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Optimised random structure vehicular sensor network

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Abstract: Providing proper coverage is one of the main applications of wireless sensor networks. In many working environments, it is necessary to take advantage of mobile sensor networks (MSNs), with the capability of having cooperation between sensor nodes and moving into appropriate positions, to provide the required coverage. However, in some applications such as intelligent transport system (ITS), where sensors are applied in complex dense urban environments, traditional MSN cannot properly cover the defined area. In this study, the authors study the use of a few unreserved selected cars as a vehicular sensor network (VSN) to cover a defined area and in this scenario, the sensors movements are assumed to be random from the network viewpoint. In the proposed random structure VSN, the coverage property is managed and controlled by introducing a suggested method for resource allocation and coverage control based on the real vehicle mobility model. Major advantages of this VSN are considering the real car mobility model, compatibility with the deployed infrastructure and processing simplicity and efficiency. The implementation results of suggested method verify the analytical results that are mentioned in the simulation section.

1 Introduction

Area monitoring is a typical application of wireless sensor networks (WSNs). In this case, sensor nodes must be deployed appropriately to achieve an adequate coverage level for the successful completion of the issued sensing tasks. In traditional sensor networks, which are equipped with micro-electro-mechanical systems, the network coverage is controlled by using a large number of sensors that are distributed in the defined area by aircraft [1]. In traditional WSNs, suitable coverage in many working environments, especially in high-dense urban environments, cannot be achieved because the landing positions and distribution of the sensors is uncontrollable because of the natural obstacles and environment properties. Mobile sensors are a solution to this problem in some degree [2–5].

In some cases mobile sensors are used to correct deployment positions by moving the sensors to proper places for providing the required coverage [5–8]. Recently, many coverage analysis and control methods in the mobile sensor networks (MSN) use the Voronoi-based approaches [9–11]. The Voronoi-based approaches require exhaustive computational effort to compute the Voronoi cells continuously during a real-time implementation of the controllers, and hence they have more hardware/software complexity, and they need vast power supply.

The major deficiency of almost all the previous works in MSN is the assumption of the free space movement of the sensors, resulting in the elimination of the effects of obstacles and environmental limitations (such as the topology of the streets in the coverage analysis and control) [9–12]. The topology of the obstacles and environment has major effects on sensors movement, landing possibility and inter-sensors communication/cooperation, especially in urban sensor networks [13]. Finally, because of the complexity of the topology of real environments and communication connectivity problem in some working areas (such as high-dense urban in intelligent transport system (ITS) applications), MSNs cannot solve the coverage problem.

A vehicular sensor network (VSN) that uses vehicles for sensor deployment is one solution to achieve proper coverage in dense urban environments. Traditional VSNs have three major types and applications. In some cases, a VSN is a part of automatic car control systems which sends information to control centre and shares some information with other cars [14, 15]. In other cases, the VSN is used for random sensor deployment by employing a large number of random deployed vehicular sensors (VSs) as a sub-class of mobile *ad hoc* networks [15–17]. MobEyes and CarTel are two major implementations of such class of VSN to which more attention is being paid at present [16, 17]. In the last case, one uses reserved cars to achieve VSN for coverage control [3, 18, 19]. In this case, the network determines car travelling trace at each instance to control and manage VSN coverage.

There are some ITS applications that can be implemented by WSN. For example car-guardrail collision accident building by WSN is introduced in [20]. VSN can be used for real-time traffic data extraction. Several works on VSN for traffic monitoring have been carried out in recent years [21–24]. Traffic data are a base of many other ITS applications such as travelling path suggestion, travelling time estimation and so on. Free-way real-time velocity monitoring, is another ITS application that can be implemented by VSN [22]. Road surface monitoring is one of the recent applications uses the inherent mobility of the participating vehicles, opportunistically gathering data from vibration and global positioning system (GPS) sensors, and processing the data to assess road surface conditions [25]. Road surface conditions map would be used in ITS application (e.g. travelling path suggestion). Also MobEyes as VSN can be used for automatic accident detection and automatic crash notification. Multi-purpose VSs may be used to study traffic effects on environmental data (e.g. air pollution and so on) in these cases traffic and some environmental data combined and process simultaneously [26]. In our proposed method, sensors are installed on un-reserved selected cars (the network has no authority to control cars traveling trace but for the reserved car [3] the network controls car traveling trace).

In our proposed method, sensors are installed on un-reserved selected cars which the network has no authority to control their travelling trace (vice versa in the reserved car [3]). VS drive across the streets of the defined area to observe the environment and communicate the measurements with some specified centres. Because of the effects of the vehicles mobility on the properties of the VSN (e.g. coverage, communication connectivity and data redundancy), resource allocation and car selection scenario in the proposed method is based on the real-world vehicle mobility model (VMM). This method reduces the number of required sensors with respect to the traditional methods by applying proper resource allocation and network management based on an analytical method extracted from VMM.

The rest of this paper is organised as follows: first, the principle of proposed VSN is described; also, the design procedure and the management method are analysed. Next, the coverage property in the proposed VSN is explained. Then the performance of the proposed method is evaluated for different scenarios through simulations. Finally, the conclusion summarises the important results of the paper.

2 Optimised random structure VSN

Traditional VSN [3, 15] is one solution for this problem especially in high-dense urban environments, but it is not cost effective and suitable because it requires a large number of VSs for sensing missions. Here, a new method for sensing in high-dense urban environments is proposed.

