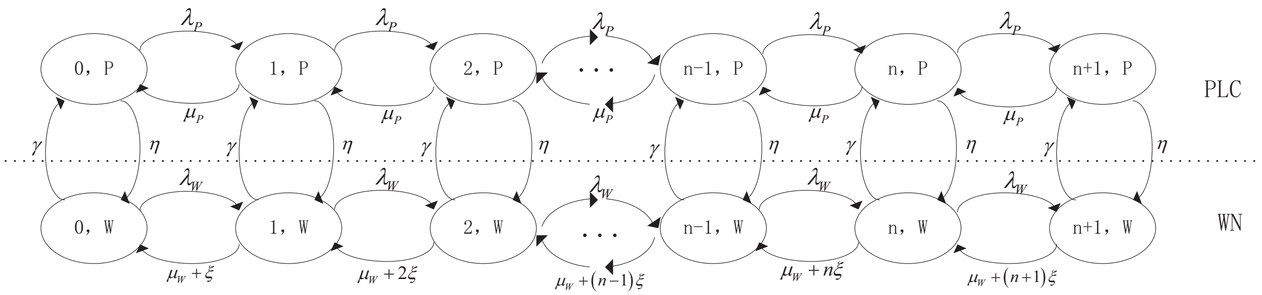


Fig. 6. The 2D Markov chain for the HIoT queue

TABLE I.

Variable	Definition/Description
λ_P/λ_W	The arrival rate of PLC or WiFi
$\mathrm{E}\left[L_W\right]/\mathrm{E}[L_P]$	The average queue length of PLC or WiFi
γ	The rate of leaving the WiFi
η	The rate of leaving the PLC state
$\mathrm{E}\left[n_W\right]/\mathrm{E}[n_P]$	Stationary probability of finding n files in WiFi state or PLC state
ξ	The reneging rate

the α. Following, we introduce the queuing model of the HIoT model.

A. Makrov Queue Model

In order to calculate the queue length, the HIoT model queueing phenomenon can be treated as an $M/M/1$ type queue operating in a 2-phase random environment as shown in Fig. 6. It is assumed that this environment Markov process is independent of the arrival, service and impatience processes. And the queuing model is in steady-state.

As shown in Fig. 6, there are two queue environment (PLC or WiFi). Let $P_(n,w)$ and $P_(n,p)$ be the steady-steady probabilities of the queue environment of WiFi or PLC respectively. The total number of users in the queue model is L. We summarize some useful notation in the Table 1.

We can get the set of balance equations from the Markov chain. In the WiFi network, we have

$$\begin{array}{ll} n=0 & \begin{array}{c}\left(\lambda_W+\gamma\right)P_{W,0}= \\ \eta P_{P,0}+(\mu_W+\xi)P_{W,1}\end{array} \\ n\geq 1 & \begin{array}{l}\left(\lambda_W+\gamma+\mu_W+n\xi\right)P_{W,n}= \\ \lambda_W P_{W,n-1}+\eta P_{P,n}+(\mu_W+(n+1)\xi)P_{W,n+1}\end{array}\end{array} \tag{7}$$

In the PLC network, we have

$$\begin{array}{ll} n=0 & \left(\lambda_P+\eta\right)P_{P,0}=\gamma P_{W,0}+\mu_P P_{P,1} \\ n\geq 1 & \begin{array}{l}\left(\lambda_P+\mu_P+\eta\right)P_{P,n}= \\ \lambda_P P_{P,n-1}+\gamma P_{W,n}+\mu_P P_{P,n+1}\end{array}\end{array} \tag{8}$$

The long term probabilities of users in PLC or WiFi state are $P_P=\frac{\eta}{\eta+\gamma}$ and $P_W=\frac{\gamma}{\eta+\gamma}$, respectively[22]. We now calculate mean queue sizes, employing vertical cuts Fig. 6, as follows,

$$\begin{array}{l}\lambda_W P_{W,n}+\lambda_P P_{P,n}= \\ \mu_P P_{P,n+1}+(\mu_W+(n+1)\xi)P_{W,n+1}, n\geq 0\end{array} \tag{9}$$

