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Urban Infrastructure Deployment for Wireless On-Street Parking Sensor Networks

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Abstract

The deployment strategy of wireless applications in metropolitan areas is essential for their efficiency and functionality. In this paper, we introduce and study a deployment strategy for wireless on-street parking sensor networks. We define a multiple-objective problem in our analysis, and solve it with two real-world street parking maps. We present the results on the tradeoff among minimum energy consumption, sensing information delay and the amount of deployed mesh routers and Internet gateways, i.e., the cost of city infrastructure. These results yield engineering insights for appraising and deploying city mesh infrastructure to provide smart parking services to urban users. We also analyze these tradeoffs to see how different urban layouts affect the optimal solutions.

Keywords: Deployment, multi-hop sensor network

1. Introduction and background

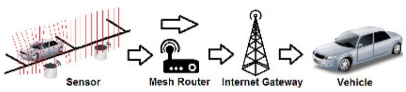

Fig. 1. Smart parking information flow

As traffic congestion increases in cities, a smart parking system that assists drivers to find a parking place is of vital importance. There are plenty of low-cost off-street parking solution available in the market, but there is still not an optimal solution for on-street parking. Some cities have started their smart parking projects, e.g., SFpark (San Francisco) [1] and SmartSantander (Santander) [2]. These cities adopt a sensor-enabled on-street parking system that installed ferromagnetic parking sensor on each spot and indicate its vacancy. To obtain the parking occupancy status, sensors can send messages via either long-range communication, like Sigfox or LoRa, or short-range communication, such as 802.11ah, low-power WiFi or Zigbee. These parking detection sensors are mostly installed underground and it is costly to replace their battery. An common objectvie is that each sensor should be autonomous for at least 5-20 years. Long range low-power cellular networks give great energy efficiency thanks to the ultra-narrow band technology, but it

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is limited in terms of bandwidth and reactivity, e.g., Sigfox nodes can send at most 140 12-byte transmission messages a day. In a previous work [3], we have shown that the generated messages for smart parking application follow a heavy-tailed distribution [2]. The limits of low-power cellular networks can be overpassed by the sensors in the most dynamic parts of cities. In such settings, the short-range communication that provides more capacity at low-power energy levels is usually favorable. In this work, we consider a city-wide wireless mesh infrastructure (WMI) comprising mesh routers (MR) and Internet gateways (IGW). The deployment of WMI networks at a citywide level with reasonable costs [4] is the primary concern. Due to the limitation of the soil medium and battery energy [5], the underground sensors communicate directly with roadside overground MRs or IGWs. Sensors, MRs and IGWs form wireless parking sensor networks in metropolitan areas and provide real-time information to users in Fig. 1. The deployed sensors are generally scattered with a minimum adjacent distance of $2-5$ meters (angle or parallel parking) in order to avoid multiple detections. The network topology is mostly linear and uniform along the street layout. In Fig. 2, we see that MR (repeater) and IGW (gateway) are mostly installed at crossroads in the real-life deployment because most traffic panels are installed at crossroads with electrical cable. Some sensors might be too far from MR/IGW, thus multispace parking meters are often used as a network relay. MR/IGW can also benefit from the line-of-sight situation to reach the maximum coverage. As IGW provides more functionality as an Internet portal, it is more expensive than MR, which simply serves as a relay or message collector. There are three main characteristics of the deployment of smart parking sensor network: energy, connectivity and timeliness. From literature, the network performance is strongly determined by the density of MR and IGW. [6] highlights the most important objectives while deploying wireless sensor networks. [7] studied the relationship between MR/IGW capacity and deployed amount using two tree set partitioning approaches. [8] proposed a grid-like gateway deployment to achieve the optimal throughput. This method is somehow similar to a crossroad-based deployment. [9] and [10] both proposed a multi-objective evolutionary approach to aid the sensor deployment. [11] optimized the IGW deployment with a multi-objective problem as well. However, we do not see an actual map of real world street being considered in a multi-objective optimization. In this paper, we are mainly interested in the impact of the map on the deployment of city infrastructure. We consider a multi-objective problem and optimize it by using the real on-street parking maps.