2.1 General description and motivation

In this paper, a new VSN scenario including two major elements, road-side gateways (RSG) and VSs, is proposed. In this scenario, sensors are installed in cars and some of them remotely activated (by RSG) for dynamic sensors deployment, also the sensing method has a dynamic random configuration and the sensor network structure cannot be controlled directly. In the proposed method, VS deployment configuration is optimised by resource allocation based on real VMM; therefore we call the proposed scenario as optimised random structure VSN (ORSVSN). An ORSVSN, the main goal of the resource allocation and optimisation is the coverage control by using minimum number of required VSs. The minimisation of the number of VSs tends to minimise data redundancy, complexity reduction and cost-efficiency improvement. The VS data redundancy increases processing cost in the processing stations and increases the required processing power and storage needs. Also, reduction of the number of VSs not only decreases the processing cost of VSNs (e.g. localisation) but also increases the efficiency and simplicity of the system. On the other hand, the number of VSs has major effect on the coverage conditions; hence, the VS number must be chosen to achieve proper coverage. Therefore there is a trade-off between coverage condition and cost efficiency or simplicity. For example, reduction in the number of active VSs leads to increase in the sensing time; consequently, there is a compromise between the number of sensors and sensing time in the ORSVSN scenario.

For this purpose, the vehicles are chosen from the public transport system or any candidate private vehicles to start driving in the study area at predetermined times. In the ORSVSN, in order to reduce the number of sensors for converging the area under study, we must choose the vehicles from uncorrelated roads. This selection tends to the reduction of the connectivity of the sensors; hence, unstructured communication systems (e.g. inter-vehicle *ad hoc*) between VSs cannot be used. On the other hand, cooperation of other vehicles with VSs, to create a vehicular *ad hoc* network is possible but it leads to lack of security. Therefore we use structured systems, such as RSGs, for communicating the management commands and observations between networks and appropriate active VSs. The RSGs also manage the network by proper VS activation; also, they process, store and communicate the information within the network.

2.2 ORSVSN process and management strategy

ORSVSN has a simple management strategy. The RSGs play an important role in ORSVSN management. ORSVSN network has two major layers: RSG layer and VS layer. The RSG layer is configured as full or semi-full mesh, and there is no defined communication between VSs. The RSGs share their information about active VSs, covered regions, and their management commands with each other. The RSG must cover the major inputs, outputs, boundary and the centre of region under study by radio signals. The full radio coverage is needed if and only if the VSs use the RSG signals for localisation and GPS-based VS localisation is not available. The ORSVSN reduces the number of required VSs for coverage; accordingly, the GPS-based localisation is suggested in this paper. Also, the IEEE802.16e standard is proposed for communication. In the ORSVSN, the sensors have the ability to store measurements and communicate the information with the RSGs whenever communication is possible. This information includes measured data, VS identity and position indices.

To start the sensing process, first, the RSGs broadcast an ‘activation request’ message to all VSs and VSs should send their positions to RSGs. In the next step, RSGs activate proper VSs according to the VS position and design parameters. After starting the sensing process the RSGs can control the number of VSs. In this scenario, three major works must be done to control the number of VSs. First, when an active VS leaves the area under study, the RSG should broadcast an ‘activation request’ message to VSs and activate another VS in a proper position. Second, when an active VS stops for more than a predetermined time (which is defined based on the traffic condition) it will send a ‘stop alert’ message to RSG to inactivate the process and activate another VS in a suitable position. Finally, the RSG can inactivate one or more VSs which have similar paths and activate another VS in the proper position to achieve VS path independency. A suitable position is selected by RSGs according to the design parameters and the considerations of real uncovered area.

2.3 ORSVSN design algorithm

The ORSVSN management algorithm was described in the previous section; here, the ORSVSN design algorithm is described. As can be seen from the description of the proposed model, the vehicle mobility behaviours have an important role in the design and analysis of the ORSVSN. Therefore a critical requirement for ORSVSN planning and management is the real-world VMM. Hence, in the following section, a suitable real VMM is suggested for our scenario.

2.3.1 Suitable mobility modelling technique for ORSVSN design and analysis: As it was described in the previous section, the ORSVSN method must be designed and optimised based on a real VMM with the capability of adaptation based on the real-world conditions. In [27], an adaptive stochastic model is used to represent different features and parameters of the real environments with low complexity and adaptation capability. The vehicle movement model in [27] is a modification of the models represented in [28–30]; it realises the velocity model and modifies the direction control method using wireless network status, extracted from GSM network operation and maintenance center. A modified version of [27], which is used in this paper for ORSVSN design and analysis, is described in the following section.

VMM description: In [27], it is assumed that the vehicles drive on the streets in the same direction (with respect to the reference direction); therefore all the streets of the area under study are classified into different groups with the same direction. For this purpose, it utilises a Gaussian hidden Markov model (GHMM) to model the direction of the movement of the users. The parameters of the GHMM are calculated based on the topological and practical data [27]. Furthermore, the mean velocity of vehicle in each group of the streets is modelled according to the traffic conditions and topological data in the steady-state case as [27]

$$V_{\text{mean}}(i) = 16.1 \times \left(\frac{L_i}{l_n} - \frac{N_{\text{tot}} \cdot \pi_i}{N_i . w_n(i)} - 1\right) \quad (1)$$

where L_i, $w_n(i)$, N_i and π_i are the average length of the streets, the average number of street lanes, the number of streets and the steady-state probability of the ith group, respectively. Also l_v is the mean length of the vehicles and N_{tot} is the total number of the vehicles in the area under study. Here, a modified version of [27] is chosen to be used in the ORSVSN method, in which GHMM and Gaussian vector in [27] are substituted by HMM and mean travelling length for movement direction and movement distance modelling, respectively.

