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Optimised Sensor Networks Deployments Through a Semi-Markovian Predictive Model

Francisco Prieto-Castrillo[1,†], Manuel Rubio-del-Solar[1] and José M. Franco-Valiente[1]

[1] *CETA-CIEMAT, Extremadura Research Centre for Advanced Technologies*

Abstract. This work proposes an optimised scheme to deploy sensor networks. The network growth model is based on cellular automata to improve measurement quality at those locations likely to report sensor activity. Then, a population-based optimisation scheme is performed to identify those solutions maximising measurement quality while minimising cost at every time step. A Markovian formalism which includes a non-homogeneous term proportional to measurement is used as a prediction model for the computation of activity likelihood at a given location during a time interval. By numerical simulation it is found that, under suitable parameter conditions, the optimised solution outperforms the random deployment.

Keywords: Sensor Networks, Markov, Agent-Based Modelling, Optimisation.

† **Corresponding author:** francisco.prieto@ciemat.es
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1. Aims and Scope

Wireless Sensor Networks (WSNs) [1] are increasingly pervading almost every scientific or technological field. In the case of *Smart Cities* many problems are highly coupled to the effectiveness and reliability of the *smart monitoring* solution adopted. Moreover, different complex systems based heuristics for WSNs deployment can be found in related works. In [2] the area coverage problem is considered in terms of computational cost; complex systems based solutions rendering polynomial times. Also in [3] a quality-driven deployment is made through probabilistic models.

In this work we improve a previous model [4] by implementing an optimisation scheme inspired on Cellular Automata [5] to provide network growth mechanisms. Sensors are incrementally deployed according to both predictions and simulated measurements of an evolving resource. Every deployment maximises matching between simulated sensor measurements and predicted resources values while minimises costs. The resulting system is adaptive and develops complex behaviour under particular conditions. The paper is structured as follows: In Sec 2. we provide the mathematical model and the main results obtained from numerical investigation are addressed in Sec 3.

2. Sensor Network Evolution Model

We start by discretizing space and time in a set G of $|G|$ possible locations g and $t_n = n\Delta T$, $n \in \mathbb{N}$ respectively. For every g we define a neighbourhood $U(g) = \{g' \in G | d(g, g') \leq h\}$, where $d(g, g') : G \times G \to \mathbb{N}$ is a distance function and h the *neighbourhood size* [1].
Let now $R(n, g) \in [0, 1] \subset \mathbb{R}$ denote the probability of observing a measurable quantity (e.g. wind, temperature, solar radiation, etc.) at location g and time step n. Further, a sensor set $S(n)$ composed by $|S(n)| \leq |G|$ sensors is defined. Every sensor $s(n, g)$ measures an amount of resource proportional to $R(n, g)$ at every location [2]. Hence, at every step n the *world* G is partitioned into locations containing sensors $GS(n) \subset G$ and free locations $\overline{GS}(n)$.
Every sensor is assumed to hold a space state $\Omega = \{1, 0\}$, where status 1 and 0 represent *activated* and *non-activated* respectively. A discrete random variable $X(n, g)$ with support Ω is also introduced. The resulting one-step transition diagram is represented in Fig.1 where the one-step transition probabilities:

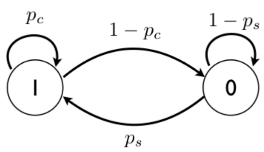

Figure 1: Transition diagram for the Markov model.

$P[X(n + 1, g) = 1|X(n, g) = 0]$ and $P[X(n + 1, g) = 1|X(n, g) = 1]$ are denoted as p_s and p_c respectively.
By denoting $P(n; g) \equiv P[X(n, g) = 1]$ the Chapman-Kolmogorov evolution equation renders:

$$P(n; g) = p_s + (p_c - p_s)P(n - 1; g). \quad (1)$$

[1] In this work we will focus on a two-dimensional grid of cells where the neighbourhood of every cell consists of its eight adjacent cells

[2] We will simply assume that this measure is $M(n, g) = R(n, g)$.

The state of a sensor located at g is set according to $P(n;g)$ at every n and we add a non-homogeneous term to Eq.1 as follows:

$$p_c = p_{co} + \eta \tilde{M}(n,g) \tag{2}$$

where $p_{co} \in [0,1] \subset \mathbb{R}$ and $\eta \in [0, 1-p_{co}]$ are two parameters and $\tilde{M}(n,g)$ is the *normalised measure* defined as:

$$\tilde{M}(n,g) = \frac{M(n,g)}{\sum_{g' \in GS(n)} M(n,g')} \tag{3}$$

This way, real measurements and predictions are coupled through the constant η [3] resulting in a non-homogeneous Makovian process.