Fig. 2. The deployment of SFpark [1]

Problem Formulation. Our previous study [3] shows the essential issues when constructing parking sensor networks in urban areas: in-ground sensor lifetime, network connectivity, load balancing of WMI and sensing information delay. These issues correlate with the two following deployment problems: The first is the WMI deployment: Sensor lifetime is generally affected by the radio module on sensor boards, especially the wireless transmission power. The transmission power depends upon the transmission distance from a sensor itself to the closest WMI. To ensure its connectivity, a minimum transmission power will be applied. This means a denser WMI deployment will help extend a sensor's lifetime. Second is the IGW deployment: In a multi-hop mesh network, each MR has to process its own packets and those from their descendants. A longer route path increases network load, packet loss rate and information delay. Thus, load balancing and network delay both have to be both taken into account when deploying IGWs.

Contribution. Our contribution is to formulate the problem of deploying a smart parking multi-hop mesh networks within city infrastructure and solve it with a multi-objective optimization approach. We also highlight the following insights on the design of parking sensor network: First, the sensor's total energy is determined by the amount of intersections and is inversely proportional to the number of active WMIs. Second, the sensing information delay is related to the average degree of complexity of the street-parking graph. Thus, the complexity of city street layout is an important factor while building urban infrastructure. Third, the IGW deployment can be seen as a cluster problem on parking sensors' geographical position. Once the selection of WMI is done, the cluster number will be the minimum amount of deployed IGWs.

Fourth, we show the tradeoffs between sensor's lifetime, information delay and the cost of city infrastructure to be provided as a guideline, and take it into account while integrating with the pre-existing infrastructure.

2. Methodology and modeling of city mesh infrastructure

To analyze the problem above, we propose the following methodology: We define four objectives in our scenario: energy, connectivity, cost and latency of the multi-hop mesh network. From these constraints, we can also get some parameters, which are relevant to sensor's lifetime and sensing information delay. We build two graphs: an on-street parking network and a wireless link set, to indicate the relationship between any two given intersections. We then consider two different maps, which have the same length of street parking area, but with completely different street layout. Finally, we take the adjacency matrices as the data inputs of our constraints and try to optimize them.

2.1. Multi-objective problem

We define the graph of a city by the set of street intersections (V) and the set of road segments (E) between them. Then, $C = (V, E)$ represents city graph. For all v_i and $v_j \in V$, we give two binary variables to express the status of each crossroad v_i:

$$x_i = \begin{cases} 1 & \text{if a WMI is installed in } v_i \\ 0 & \text{otherwise} \end{cases} \qquad \phi_x = \sum\nolimits_{i \in V} x_i \tag{1}$$

$$y_i = \begin{cases} 1 & \text{if an IGW is installed in } v_i \\ 0 & \text{otherwise} \end{cases} \qquad \phi_y = \sum\nolimits_{i \in V} y_i \tag{2}$$

The amounts of deployed WMIs and IGWs are expressed in Eq. 1 and 2 respectively. In such a case, there are $(\phi_x - \phi_y)$ MRs. For formulating our deployment problems, we define some variables in Table 1.

2.1.1. WMI deployment and sensor lifetime

If a WMI is installed in v_i, it can manage a part of the sensors deployed in the adjacent road segment (i, j). We assume that it manages a segment of length $\Gamma_{i,j}$ starting at v_i. As a consequence, the sum of the partial segments managed by both intersections has to be greater than the length of road segment (Eq. 3). Moreover, the road length managed by each WMI cannot be greater than the road segment (Eq. 4 and 5). The density of parking sensors varies according to the parking type. For example, in a common parallel parking, the average distance between adjacent parking sensors is 5 meters, thus sensor density $\rho_{i,j}$ is 0.2. In Eq. 6 the amount of sensors managed on each WMI can be calculated by the sum of each managed road length multiplied by sensor density. M_{ns} is limited by the bandwidth allocation/scheduling method, e.g., a contention-based MAC protocol cannot serve more than 70 sensor nodes simultaneously when the traffic intensity is high. In Eq. 7, if $\Gamma_{i,j}$ is not zero, it implies that there must be one WMI in v_i who manages one part of road segment (i, j). d_{max} is a normalizing constant greater than all road segments.