Therefore the VMM is represented by an HMM; each state of the HMM indicates travelling in the direction of that state vector (see Fig. 1) and its average length $d_{\text{mean}}(i)$ is calculated as

$$d_{\text{mean}}(i) = V_{\text{mean}}(i) \times t_{\text{p}} \quad (2)$$

where t_{p} is the Markov process run time (MPRT) and $V_{\text{mean}}(i)$ is calculated using (1). This model is used in the analysis and design of our ORSVSN.

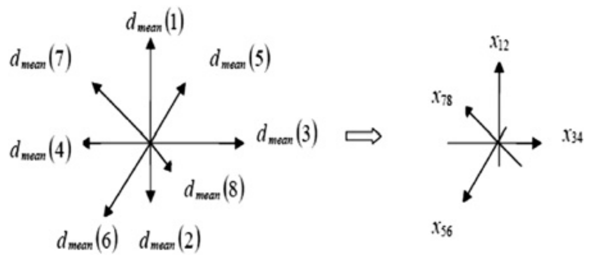

Fig. 1 *Original system (left) and its equivalent Gaussian model [27]*

2.3.2 Analytical approach for the design of the ORSVSN scenario: Here, the VMM presented in the above section is applied to develop the ORSVSN scenario with the capability of the adaptation to any real environment conditions, considering the real-world parameters. There are two important parameters in the ORSVSN design that are calculated in this section: (i) the number of required VSs for the coverage, and (ii) the optimum VS assignment method.

Number of required active VSs: The number of required VSs for coverage has a relationship with the coverage time. Coverage time is an important parameter in the suggested method and it depends on the type of application. In some applications, in order to compare the observed data in the coverage time with each other, the completion of the coverage must not take more than a predefined time. Therefore the predefined step time k_T (where $k_T = T_i/t_{\text{p}}$ and T_i is the predefined time interval) is defined for the data gathering process. Another parameter that has an important role in the determining of the number of required active VSs for coverage is the average length of the streets scanned by one VS in the predefined time interval. This parameter depends on the traffic condition and the mobility behaviour of the vehicles in the region and it must be calculated using VMM. Accordingly, $l_{\text{ave}}(k_T)$ is calculated as

$$l_{\text{ave}}(k_T) = \sum_{j=1}^{N} d_{\text{mean}}(j) M(y_j^{(k_T)}) \quad (3)$$

where $M(y_j^{(k_T)})$ is the mean number of time periods of being in the jth state after passing period k_T, and is given by

$$M(y_j^{(k_T)}) = E_i\{E\{y_j^{(k_T)}|S_1 = S_i\}\} = \sum_{i=1}^{N} \pi_i \cdot M_i(y_j^{(k_T)}) \quad (4)$$

where $M_i(y_j^{(k_T)})$ is the mean number of time periods that the process remains in the state (S_j) when the user starts from the state (S_i) and is given by [30]

$$M_i(y_j^{(k_T)}) = E\{y_j^{(k_T)}|S_1 = S_i\} = (\boldsymbol{Z}_{ij} - \pi_j) + k_T \pi_j \quad (5)$$

where π_j is the steady-state probability of jth state and $\boldsymbol{Z}$ is the fundamental matrix of the Markov process [30]; also, $y_j^{(k_T)}$ is defined as the number of time periods during which the process remains in a particular state (S_j) or the user stays in a specific group in the first k_T steps.

Note that the travelling paths of the vehicles are roughly uncorrelated (as the proposed management method described in Section 2.2) if the VSs are chosen from vehicles that approximately start driving from the centre of the defined area, in different streets of a variety of groups. Then, the number of vehicles needed to scan the area under study is estimated by

$$\mathrm{NR}_T = L_D / \sum_{j=1}^{N} d_{\mathrm{mean}}(j) M(y_j^{(k_r)}) \tag{6}$$

where NR_T is the number of sensors required to cover the specific area in the predefined time interval and L_D is the length of the paths required to be scanned in the area under study.

Required number of vehicles to serve as VS?: The number of vehicles needed to work as VSs plays a crucial role in the implementation cost and complexity of the proposed VSN method. As it was described in Section 2.1 some of these VSs are activated by RSG at the observation time interval. Since some of the VSs leave the area under study after passing the predefined time, due to the dynamic behaviour of the movement of VSs, the RSGs attempt to fix the number of activated VSs by substituting new VSs in the defined area. Therefore the ratio of active VSs to the total number of VSs in the study area must be carefully designed based on analysis of the movement behaviour of the VSs.