Let $\mathrm{P}_P=\sum\limits_{n=0}^{\infty}P_{P,n}$ and $P_W=\sum\limits_{n=0}^{\infty}P_{W,n}$. Summing (9) over n yields, we get

$$\begin{array}{l}\lambda_W P_W+\lambda_P P_P=\mu_P\left(P_P-P_{P,0}\right)+ \\ \mu_W\left(P_W-P_{W,0}\right)+\xi\sum\limits_{n=0}^{\infty}(n+1)P_{W,n+1}\end{array} \tag{10}$$

Define $G'_P\left(z\right)|_{z=1}=E\left[L_P\right]=\sum\limits_{n=0}^{\infty}nP_{P,n}$ and $\mathrm{G'}_W\left(z\right)|_{z=1}=E\left[L_W\right]=\sum\limits_{n=0}^{\infty}nP_{W,n}$ are the average queue length in PLC or WiFi state, respectively. Then, (10) can be written as

$$\begin{array}{l}\lambda_W P_W+\lambda_P P_P=\mu_P\left(P_P-P_{P,0}\right)+ \\ \mu_W\left(P_W-P_{W,0}\right)+\xi E[L_W]\end{array} \tag{11}$$

Then, we get

$$\mathrm{E}\left[L_W\right]=\frac{(\lambda_W-\mu_W)\eta+(\lambda_P-\mu_P)\gamma}{(\gamma+\eta)\xi}+\frac{\mu_P P_{P,0}+\mu_W P_{W,0}}{\xi} \tag{12}$$

Following the value of is calculated. Define the (partial) probability generating functions (PGFs) as

$$G_W=\sum_{n=0}^{\infty}P_{W,n}z^n,\quad G_P=\sum_{n=0}^{\infty}P_{P,n}z^n \tag{13}$$

Then multiplying (7) and (8) with z^n. Summing over n and rearranging terms, we get

$$\begin{array}{c}\mathrm{G'}_W\left(z\right)\left[\xi\left(1-z\right)z\right]=G_W\left(z\right)\left[\left(\lambda_W z-\mu_W\right)\left(1-z\right)+\gamma z\right] \\ -\eta z G_P\left(z\right)+\mu_W(1-z)P_{W,0}\end{array} \tag{14}$$

and

$$\begin{array}{l}G_P\left(z\right)\left[\left(\lambda_P z-\mu_P\right)\left(1-z\right)+\eta z\right]= \\ \gamma z G_W\left(z\right)-\mu_P(1-z)P_{P,0}\end{array} \tag{15}$$

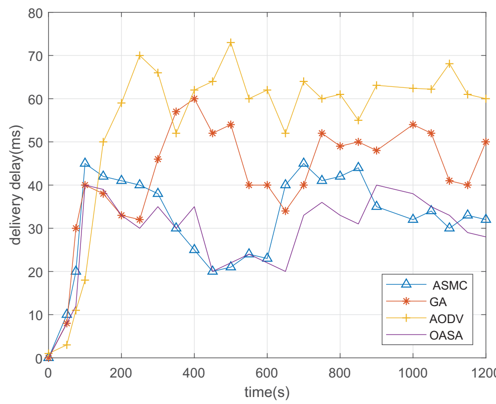


Fig. 7. The deliver delay of ASMC, GA, AODV and OASA

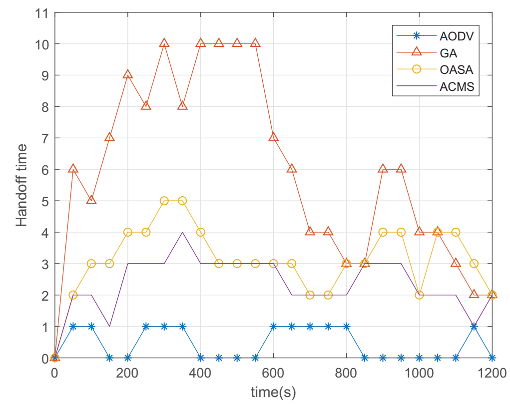


Fig. 8. Handoff times of ASMC, GA, AODV and OASA

where $G'_W(z) = \frac{d}{dz} G_W(z)$. After solving the system of (14) and (15), we have

$$G'_W(z) - \frac{\alpha(z)\beta(z) - \eta\gamma z^2}{\xi z(1-z)\alpha(z)} G_W(z) = \frac{\mu_P \eta P_{P,0}}{\xi\alpha(Z)} + \frac{\mu_W P_{W,0}}{\xi Z} \tag{16}$$