Table 1. Variable index

V	$\{v_0, v_1, ...\}$ list of intersections
E	list of road segments where are parking places
W	list of wireless links between each intersection
$d_{i,j}$	segment distance between v_i and v_j
d_{max}	maximum road segment length
Ω_s	per-sensor energy consumption
Ω_{WMI}	per-WMI energy consumption
$\rho_{i,j}$	sensor density uniformly distributed on the road segment between v_i and v_j
f_i	packets aggregated from WMI in v_i (packets/s)
$\Gamma_{i,j}$	the managed length on road segment (i,j) on the WMI in the intersection v_i
$k_{i,j}$	the managed sensor amount of each road segment around the intersection v_i
h_i	path distance (hop count) from WMI in v_i to the its corresponding IGW
M_{ns}	maximum sensor numbers per MR
M_{mr}	maximum capacity of MR (packets/s)
M_{igw}	maximum capacity of IGW (packets/s)
M_{hop}	maximum hop count

$$\Gamma_{i,j} + \Gamma_{j,i} \geq d_{i,j} \quad \forall (i, j) \in E \tag{3}$$

$$\Gamma_{i,j} \leq d_{i,j} \quad \forall (i, j) \in E \tag{4}$$

$$\Gamma_{i,j} \leq (1 - 0.5 \cdot x_j) \cdot d_{i,j} \quad \forall (i, j) \in E \tag{5}$$

$$\sum\nolimits_{(i,j) \in E} \Gamma_{i,j}\, \rho_{i,j} \leq M_{ns} \quad \forall i \in V \tag{6}$$

$$x_i \geq \Gamma_{i,j} / d_{max} \quad \forall j \in V \tag{7}$$

$$k_{i,j} = \left\lfloor \Gamma_{i,j}\, \rho_{i,j} \right\rfloor \quad \forall (i, j) \in E \tag{8}$$

Once we get $\Gamma_{i,j}$, the amount of parking sensors managed by v_i on the road segment (i, j) is $k_{i,j}$ (Eq. 8). In [3], we remarked that sensor's power consumption mainly comes from the transmission packets correlating with the traffic intensity. Sensors mainly transmit their sensed information to WMI and only receive control messages from WMI, thus each sensor has a similar reception power $P_{rxmw.s.i}$. Since each sensor has to be aware of any happening around itself, it always applies a sensing cycle for event detection. It costs $P_{sensingmw.s.i}$, which is similar in every sensor because it is very low. We assume that each sensor (initialed s) has a transmission power determined by the transmission distance so that the total energy consumption is shown in Eq. 9. Obviously, to minimize $\Omega_{s.total}$, we shall optimize $k_{i,j}$, which is proportional to $\Gamma_{i,j}$. That is why deploying more WMIs can improve the energy efficiency of in-ground sensors.

$$\begin{aligned}\phi_{\Omega_s} = \Omega_{s.total} &= \sum_{v_i \in V} \sum_{s \in v_i} \Omega_{s.i} = \sum_{v_i \in V} \sum_{s \in v_i} \Theta(P_{txmw.s.i} + P_{rxmw.s.i} + P_{sensingmw.s.i}) = \sum_{v_i \in V} \sum_{s \in v_i} \Theta(10^{\frac{P_{txdbm.s.i}}{10}}) \\ &= \sum_{v_i \in V} \sum_{s \in v_i} \Theta(d_{s,i}^{\frac{1}{10}}) = \sum_{v_i \in V} \sum_{(i,j) \in E} \sum_{l=1}^{k_{i,j}} \Theta((\frac{l}{\rho_{i,j}})^{\frac{1}{10}}) = \sum_{v_i \in V} \sum_{(i,j) \in E} \sum_{l=1}^{k_{i,j}} \Theta(l) = \sum_{v_i \in V} \sum_{(i,j) \in E} \Theta(\frac{1}{2} k_{i,j}(k_{i,j}+1))\end{aligned} \tag{9}$$

2.1.2. IGW deployment and sensing information delay

The establishment of a multi-hop network is the main concern in this part. Here, we first define some binary variables to express the relationship between intersections in Eq.s 10–12. For a node, its parent is the node that has direct communication and forward its packets to the Internet; its ancestor is the node which involves in forwarding its packets to the Internet; its IGW is its portal of the Internet.

