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Optimal Deployment of a Heterogeneous Air Quality Sensor Network

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ABSTRACT. Accurate assessment of air pollution exposure is crucial to better public health. Routine monitoring is done by standardized Air Quality Monitoring (AQM) stations, which are spread thinly due to size and cost. Recent technological developments have made Wireless Distributed Environmental Sensor Networks (WDESNs) that consist of low-cost Micro Sensing Units (MSUs) feasible. These MSUs can be spread more densely and provide higher spatial resolution data. The availability of MSUs, however, poses the challenge of selecting optimal sensors' locations. Previous attempts assumed prior knowledge on pollution levels in the region of interest, and considered MSUs which measured only one pollutant. This paper presents a scheme for finding an optimal deployment of heterogeneous WDESN, which is based only on MSUs characteristics and land use analysis. To this end, a set of optional deployment locations (OLs) is defined. Each OL is characterized by a set of utilities of placing the various MSUs in that location. The optimization process seeks for the set of locations, under budget and resources constraints, that maximizes the overall utility. Using the suggested method leads to an intelligent deployment under a set of given premises. This is demonstrated vs. a real-world deployment scenario, with multiple types of MSUs.

Keywords: air pollution, wireless distributed environmental sensor network, optimal deployment, monitoring

1. Introduction

Air pollution is well known as a contributing factor to various health outcomes, and has been associated with public health risks (Straif et al., 2015). Any study aiming at evaluating the impact of air quality on health, must assess accurately the ambient concentrations of different air pollutants. Up until recently, ambient pollutant concentrations were obtained solely by two methodologies: either short-termed measurement campaigns, using a large number of monitoring devices (Crouse et al., 2009), or based on routine measurements reported by standard Air Quality Monitoring (AQM) stations (Pope et al., 2002). These two approaches are inherently limited; the short-term campaign represents only the limited time-span when monitoring took place, and might fail to describe variations throughout longer periods of time, while the routine monitoring is both general, typically measures only criteria pollutants, as determined by the local authorities (Bishoi et al., 2009), and is limited in its ability to represent a large area (Moltchanov et al., 2015). This limitation arises from AQM stations' operational demands, as an extensive set of procedures is required to maintain a satisfactory quality of monitoring data. These procedures (i.e. calibration, maintenance and data validation) result in high fiscal and operational cost, thus decreasing the number of AQM stations in use. As a result, the AQM stations array data does not fully represent pollution levels in heterogeneous regions such as urban areas, which in return, renders exposure assessment as a very difficult task (Rao et al., 2012). Moreover, the standards that regulate AQM stations mandate the sampling to take place high above the ground. Thus, AQMs often misrepresent the true exposure of any individual at nose height.

Recent developments in sensory and communication technologies have made the deployment of portable and relatively low-cost Micro Sensing Units (MSUs) feasible. These MSUs operate as independent nodes, or may be interconnected to form a Wireless Distributed Environmental Sensor Network (WDESN), to cover larger area. WDESNs gather high-resolution spatial and temporal data, enabling the generation of dense pollution maps via interpolation. These maps are closer to real-life pollution dispersion scenarios, thus enabling a better exposure assessment (Kanaroglou et al., 2005). Recent studies that evaluated MSUs in laboratory and field trials show that these units are relatively less accurate compared to standard laboratory equipment or AQM stations, however they do capture air pollution spatio-temporal variability effectively (Becker et al., 2000; Lee and Lee, 2001; Mead et al., 2013; Williams et al., 2013; Piedra-

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hita et al., 2014; Lerner et al., 2015; Moltchanov et al., 2015). Recent work by Fishbain et. al. (2017) suggest a new observation on quality assessment of MSUs, not only by absolute pollutant values, but also by the MSUs compatibility to various uses. Thus, the topic of accuracy is dealt with, allowing further use of these MSUs for monitoring campaign and exposure assessment.

As mentioned above, MSUs have two major advantages over AQM stations: their small form factor and lower cost. This combination, which enables the deployment of a wide-area W-DESN, raises a new question: what deployment plan would serve best the monitoring purposes? Unlike AQM stations, which require a dedicated location (roof top of a large structure, empty lot, etc.), MSUs can be placed on a balcony, street light, street sign and almost everywhere. However, as low-cost as the MSUs might be, budget is still a limited resource. Thus, a mandatory step in WDESN deployment design is the decision where to place the MSUs constituting the WDESN. While this placement decision is a critical component in any WDESN design and deployment, many studies avoid this important question (Barrenetxea et al., 2008).