We can use the same method as referred in [23] as follows,

$$P_{W,0} = \frac{\eta\xi k_2(1)\int_0^{z_1}\frac{k_1(x)}{\alpha(x)}dx}{\mu_W(\eta+\gamma)(\int_0^{z_1}\frac{k_1(x)}{\alpha(x)}dx\int_{z_1}^1\frac{k_2(x)}{x}dx - \int_0^{z_1}\frac{k_1(x)}{x}dx\int_{z_1}^1\frac{k_2(x)}{\alpha(x)}dx)} \tag{17}$$

,

$$P_{P,0} = \frac{\xi k_2(1)\int_0^{z_1}\frac{k_1(x)}{x}dx}{\mu_P(\eta+\gamma)(\int_0^{z_1}\frac{k_1(x)}{\alpha(x)}dx\int_{z_1}^1\frac{k_2(x)}{x}dx - \int_0^{z_1}\frac{k_1(x)}{x}dx\int_{z_1}^1\frac{k_2(x)}{\alpha(x)}dx)} \tag{18}$$

and

$$G_W(z) = \begin{cases} \frac{\frac{\eta\mu_P}{\xi}P_{P,0}\int_0^z\frac{k_1(x)}{\alpha(x)}dx + \frac{\mu_{W,0}}{\xi}P_{W,0}\int_0^z\frac{k_1(x)}{x}dx}{k_1(z)} & z \le z_1 \\ \frac{\frac{\eta\mu_P}{\xi}P_{P,0}\int_{z_1}^z\frac{k_2(x)}{\alpha(x)}dx + \frac{\mu_w}{\xi}P_{W,0}\int_{z_1}^z\frac{k_2(x)}{x}dx}{k_2(z)} & z \gg z_1 \end{cases} \tag{19}$$

where $\alpha(z) = (\lambda z - \mu)(1-z) + \eta z$

$$k_1(z) = e^{-\frac{\lambda_w z}{\xi}} z^{\frac{\mu_w}{\xi}} (z_1 - z)^{\frac{\gamma z_1(z_2-1)}{\xi(z_2-z_1)}} (z_2 - z)^{-\frac{\gamma z_2(z_1-1)}{\xi(z_2-z_1)}} \quad z \le z_1 \tag{20}$$

$$k_2(z) = e^{-\frac{\lambda_W z}{\xi}} z^{\frac{\mu_W}{\xi}} (z - z_1)^{\frac{\gamma z_1(z_2-1)}{\xi(z_2-z_1)}} (z_2 - z)^{-\frac{\gamma z_2(z_1-1)}{\xi(z_2-z_1)}} \quad z \ge z_1 \tag{21}$$

Subsequently, by substituting (17), (18), (19) into (12), we can get the following equation

$$E[L_P] = \frac{(\gamma+\xi)[(\lambda_P-\mu_P)P_P+\mu_P P_{P,0}]+\gamma[(\lambda_W-\mu_W)P_W+\mu_W P_{P,0}]}{\xi\eta} \tag{22}$$

The mean number of customers in the system $E[L]$ is given by $E[L] = E[L_W] + E[L_P]$.

B. Map Activity

According to above analysis, the queue length of users in the HIoT model reflects the model condition. For example, when the L_W is small, the model condition of WiFi is good to data transmission. On the other hand, L_W increase as date packets of the WiFi model increased. It means that this condition is bad for the HIoT model. So the activity must be an increasing function for the goodness of the conditions of the HIoT model. Hence, we map the $L_i(i = L, W)$ into the activity which represents the HIoT model conditions. And it can be expressed as

$$\frac{d(\alpha)}{dt} = \delta(\alpha^* - \alpha) \tag{23}$$

where δ is the gain factor, α^* is the instant activity and based on the condition of current access network

$$\alpha^* = \begin{cases} 1 & L_{cp} - \min(L_W, L_P) = 0 \\ 0.8 & 0 < L_{cp} - \min(L_W, L_P) < \Delta \\ 0 & L_{cp} - \min(L_W, L_P) \ge \Delta \end{cases} \tag{24}$$

where L_{cp} is the queue length of current access path.