$$b_{i,j} = \begin{cases} 1 & \text{if WMI in } v_j \text{ is parent of the one in } v_i \\ 0 & \text{otherwise} \end{cases} \tag{10}$$

$$a_{i,j} = \begin{cases} 1 & \text{if WMI in } v_j \text{ is ancestor of the one in } v_i \\ 0 & \text{otherwise} \end{cases} \tag{11}$$

$$g_{i,j} = \begin{cases} 1 & \text{if IGW in } v_j \text{ manages MR in } v_i \\ 0 & \text{otherwise} \end{cases} \tag{12}$$

$$y_i \leq x_i \quad \forall\, i \in V \tag{13}$$

$$b_{i,i} = 0 \quad \forall\, i \in V \tag{14}$$

$$b_{i,j} \leq a_{i,j} \quad \forall\, (i,j) \in W \tag{15}$$

$$b_{i,j} + b_{j,i} \leq W_{i,j} \quad \forall\, (i,j) \in W \tag{16}$$

$$\sum_{v_j \in V} b_{i,j} = x_i - y_i \quad \forall\, (i,j) \in W \tag{17}$$

In the wireless urban sensor network, a gradient-based routing is often adopted thanks to its fewer control messages. Each sensor can forward a packet to its available neighbor with the smallest height (shortest network distance) [12]. We define the multi-hop constraints according to the gradient-based routing protocol. Once the intersections to install WMIs are decided, we will choose some to install IGWs and keep the remains for MRs (Eq. 13). In Eq. 14, each node cannot be its own parent. If v_j is the parent of v_i, it is its ancestor as well (Eq. 15). However, it will not be the child of v_i simultaneously (Eq. 16). In Eq. 17, each MR has only one parent-node, and each IGW has no parent. In Eq. 18, each WMI is its own ancestor. In Eq.s 19, if $a_{i,j}$ is equal to 1, it implies that there are WMIs installed both in v_i and v_j. In Eq. 20, v_i and v_j cannot be the ancestor of each other at the same time, i.e., the link is unidirectional. In Eq. 22, each IGW is managed by itself. In Eq. 23, if $g_{i,j}$ is equal to 1, it implies that there is an IGW installed v_j. Since each IGW manages itself, it cannot be directed by another IGW (Eq. 24). In Eq. 21, if the IGW in v_j manages the MR in v_i, the IGW is the ancestor of the MR. In Eq. 25, each MR is managed by exact one IGW.

$$a_{i,i} = x_i \quad \forall\, i \in V \tag{18}$$

$$a_{i,j} \leq x_i,\ a_{i,j} \leq x_j \quad \forall\, i,j \in V \tag{19}$$

$$a_{i,j} + a_{j,i} \leq 1 \quad \forall\, i \neq j \in V \tag{20}$$

$$g_{i,j} \leq a_{i,j} \quad \forall\, i \in V \tag{21}$$

$$g_{i,i} = y_i \quad \forall\, i \in V \tag{22}$$

$$g_{i,j} = y_j \quad \forall\, i \in V \tag{23}$$

$$g_{i,j} + g_{j,i} \leq 1 \quad \forall\, i \neq j \in V \tag{24}$$

$$\sum_{v_j \in V} g_{i,j} = x_i \quad \forall\, i \in V \tag{25}$$

In Eq. 26, if the MR in v_i is the child of the one in v_j and the descendant of the one in v_k, the MR in v_j is the descendant of the one in v_k as well. In Eq. 27, if the MR in v_i is the descendant of the one in v_j and managed by the IGW v_k, the MR in v_j is also managed by the IGW in v_k. Hence, the hop distance of WMI in v_i can be counted by the amount of its ancestors (Eq. 29). M_{hop} is the maximum hop distance in the network (Eq. 28). The average sensing information delay is calculated by the average hop count, which we divide the sum of the required hop counts of each WMI by the amount of WMI (Eq. 30). Fig. 3 gives an example of 4 WMIs: Node 3 is the Internet portal for all the others; Node 2 and 4 connect directly to node 3; Node 1 connect to node 3 via node 2. Then, node 2 is the parent of node 1; node 3 is the parent of node 2 and 4; node 2 and 3 are both the ancestors of node 1 and node 3 is the ancestor of node 4. Fig. 4 shows the