Fig. 1 shows the general description of the proposed VMM. Each vector has a twin, which is a reciprocal vector. Therefore each pair of the reciprocal vector is equal to an asymmetric random walk process, which is approximated by a Gaussian process [31]. Therefore we have one Gaussian vector instead of each reciprocal vector pair with the Gaussian distribution (e.g. $x_{1,2} \sim N(\mu_{1,2}, \delta^2_{1,2})$) and reciprocal direction according to the sign of the Gaussian variable

$$\begin{aligned} \mu_{1,2}(k) &= k(\pi_1 d_{\mathrm{mean}}(1) - \pi_2 d_{\mathrm{mean}}(2)) \\ \delta^2_{1,2}(k) &= k(d^2_{\mathrm{mean}}(1)\pi_1(1-\pi_1) + d^2_{\mathrm{mean}}(2)\pi_2(1-\pi_2) \\ &\quad + 2\pi_1\pi_2 d^2_{\mathrm{mean}}(1) d^2_{\mathrm{mean}}(2)) \end{aligned} \tag{7}$$

where $(\mu_{1,2}, \delta^2_{1,2}$ are the means and variances of the equivalent Gaussian process of $\{1, 2\}$ (which are twins), respectively; also, π_1 and π_2 are the steady-state probability of states 1 and 2, respectively. In the next step, each Gaussian vector is represented by its projections on the horizontal and vertical axis. The projection of the Gaussian vector in each axis has a Gaussian distribution, thus, their summation also has a Gaussian distribution too [31]

$$\begin{aligned} &R_x = \sum_{i=1}^{N/2} x_{ii+1}\cos\varphi_i, \quad R_y = \sum_{i=1}^{N/2} x_{ii+1}\sin\varphi_i \\ &(R_x, R_y) \sim N(\mu_x(k), \mu_y(k), \delta^2_x(k), \delta^2_y(k), \rho_{xy}(k)) \\ &\mu_x(k) = \sum_{i=1}^{N/2}\mu_{ii+1}(k)\cos\phi_i, \quad \mu_y(k) = \sum_{i=1}^{N/2}\mu_{ii+1}(k)\sin\phi_i \\ &\delta^2_x(k) = \sum_{i=1}^{N/2}\delta^2_{ii+1}(k)\cos^2\phi_i, \quad \delta^2_y = \sum_{i=1}^{N/2}\delta^2_{ii+1}(k)\sin^2\phi_i \\ &\rho_{xy}(k) = \left(\sum_{i=1}^{N/2}\sum_{j=1}^{N/2}\mu_{ii+1}(k)\mu_{jj+1}(k)\cos\phi_i\sin\phi_j \right. \\ &\qquad \left. - \mu_x(k)\mu_y(k)\right) \Big/ (\delta_x(k)\delta_y(k)) \end{aligned} \tag{8}$$

Assuming that the VSs near the centre of the area under study are selected for sensing, then with this assumption the probability of remaining a car in the sensing area at the kth instance is calculated as

$$p_R(k) = p(R_x(k) < D, R_y(k) < D) \tag{9}$$

where D is the radius of area. Furthermore, since vehicles move independently, the process of leaving the sensing area is a Binomial process and the mean number of remaining vehicles in the sensing area at the kth instance ($\mathrm{nm}(k)$) is obtained by [31]

$$\begin{aligned} \mathrm{nm}(k) &= \sum_{n=0}^{NM} n \times \binom{NM}{n} (p_R(k))^n \times (1 - p_R(k))^{NM-n} \\ &= \mathrm{NM} \times p_R(k) \quad 0 \le k \le k_T \end{aligned} \tag{10}$$

in which NM is the total number of vehicles prepared to work as VS. Hence, in each instance $\mathrm{nm}(k)$ should be more than NR_T to achieve an appropriate design. Then the total number of VSs is determined as

$$NM = \frac{NR_T}{\arg\min_k(p_R(k))}, \quad 0 \le k \le k_T \tag{11}$$

Proposed VSs assignment method: For determining optimum VS assignment, first, we must consider the length of the paths required to be scanned in each group of the area under study (L_{Si}). At each state the path travelled by a vehicle is determined through (5) wherever a user starts from a specific state. Accordingly, the cars are allocated to each group so that the coverage is maximised.

This problem leads to a constraint optimisation problem described as

$$\begin{cases} \sum_{i=1}^{N} L_{Si} = L_D \\ \sum_{i=1}^{N} r_i = NR_T \\ \sum_{j=1}^{N} r_j M_j\left(y_1^{(k_T)}\right) = \dfrac{L_{S1}}{d_{\mathrm{mean}}(1)} + e_1 \\ \vdots \\ \sum_{j=1}^{N} r_j M_j\left(y_N^{(k_T)}\right) = \dfrac{L_{SN}}{d_{\mathrm{mean}}(N)} + e_N \end{cases}$$

$$\Rightarrow R = [r_1, \ldots, r_N] = \arg\min\left(\sum_j e_j^2\right) \tag{12}$$

where $M_i(y_j^{(k_T)})$ and NR_T are calculated from (5) and (6), respectively. The above integer optimisation problem can be numerically solved by several methods according to amount of NR_T or size of response space. In low NR_T, (12) can be solved by substituting all possible values of r_i into the relation and finding the optimum one. When NR_T is at the middle (e.g. $30 \ge \mathrm{NR}_T \ge 15$), then some exact integer programming (IP) method such as branch-and-bound, and branch-and-cut would be of interest [25]. Finally, for large NR_T the exact IP methods become too heavy to execute and heuristic solutions such as genetic algorithms are proposed [27].