Inspired by the Cellular Automata evolution model [5] we now introduce a network growth model as follows. At every step n we evaluate every free location by averaging the predictions of the sensors within its neighbourhood. The location is set as a candidate for possible placement of a new sensor if the following relation holds:

$$\frac{1}{|\{g' \in GS(n) \cap U(g')\}|} \sum_{g' \in GS(n) \cap U(g')} P(n;g') \geq \epsilon \tag{4}$$

where $\epsilon \in [0,1] \subset \mathbb{R}$ is a parameter. The resulting set of locations where Eq.4 holds is denoted as $\Gamma(n) \subset \overline{GS}(n)$ (see Fig.2).

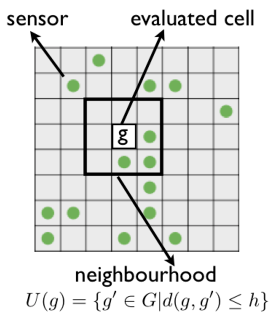

Figure 2: Network evolution model.

Once the free cells are evaluated, a deployment solution consists of choosing a random amount cells in $\Gamma(n)$ at every n. The resulting set $\Gamma^*(n) \subset \Gamma(n)$ is filled with new sensors with state equal to 1 and a prediction of 1. By iterating this process different network growth patterns are observed.

[3] Notice that for $\eta = 0$ we recover the Markovian limit

Instead of keeping a single solution we use a population-based optimisation scheme. Firstly, a population of N feasible solutions is generated. Each solution m is evaluated through a fitness function defined as:

$$F(n,m) = \frac{1}{c \cdot |\Gamma^*(n)|} \sum_{g \in \Gamma^*(n)} M(n,g) \tag{5}$$

where c is a parameter accounting for the cost per sensor. The final solution for every step n is that reporting the highest value: $\max\{F(n,m)|m = 1,\dots,N\}$.

3. Main Results and Summary

In our numerical tests we monitored the performance of optimised solutions with respect to a random allocation of sensors. To simulate resources we used both a static map and a simple evolution model (Eq.6).

$$R(n+1) = \frac{1}{2}R(n) + \sigma\cos(n\omega + r)^2 \tag{6}$$

where ω is a constant and σ and r are random samples from a uniform distributions with ranges $[0, 1/2]$ and $[0, \pi]$ respectively.
Although an exhaustive parametric analysis of the possible emerging patterns is out of the scope of this contribution, we observed a set of remarkable trends. In Fig.3 we compare the evolution of the fitness functions for two optimised solutions of size $N = 1, 100$ and a random deployment strategy. A configuration with a grid of 20×20 cells with 5 initial randomly allocated sensors for the parameters $p_s = 1.0$, $p_c = 0.3$, $\eta = 0.5$, $r = 0.0$, $\omega = \pi$, $\epsilon = 0.5$ and $c = 1$ was used. It is noticed how the optimised solutions outperform the random deployments when population size increases. The main conclusions derived from the numerical tests are:

- As expected, the optimised solutions outperform the random deployments when population size increases and when sensors are more likely to *awake* faster (higher p_s) and to remain in activity (larger p_c values). For the transition probabilities p_c and p_c, abrupt changes in the behaviour are found for $p_s \geq 0.5$ and $p_c \geq 0.1$.

- Since the network growth model is very sensitive to the threshold value ϵ, beyond $\epsilon \approx 0.45$ optimised solutions are unable to deploy new sensors and the random solution renders a better performance.

- Finally, the non-homogeneity in the model assures that optimised solutions outperform the random deployments $\forall n$ if $\eta \geq 0.6$, which suggests that the coupling between predictions and measurement addressed in the proposed model is a reliable choice.

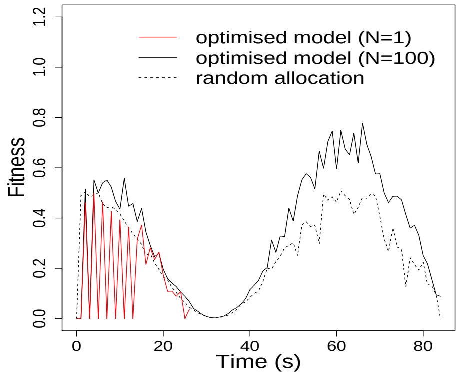

Figure 3: Evolution of the fitness function for optimised sensor deployments with populations of size $N = 1$ and $N = 100$ compared with a random allocation.

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