IV. RESULTS

The performance of the HIoT model based on ASMC is verified via computer simulations in this section. The delivery delay and handoff time are found to discuss in the HIoT model. Moreover, the comparison between the ASMC , GA, AODV and OASA are given to show the better performance of the proposed model. We assume that the data rate for WiFi and PLC is 2Mb/s as referred in [24][25], $\eta = \gamma = 2$ and $\xi = 1$.

A. Comparison of delivery delay

Fig. 7 depicts the comparison between the ASMC, GA, AODV and OASA with the transmission delay. As seen in Fig. 7, at beginning of the simulation, the variation between these algorithms is very small. And, the delay of those four algorithms increases as the number of users in the HIoT model increased before $t = 100$. Then, the delay of GA becomes the smallest due to that it makes the best path selection at present without overall optimization. Thus, the increased users lead to the corresponding delay increase of GA after $t = 250$.

The delay of ASMC decreases after 100s, because of this algorithm having ability to select an optimal path to transmit data adaptively. Overall, the delay of OASA and ASMC is smaller than other two algorithms.

B. Comparison of robustness

The handoff times between these four algorithms are compared as shown in Fig. 8. From the experiment results, the handoff time of AODV is the least because the users handoff spontaneously. And the handoff time of GA is lager due to that users tend to choose the best path with the minimum delay. The both handoff time of ASMC and OASA are less than GA. Especially, the ASMC can adapt to the suboptimal choice within the threshold which increases the stability of the HIoT model. Considering the HIoT model with delivery delay and handoff time, the ASMC can not only has low latency but also keep the model robust.

V. Conclusion

In this paper, the adaptive HIoT model was proposed which consists of two steps. The one step is protocol conversion of the packet/data which made the end-users access to the HIoT model seamlessly. The second step is the ASMC which is an algorithms based on OASA for an optimal path selection according to the queue length of the users. We compare GA, AODV, ASMC, OASA in the HIoT model. Simulation results show that the ASMC achieves a more stable state with low delivery delay according to the environment. For our future network, we will focus on the priority of end-users in the HIoT model.

References

[1] Cisco, "Visual Networking Index: Global Mobile Data Traffic Forecast Update," *2016-2021 White Paper*, 2017.

[2] Cisco Internet Business Solutions Group, "The Internet of Things How the Next Evolution of the Internet Is Changing Everything," *White Paper*, 2011.

[3] Sujatha Kolipaka, B.N.Bhandari, Abhijit Dey, "Joint Admission Control and vertical handoff between WLAN and WIMAX in wireless mesh networks for QoS," *2016 IEEE International Conference on Engineering and Technology*, pp. 1018-1023, 2016.

[4] Abhishek Gehlot, Anand Rajavat, "Handoff between WiMAX and WiFi wireless netwroks," *2016 Symposium on Colossal Data Analysis and Networking*, pp. 1-5, 2016.

[5] Angoma Blaise, Erradi Mohammed, Benkaouz Yahya, et al., "HaVe2W3G: a vertical handoff solution between WLAN, WiMAX and 3G networks," *International Wireless Communications and Mobile Computing Conference*, pp. 101-106, 2001.

[6] Cedric Lavenu, Damien Dufresne, Xavier Montuelle, "Innovative solution sustaining supervisory control and data acquisition to remote terminal unit G3-PLC connectivity over dynamic grid topologies," *CIRED-Open Access Proceedings Journal*, vol. 1, no. 10, pp. 719-723, 2017.

[7] Andreas Abart, Markus Flohberger, Reinhard Hirtler, "Assessment of electromagnetic field-exposure in residential buildings caused by smart metering systems using PLC," *CIRED-Open Access Proceedings Journa*, vol. 1, no. 10, pp. 526-530, 2017.