3 Analytical analysis of VS coverage

In this section, the coverage of the suggested method is analysed. For simplicity suppose that the sensing area is large and a long time is needed to sense. Hence, in this case the steady-state analysis is valid. The coverage is completed if all the streets of the area are scanned by VSs and the coverage deficiency probability (CDP) after the k step (based on the vehicle path independency in the steady-state case and considering the previous assumption in VS distribution) is

$$\mathrm{CDP}(k) = p\left(\bigcup_{j=1}^{N} e_j\right) = \sum_{j=1}^{N} p(e_j) - \sum_{j,i} p(e_j \cap e_i) + \sum_{i,j,k} p(e_i \cap e_j \cap e_k) - \cdots + (-1)^{N-1} \times p(e_1 \cap e_2 \cap e_k \cap \cdots \cap e_N) \tag{13}$$

where $p(e_j)$ is the probability of coverage deficiency in the jth state, up to the kth instance. The coverage is proportional to the amount of k (travelling time). For example, if the scanning time is lower than the minimum required scanning time given in (8), then the CDP is approximated to one; that is

$$\mathrm{CDP}(k) = 1 \quad \text{if } k < \frac{1}{Nm}\left(\sum_{j=1}^{N} [L_{Sj}/d_{\mathrm{mean}}(j)]\right) \tag{14}$$

where [ ] is defined as rounding to the nearest integer and can be expressed as $[x] = \lfloor x + 0.5 \rfloor$, $x > 0$ where $\lfloor\ \rfloor$ is the floor operator, which is defined as $\lfloor x \rfloor = \max\{n \in Z | n \le x\}$. The term $(\sum_{j=1}^{N} [L_{Sj}/d_{\mathrm{mean}}(j)])$ is the total required time to complete the coverage by one VS, and $Nm \ge NR_T$ is the number of active VSs. In the following, first, suppose that (14) is not satisfied and then the calculation of the CDP is described. The coverage deficiency in each state is $p(e_j) = p(\sum_{j=1}^{Nm} m_{ij}(k) < L_{Sj}/d_{\mathrm{mean}}(j) + Nm)$ where $m_{ij}(k)$ is number of times that the ith vehicle goes to the jth state up to the kth instance and N_m is the mean number of active VSs in the area under study (which is equal to Nm in this case). Because of the assumption that all vehicles in the sensing area have a unique mobility model we arrive at the Binomial distribution with $Nm \times k$ independent experiments in the steady-state case. Then the probability that the jth state is observed l times by VSs up to the kth instance is calculated by (15); here, it is assumed that there is no overlap between the travelling paths of VSs. Also, the quantity $p(e_j)$ is calculated by (16)

$$p\left(\sum_{i=1}^{Nm} m_{ij}(k) = l | N_m\right) = \binom{Nm \times k}{l} \pi_j^l (1 - \pi_j)^{Nm \times k - l} \tag{15}$$

$$p\left(\sum_{i=1}^{Nm} m_{ij}(k) < L_{Sj}/d_{\mathrm{mean}}(j) | N_m\right) = \sum_{l=1}^{[L_{Sj}/d_{\mathrm{mean}}(j)]-1} \binom{Nm \times k}{l} \pi_j^l (1 - \pi_j)^{Nm \times k - l} \tag{16}$$

The first term of CDP in (13) is calculated by the summation of (16) over all possible states of the proposed VMM. Other terms in (13), except for the final term, have the following format $(\sum_{i,j,\ldots,l} p(e_i \cap e_j \cap e_k \cap \cdots \cap e_l))$ and because of the independency of travelling paths and steady-state considerations, the coverage deficiency in each state are independent; thus

$$\sum_{\forall i,j,\ldots,q} p(e_i \cap e_j \cap e_k \cap \cdots \cap e_q) = \sum_{\forall i,j,\ldots,q} \left(\prod_{t=i}^{q} p(e_t)\right) \tag{17}$$

The final term in (13) (i.e. $p(e_1 \cap e_2 \cap e_k \cap \cdots \cap eN)$) is equal to zero because of the assumption on the time represented in (14) and neglecting of the small possible overlaps between paths (see (18))

As it can be seen in (18), the number of VSs (Nn) has major effect on the CDP and if the number of VSs increases then all the terms of (18) decrease.

Therefore the RSG and the control of the number of VSs have an important effect on the coverage property. On the other hand, control of the number of VSs, increases the processing load of the RSG; hence, in the simple scenario, VS number control functionality may be disabled in the RSG and in this case, the coverage property is described as follows. In this case, first, the mean number of remaining cars in the study area in each instance must be calculated by (10). The mean number of VSs, remaining in the sensing area from the beginning up to the kth instance, is calculated as

$$N_m(k) = \frac{1}{k}\sum_{j=1}^{k} n_m(j) = \frac{Nm}{k}\sum_{j=1}^{k} p_R(j) \quad 0 < k < k_T \tag{19}$$

In the second step the probability of complete coverage (CC) is defined using the following recursive equation

$$p(\mathrm{CC}(k)) = p(\mathrm{CC}(k-1)) + (1 - p(\mathrm{CC}(k-1))) \times p(\mathrm{cc}_k) \tag{20}$$

$$\mathrm{CDP}(k) = \sum_{j=1}^{N} \sum_{l=1}^{[L_{Sj}/d_{\mathrm{mean}}(j)]-1} \binom{Nm \times k}{l} \pi_j^l (1 - \pi_j)^{Nm \times k - l} + \sum_{k=2}^{N-1} (-1)^{k-1} \sum_{i,j,\ldots,h} \left(\prod_{m=i}^{h} \left(\sum_{l=1}^{[L_{Sj}/d_{\mathrm{mean}}(j)]-1} \binom{Nm \times k}{l} \pi_j^l (1 - \pi_j)^{Nm \times k - l}\right)\right) \tag{18}$$