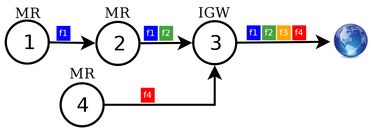

Fig. 3. An example of a multi-hop network

	[MR 1] →	[MR 2]→	[IGW 3]	←[MR 4]
if $b_{i,j}=1$:	$b_{1,2}$	$b_{2,3}$	X	$b_{4,3}$
if $a_{i,j}=1$:	$a_{1,1}, a_{1,2}, a_{1,3}$	$a_{2,2}, a_{2,3}$	$a_{3,3}$	$a_{4,4}, a_{4,3}$
if $a_{i,j}=1$:	$g_{1,3}$	$g_{2,3}$	$g_{3,3}$	$g_{4,3}$
$h_i = \sum a_{i,j}$:	$h_1 = 3$	$h_2 = 2$	$h_3 = 1$	$h_4 = 2$

Fig. 4. An example of the variables for the multi-hop network in Fig 3

values of $a_{i,j}$, $b_{i,j}$ and $g_{i,j}$ when they are equal to 1. h_i signifies the hop count from the sensors managed by MR_i to its IGW.

$$b_{i,j} + a_{i,k} \leq a_{j,k} + 1 \;\; \forall\, i, j, k \in V \tag{26}$$

$$a_{i,j} + g_{i,k} \leq g_{j,k} + 1 \;\; \forall\, i, j, k \in V \tag{27}$$

$$h_i \leq M_{hop} \;\; \forall\, i \in V \tag{28}$$

$$\sum_{v_j \in V} a_{i,j} = h_i \;\; \forall\, i \in V \tag{29}$$

$$\phi_{h/x} = (\sum_{v_i \in V} h_i)/(\sum_{v_i \in V} x_i) \tag{30}$$

Network capacity can be expressed in Eq. 31. According to the network distance of each MR, the collected packets will be re-transmitted h_i times, which generate more traffic on each ancestor. Thus the traffic capacity will be restricted by the maximum capacity of each WMI, i.e., M_{igw} and M_{mr} for IGW and MR, respectively. Packet generation rate f_i depends on the vehicle's arrival and departure. This process has been shown to have a heavy-tailed distribution similar to the Weibull distribution [2]. In Eq. 32, the energy consumption is estimated to be proportional to the WMI's capacity, IGW amount and traffic intensity.

$$\sum_{v_i \in V} f_i\, a_{i,j} \leq M_{mr} + y_j\,(M_{igw} - M_{mr}) \;\; \forall\, j \in V \tag{31}$$

$$\begin{aligned} \Omega_{WMI.total} &= \sum_{v_i \in V} \Omega_{WMI.i} = \sum_{v_i \in V} \Theta(P_{txmw.WMI.i} \cdot (\#packet_{tx}) + P_{rxmw.WMI.i} \cdot (\#packet_{rx})) \\ &= \sum_{v_i \in V} \Theta(P_{txmw.WMI.i} \cdot (\sum_{v_j \in V} f_j\, a_{j,i}) + P_{rxmw.WMI.i} \cdot ((\sum_{v_j \in V} f_j\, a_{j,i}) - f_i)) = \sum_{v_i \in V} \Theta(2\,(\sum_{v_j \in V} f_j\, a_{j,i}) - f_i) \\ &\leq \sum_{v_i \in V} \Theta(2\,(M_{mr} + y_i\,(M_{igw} - M_{mr})) - f_i) = \Theta(2(M_{igw} - M_{mr})\,\phi_y - \sum_{v_i \in V} fi) \end{aligned} \tag{32}$$

2.1.3. Multi-objective optimization

With the above equations, we try to solve a multiple-objective problem $min(\phi_x, \phi_{\Omega_s}, \phi_y, \phi_{h/x})$. ϕ_x, the amount of deployed WMIs, stands for network connectivity. ϕ_Ω indicates sensor's lifetime. ϕ_y, the amount of deployed IGWs, deals with load balancing. $\phi_{h/x}$, the average hop distance from managed sensors to the closest IGW, demonstrates the information delay. The computations are performed in Sage [13] using the CPLEX solver.