[8] Sunisa Kunarak, Raungrong Sulessathira, "predictive RSS with fuzzy logic based vertical handoff algorithm in heterogeneous wireless networks" *IEEE International Conference on Advanced Technologies for Communicaitons*, vol. 53, no. 9, pp. 1235-1240, 2010.

[9] Julang Ying, Kaveh Pahlavan, Xinrong Li, "Precision of RSS-based indoor geolocation in IoT applications," *IEEE Annual International Symposium on Personal, Indoor, and Mobile Radio Communications*, pp. 1-5, 2017.

[10] Kalpana Shanmugam, "A novel candidate network selection based handover management with fuzzy logic in heterogeneous wireless netwroks," *IEEE International Conference on Advanced Computing and Communicaiton Systems*, pp. 1-6, 2017.

[11] C.Chi,X. Cai and R. Hao, et al, "Modeling and analysis of handover algorithms," *IEEE GLOBECOM*, pp. 4473 - 4477, Nov. 2007.

[12] D. Ma and M. Ma, "A QoS oriented vertical handoff scheme for WiMAX/WLAN overlay netwoks," *IEEE Trans. Parallel Distrib. Syst.*, vol. 23, no. 4, pp. 598-606, 2012.

[13] S.Lee, K, Kim, et al, "Vertical handoff decision algorithms for providing optimized performance in heterogeneous wireless networks," *IEEE Trans. Veh. Technol*, vol. 58, no. 2, pp. 865-881, 2009.

[14] R. Trestian, O. Ormond and G.Muntean, "Game theory-based network selection: Solutions and challenges," *IEEE Commun.Surveys Tutorials*, vol. 2, no. 99, pp. 1-20, 2012.

[15] J.Hou and D. C.O'Brien, "vertical handover-decision-making algorithm using fuzzy logic for the integrated Radio-and-OW system," *IEEE Trans. Wireless Commun.*, vol. 5, no. 1, pp. 176-185, 2006.

[16] Tarik Taleb, Adlen Ksentini, "VECOS: a vehicular connection steering protocol", *IEEE Trans. Vehicular technology*, vol. 64, no, 3, pp. 1171-1187, Mar. 2015.

[17] Lin Chen, Hui Li, "An MDP- based vertical handoff decision algorithm for heterogeneous wireless netwroks," *IEEE Wireless Communications and Networking Conference*, 2016.

[18] Kashiwagi, Akiko, et al., "Adaptive response of a gene network to environment changes by fitness-induced attractor selection," *PloS one*, vol. 1, no. 1, 2006.

[19] Daxin Tian, ec al., "A dynamic and self-adaptive network selection method for multimode communications in heterogeneous vehicular telematics," *IEEE transactions on intelligent transportation transportation systems*, vol. 16, no. 6, pp. 3033-3049, Jun. 2015.

[20] Zhiqun Hu, Xiangming Wen, Zhaoming Lu, Wenpeng Jing, "AORS: Adaptive mobile data offloading based on attractor selection in heterogeneous wireless networks," *IEEE Wireless Network*, vol 23, pp. 831-842, Apr. 2017.

[21] Yan Li, Jianping Wang and Yun Xu, "Adaptive intentional connection rerouting for traffic grooming in WDN mesh networks with Biological attractor selection," *Asia-Pacific Conference on Communications*, pp .83-88, 2010.

[22] S. M. Ross, Stochastic Processes, 2nd ed. John Wiley and Sons, 1996.

[23] Nir Perel, Uri Yechiali, "Queues with show servers and impatient customers," *European Journal of Operational Research*, pp. 247-258, 2010.

[24] K. Lee, J. Lee, Y. Yi, I. Rhee, and S. Chong, "Mobile data offloading: How much can wifi deliver?" , *IEEE/ACM Transactions on Networking*, Apr. 2013.

[25] Binghui Cao, "Survey of Powerline Communication Technology," *China association of science and technology association 2004 annual conference of power division and China electrical engineering society 2004 academic year*, pp. 660-667, 2004.