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Fig. 2 *Section of Esfahan map that ORSVSN scenario implemented on it [27]*

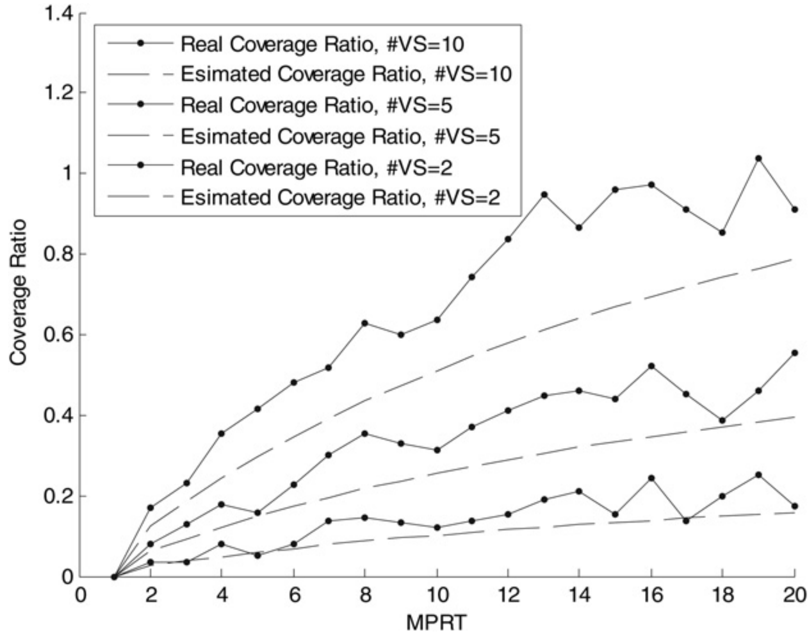

Fig. 3 *Comparison between real coverage and simulation coverage data with respect to MPRT and number of active VSs*

in which $p(\mathrm{CC}(k))$ is the probability of coverage at the kth instance and $p(\mathrm{cc}_k)$ is the probability of completing the coverage at the kth instance for k's that satisfy (14). Note that, when $p(\mathrm{CC}(k-1)) = 0$, it is not possible to complete the coverage at kth instance ($p(\mathrm{cc}_k) = 0$) if and only if the $\mathrm{RTI}(k-1) = \sum_{j=1}^{N}(L_{Sj}/d_{\mathrm{mean}}(j) - m_j)$ or if the required time to inspect un-scanned terms up to instance $k-1$ by one VS is more than the number of VSs ($n_m(k)$) at this instance, $\mathrm{RTI}(k-1) > n_m(k)$ (where m_j is the total scanned area of jth state up to instance $k-1$). Therefore the second term in (20) can be rewritten as (see (21))

Similarly, (15)–(17) and (21) can be rewritten as

$$(1 - p(\mathrm{CC}(k-1))) \times p(\mathrm{cc}_k) = \sum_{\mathrm{RTI}(k-1)\le n_m(k)} \prod_{j=1}^{N} \left(\binom{N_m(k-1)\times k - 1}{m_j} \times \pi_j^{m_j}(1-\pi_j)^{(N_m(k-1)\times k-1)-m_j} \right)$$

$$(1 - p(\mathrm{CC}(k-1))) \times p(\mathrm{cc}_k) = \sum_{\mathrm{RTI}(k-1)\le n_m(k)} p\left(\sum_{i=1}^{Nm} m_{i1} = m_1,\ \ldots,\ \sum_{i=1}^{Nm} m_{Nj} = m_N | N_m(k-1)\right) \times p\left(\sum_{i=1}^{Nm} m_{i1} = (L_{S1}/d_{\mathrm{mean}}(1) - m_1), \ldots, \sum_{i=1}^{Nm} m_{Nj}(L_{SN}/d_{\mathrm{mean}}(N) - m_N) | n_m(k)\right) \quad (21)$$

$$\times \left(\left(\begin{array}{c} n_m(k) \\ (L_{Sj}/d_{\text{mean}}(j) - m_j) \end{array} \right) \pi_j^{(L_{Sj}/d_{\text{mean}}(j)-m_j)} \times (1-\pi_j)^{(n_m(k)-(L_{Sj}/d_{\text{mean}}(j)-m_j)} \right) \quad (22)$$

Hence, by initialising $p(\text{CC}(k_0)) = 0$ in (14) and by substituting (22) into (20), the probability of coverage can be recursively determined in each instance. Consequently, the CDP can be calculated as

$$\text{CDP}(k) = 1 - p(\text{CC}(k)) \quad (23)$$

Also coverage ratio (CR(k)) with respect to time and movement conditions in these two specified cases can be estimated as follows. In the first case that ORSVSN is implemented completely and the number of active VSs are constant, the CR is calculated as

$$\text{CR}(k) = (l_{\text{ave}}(k) \times Nm)/L_D \quad (24)$$

where $l_{\text{ave}}(k)$ is calculated from (3), L_D is the length of the paths required to be scanned in the area under study, and Nm is the number of active VSs.