2.2. Map retrieval

Before resolving our problem in Sage, we took the city OSM file from Openstreetmap. Then with Osmosis, we filtered the unnecessary information and keep only the streets and intersections. Then we trimmed the street map with respect to the parking map in Lyon City's website. Fig. 5 shows the graph from our retrieved map in Gephi. We used Osm2pgrouting and pgRouting to calculate the distance between intersections, i.e., vertexes in our graphs. By referring to [14], we only keep the line-of-sight wireless links in W. Two maps are retrieved and depicted in Fig. 5. Map 1 has a grid-like parking distribution. Map 2 is less regular because of pedestrian areas. The total parking area length in both maps is approximately the same. However, map 2 has 27% more crossroads than map 1.

3. Evaluation of the impact of two different street layouts and engineering insights

We propose two kinds of optimization methods: First, deterministic optimization assumes a blank area without any pre-existing WMIs. Second, stochastic optimization considers a set of pre-existing WMIs and calculates how many additional WMIs we shall expect to install. Then, we test our methods on the two different street layouts obtained in Section 2.2.

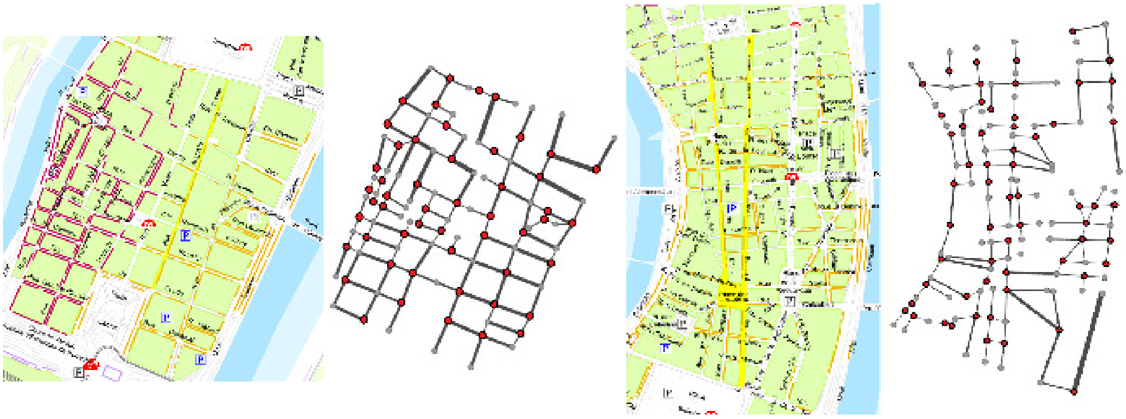

Fig. 5. Map 1 (left)–Lyon on-street parking map between Place Bellecour and Place Carnot. The red dots indicate the selected intersections to install WMIs. Map 2 (right) –Lyon on-street parking map between Place Terreaux and Place Bellecour. The red dots indicate the selected intersections to install WMIs.

Network architecture. In [3], we have studied parking sensor networks and provided the best configuration under different bandwidth allocation methods. Considering the collision problems and the traffic intensity, we compared the energy consumption with different scenarios. A schedule-based media access control protocol and an event-driven application are the most suitable for our scenarios in map 1 and 2. Thus, we assume a pre-scheduled transmission time for all sensors and MRs, and then we focus on the relationship of the multi-hop networks.

Characteristics of maps. In Fig. 5, the red dots on the nodes are optimal intersections to install WMIs, i.e., x_i equals to 1. The minimum amounts of required WMIs are 49 (over 100 intersections) and 60 (over 127 intersections) in map 1 and 2 respectively. Map 1 has a quite uniform length among all the road segments, and Map 2 has an irregular road length and most of them are very short. With the similar amounts of underground sensors, the cost of map 2 is higher because more WMIs are required to guarantee the network coverage. Thus, we see that the cost of deploying WMIs is positively correlated to the number of intersections.

Energy efficiency. From the set of x_i, we got $\Gamma_{i,j}$ and calculated the energy indicator in Eq. 9. Since the amount of WMIs signifies the cost of mesh infrastructure, Fig. 6 shows the relationship between the cost and sensor's lifetime. As the WMI increases, the energy depletion decreases due to the closer transmission distance between sensors and WMI. Two curves both drop when the deployed amount of WMI accounts for 80% of the intersections. Since the road segments are longer in map 1, more sensors have a larger transmission range, hence a higher transmission power. Thus, the maximum energy consumption in map 1 is higher than the one in map 2 in the beginning. Conversely, map 1 has fewer intersections and is covered faster than map 2 by the WMI. We concluded that the sensors lifetime correlates to the amount of intersections based on the characteristics of maps.

Cost of infrastructure. The cost of infrastructure is calculated by $\$MR \cdot \#MR + \$IGW \cdot \#IGW$, where $\#WMI = \#MR + \#IGW$ and $\$IGW > \$MR$ (#:amount, $:price). Both Fig. 7 and 8 show the relationship between the cost and the delay with the minimum amount of WMIs ($\sim 50\%$). The IGW deployment can be seen as a cluster problem on parking sensors geographical position. According to the amount of IGWs, we divide all the WMIs into several partitions and then select one IGW from each of them. In Fig. 7, the amount of WMIs in map 1 is fixed to 49 even there is only one IGW. That is because each WMI is interconnected thanks to the grid-like topology. On the contrary, in Fig. 8, the additional WMIs are required in map 2 when there are less than four IGWs. That is because those wireless links between the 60 WMIs form 4 clusters geographically. When we select one IGW in map 2, these 4 clusters require extra WMIs to be interconnected. Thus, if we want to install IGW without creating any additional wireless radio links in map 2, the minimum IGW amount will be four.

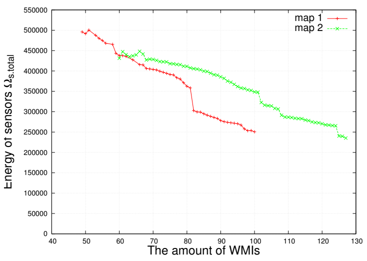

Fig. 6. Total sensor energy consumption (sensor's lifetime) v.s. the amount of deployed WMIs (cost)

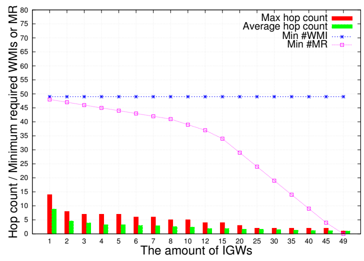

Fig. 7. Average hop count (information delay) v.s. the amount of deployed IGWs (cost) in map 1

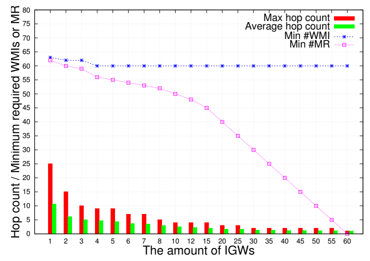

Fig. 8. Average hop count (information delay) v.s. the amount of deployed IGWs (cost) in map 2

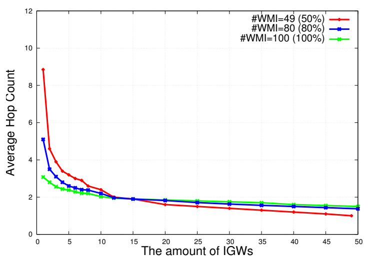

Fig. 9. Average hop count (information delay) v.s. the amount of deployed IGWs (cost) under the best (100%), the average (80%) and the worst (50%) cases for sensor lifetime in map 1

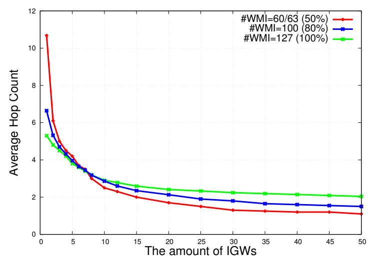

Fig. 10. Average hop count (information delay) v.s. the amount of deployed IGWs (cost) under the best (100%), the average (80%) and the worst (50%) cases for sensor lifetime in map 2

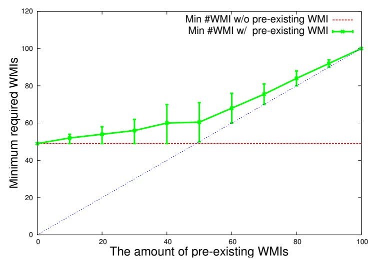

Fig. 11. The total amount of required WMIs (total cost) v.s. the amount of pre-existing WMI in map 1. The difference between the green and blue curves is the cost of the extra WMIs (extra cost).