In the second case, that the RSGs do not manage the VSs (simple implementation), then the number of VSs changes

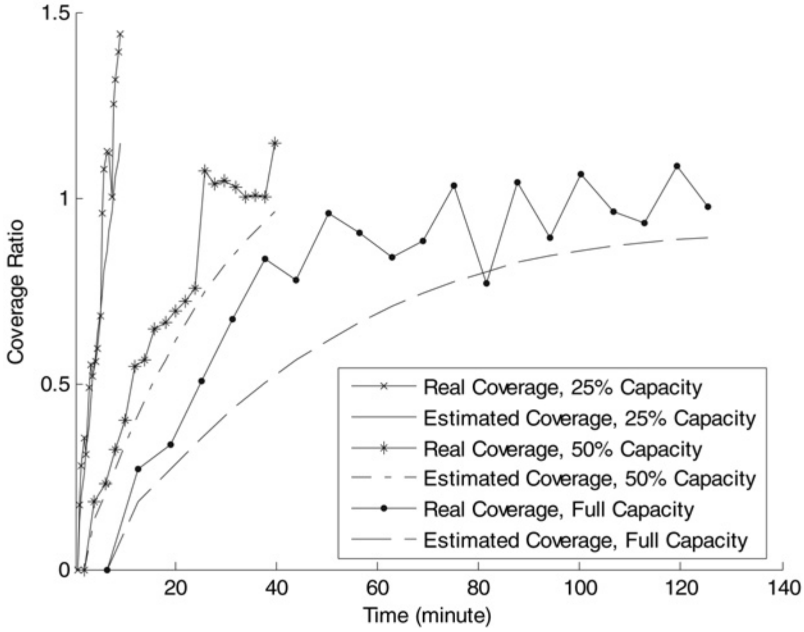

Fig. 4 *Comparison between real coverage and simulation coverage data with respect to time and traffic condition*

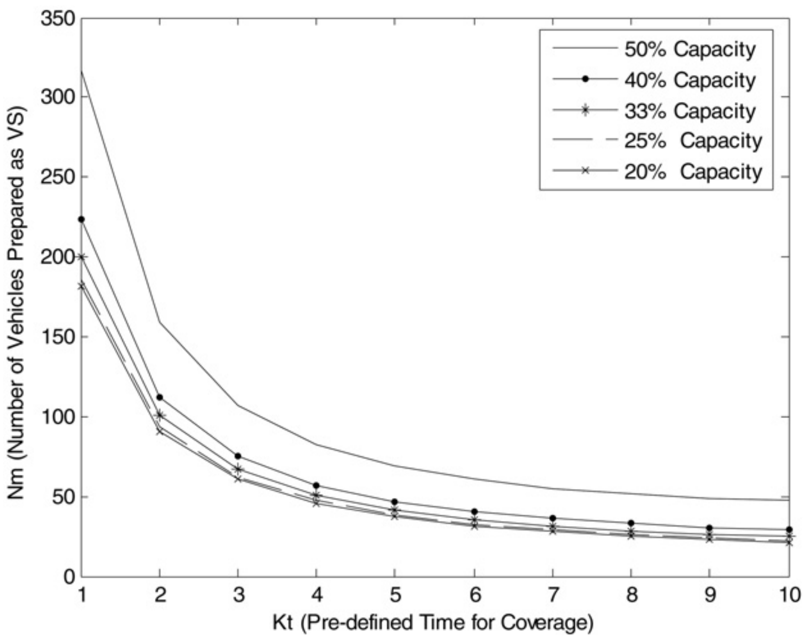

Fig. 5 *Required number of vehicles prepared as VSs for completing coverage in predefined time with respect to traffic condition*

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dynamically, and the CR is estimated as

$$\mathrm{CR}(k) = (l_{\mathrm{ave}}(k) \times N_m(k))/L_D \tag{25}$$

where $N_m(k)$ is calculated from (19). In the following the performance of this method is evaluated through computer simulations and experiments in different scenarios.

4 ORSVSN model analysis and simulation results

In this section, the proposed method is analysed by simulations based on extracted data from real wireless network information [27]. We have analysed the proposed model by implementing it into an area of Esfahan city downtown (Fig. 2 [27]) as an area under study and supposing that all the major streets on the area must be scanned. Detailed data extraction results and VMM parameter estimations are described in [27]. The RSG positions are chosen close to the proper base transceiver station (BTS) locations according to radio coverage information as described in Section 2.2 and can be seen in Fig. 2. in which the RSGs do not manage the active VSs number continually but just implement the ORSVSN design scenario at the beginning of scanning. As a result, implemented scenario presents the lower bound for proposed ORSVSN futures. For this manner, some taxicabs according to the proposed scenario are employed as VSs which have GPS for registering the taxi path. The