Information delay. From our previous work [3], the information delay is proportional to the hop count and the sleep-wake scheduling, i.e., duty cycle. To prevent packet collision caused by channel interference, each hop takes at least one duty cycle. Since the network traffic is quite scattered in most urban sensor networks, the generated packets are often sent within one duty cycle. The information delay can then be calculated by the product of hop count and the duration of duty cycle. In Fig. 6, we see that the amount of WMIs impacts the energy consumption. Thus, we take three different amounts to stand for the worst (50% of intersections), the average (80%) and the best (100%) cases of the sensor's lifetime, respectively. Fig. 9 and 10 show the relationship between the hop count and the amount of IGWs, i.e., the tradeoff between the cost of infrastructure and the information delay under different situations of sensor's lifetime. When the amount of IGWs is low, increasing the amount of WMIs helps to reduce the information delay; however it does not apply the other way around.

Integration of pre-existing mesh networks. Mobile network operators (MNO) often take advantage of domestic WiFi hotspots to expand their public WiFi service. These hotspots could also be used as WMIs in wireless urban sensor networks via a plug-and-play zigbee network adapter or an extended network of 802.11 family, e.g., 802.11s. Thus, we define z_i is a binary value which equals to 1 if there is a pre-existing WMI in v_i, so that $x_i \geq z_i \quad \forall\ i \in V$. We consider a random generated map of pre-existing WMIs $\{z_i\}$. After re-executing our equations on map 1 and 2, the results are shown in Fig. 11 and 12. The red line is the minimum amount of required WMIs. The blue line is the amount of pre-existing WMIs, i.e., existing hotspots. The difference between the green and blue curves is the extra WMIs we need to install (extra cost). Since the map of pre-existing WMIs is stochastically generated, their position is not optimized. That makes the total amount

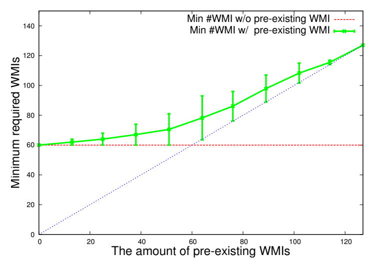

Fig. 12. The total amount of required WMIs (total cost) v.s. the amount of pre-existing WMI in map 2. The difference between the green and blue curves is the cost of the extra WMIs (extra cost).

of WMIs increases but less expensive for the city to start from scratch. Both Fig. 11 and 12 show two phases in the influence of the pre-existing WMIs. The amount of pre-existing WMIs positively correlates to better deployment. On the other hand, if the pre-existing WMIs are more than half of the intersections, less extra WMIs are required. The existing hotspots can always access the Internet directly and can be seen as IGW. Hence, the extra WMIs are the less costly MRs.

4. Conclusion & Future works

In this paper, we studied and introduced a wireless on-street parking sensor network from the viewpoint of system deployment. We highlighted some important factors and parameterized them in the linear equations. To consider a more realistic urban environment, we retrieved two different parking maps with the same parking area length. We then took their adjacency matrices as our data input and solved them by a multi-objective optimization. We provide our insight and observation based on the results of five types of figures: the characteristics of maps while deploying city mesh infrastructure, the tradeoff between sensor's lifetime and cost of infrastructure, the tradeoff between information delay and cost of infrastructure at the minimum cost (minimum amount of WMIs), the relationship between sensor's lifetime, information delay and cost of infrastructure, and the additional cost of integrating into the pre-existing infrastructure. While deploying city mesh infrastructure, our model can give a clear sketch so as to anticipate the minimum cost of city infrastructure with an expectable network performance.

The traffic intensity is not considered in the results because the packet generation rate is quite low. However, if we transform the model to an heterogeneous urban network, the traffic intensity will be an issue, and the aggregation problem will have to be considered. Since the metropolitan sensor network attracts more and more attention to urban service, the IGW can also play the rule of the road side units. This way, the buffer size and the vehicle trace will have to be considered in the equations later.

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