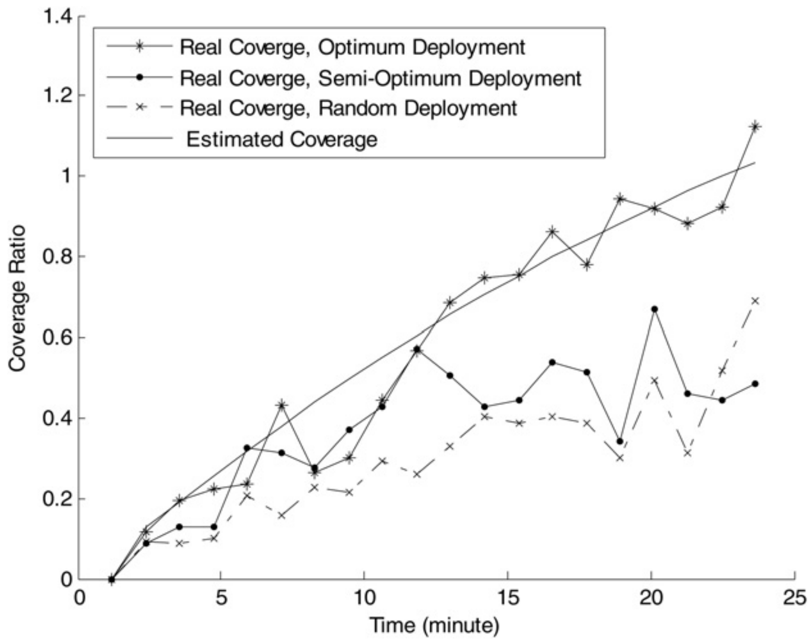

Fig. 6 *Optimum vehicle allocation is compared with sub-optimum and random resource allocation cases with respect to time in 50% capacity*

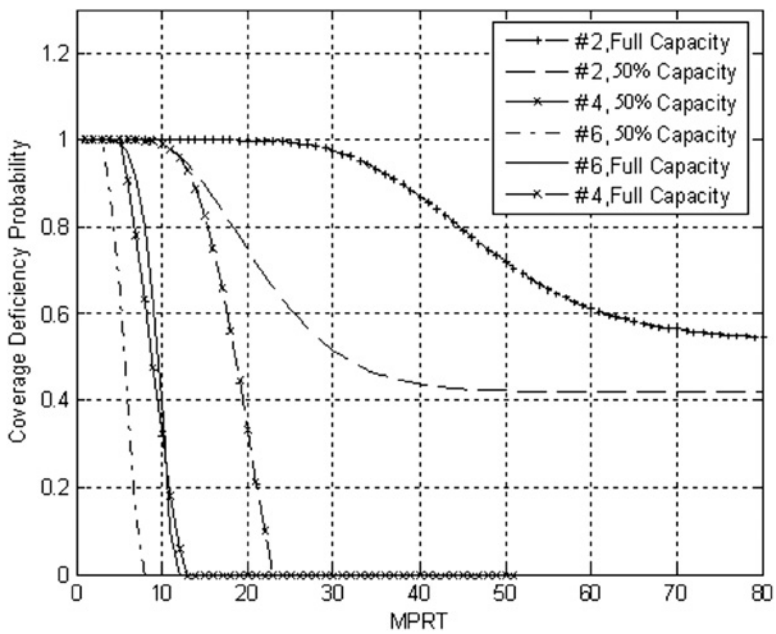

Fig. 7 *CDP with respect to number of VSs and traffic condition*

experiments are repeated at least ten times and the results are presented after averaging. For maintaining the assumption of constant traffic condition, the experiments run at the same time on regular days and also practical data as [27] are used to observe traffic status.

After ORSVSN parameters' estimation and implementation, in Fig. 3, the measured coverage is compared with the estimated coverage in 63% capacity conditions with respect to MPRT. As can be seen in this figure, the CR growth with constant slope in both cases and coverage is estimated properly. Note that the constant traffic condition is not accessible in real experiment and traffic was changed across the test.

According to this fact that MPRT changes respect to traffic condition [27] in Fig. 4, convergence is analysed in different traffic conditions with respect to time. In this figure, experiments are continued up to 20 MPRT. Estimated and measured coverages are compared with respect to time (number of active VSs in this case is 10).

In the next step the number of vehicles (prepared as VSs) are shown in Fig. 5. As can be seen in this figure the number of required VSs according to (11) has an exponential form with respect to MPRT or K_T. The effect of the optimum vehicle allocation that is found based on (12) is depicted in Fig. 6. In this figure, in low-dense traffic jam, the coverage in optimum vehicle allocation according to (12) is compared with sub-optimum and random resource allocation cases and CR is calculated by averaging it over 20 iterations. In the sub-optimum case, the sensors would be allocated half-optimally and half-randomly. As can be seen in this figure, the coverage of optimum sensor allocation between groups with four vehicles is comparable with the random allocation by applying nine VSs. The CDP for this case is shown in Fig. 7. As can be seen in this figure, the growth in number of VSs improves the CDP. Also the effect of traffic condition and vehicle velocity on coverage probability is depicted in this figure. If the mean of the vehicle's velocity increases, then $d_{\text{mean}}(i)$ increases, and so does the scanned area in each iteration. On the other hand, if $d_{\text{mean}}(i)$ is increased then the variance in (7), (8) increases and so the remaining probability ($p_R(k)$) is reduced especially after passing some iterations. As can be seen in Fig. 7, an increase of the velocity of the vehicles improves the CDP.

5 Conclusion

In this paper, we have proposed a VSN named ORSVSN that uses a few non-reserved vehicles as sensors. In the ORSVSN the network designer needs to have a real mobility model with the ability to adapt to real conditions in the region studied, such as the model proposed here. As described in this paper, a network designer can use the proposed mobility model for the ORSVSN parameter calculation and performance analysis. The coverage problem has been studied using the analytical approach presented in this paper. Also the simple implementation of the proposed scenario is used to test and verify the analytical study. Experimental results induct that for large regions, the proposed scenario needs a relatively small number of VSs especially in low traffic jam, and so it is desirable to use GPS for localisation in each set of sensors. The proposed scenario is also suitable for the spatial study of highly dense cities where solving the coverage problem in traditional WSN is too difficult. The CDP is analytically analysed in this paper and approves the results of the simulation.

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