The problem of choosing optimal deployment locations for WDESN is not new and can be found in many environmental applications. Zhang and Liu (2012) cover several approaches to this problem, and describe the challenges in WDESN optimization as follows; increase the coverage area, enhance network connectivity, prolong the network lifetime, balance the load and improve the accuracy of the data. As the majority of MSUs in use these days are independent units, transmitting the data directly to a centralized computer (Fishbain et al., 2017), out of all these topics we are left only with coverage area and data accuracy as key components.

Optimal environmental sensing of a region of interest (ROI) was suggested for disaster area investigation by mobile sensors (Kim et al., 2010) and for optimal coverage under energy consumption restrictions through turning off some the sensor nodes in an alternating fashion (Xing et al., 2005; Kim et al., 2010). In ecology studies, optimal sensors placement is sought through an optimization of animal activity coverage (Garcia-Sanchez et al., 2010; Akbarzadeh et al., 2013). All these studies, however, do not regard the observed area characteristics; thus, the optimal coverage is achieved through an optimization mechanism that is solely based on sensors' characteristics. The suitability of a given sensor to a specific location is not considered in the optimization schemes. Another limitation that these studies present, and many others, is that they address homogenous sensor network, i.e. all sensors are space invariant and present the same accuracy and suitability in all possible locations. As the ROI itself presents variation in space, this assumption typically does not hold.

Kanaroglou et. al. address the problem of deploying a network of air quality monitors for exposure assessment (NO_2 as a single pollutant) (Kanaroglou et al., 2005). Their design is based on an initial estimation of pollution levels in the desired region based on data from monitoring stations, combined with land use analysis (roads as pollution source, among other parameters), as means to create a "Demand surface", representing the locations where a monitoring station is needed most. To this demand, they add a second level of specification by incorporating interest groups, e.g. specific socio-demographic characteristics that they wish to focus on (e.g. school area). By solving the problem for the above conditions, using Location-Allocation algorithm (Modak and Lohani, 1985; Trujillo-Ventura and Hugh Ellis, 1991; Sarigiannis and Saisana, 2008), they estimate the best locations to place their WDESN nodes. This work is limited in few major aspects: First, it is based on an initial estimation of pollution levels in the desired region. Although they limit their deployment area, their demand surface is based on a much larger region, for the sole purpose of obtaining data from a larger number of existing AQM stations. This limits their method only to regions where monitoring campaigns were held, and sufficient data is available. Second, when solving the problem, all of the WDESN's nodes are isotropic in nature, i.e. they measure with the same accuracy. Furthermore, the entire solution is based on a single pollutant. As both AQM stations and MSU nodes measure a set of pollutants, each presents a different spatio-temporal pattern due to different sources and atmospheric reactions (Hastie et al., 1996; Berkowicz et al., 2006; Jerrett et al., 2007), solving the problem only for one of them leads to a sub-optimal solution for the other pollutants. A proper solution should regard all of the measured values.

Bhattacharya et. Al. (2010) suggested a different approach, that partially solved the isotropy and single pollutant problems. They defined both the Quality of Monitoring (QoM), which indicates the level of accuracy or compatibility of a sensor to a set of purposes, and a utility function, that balances the benefit of the QoM with network demands (load, communication cost, etc.). However, all nodes are de-fined based on the same QoM, thus, it is assumed that the WDESN is composed of a single type of sensors. Due to differences in sensor technology, outer case design, sampling resolution, etc., different types of MSUs are found to function at different levels of accuracy and reliability on various environmental conditions (Mead et. al., 2013; Moltchanov et. al., 2015). Moreover, one MSU type may be better suited to measure NO and CO (that present at higher concentrations near their origin, mostly traffic), while other MSU types are more accurate measuring ozone (O_3), a secondary pollutant, found mostly farther from pollution sources. WDESN consists of different types of MSU must utilize a decision mechanism that regards the differrent characteristics of the MSUs. Also, as stated above, when working with MSUs, the decision does not have to regard a single set of performance characteristics for a specific type, and it should assign specific, individual QoM set of characteristics to each sensor, as the single units are independent in that nature.

Carter and Ragade proposed a probabilistic model for placement of sensors in a WDESN, based on the probability of detection per each sensor, and an optimization schemes that ensures desired level of detection at minimal cost (Carter and Ragade, 2009). Here, they suggest a method that differentiate sensor types, by means of different detection probabilities. However, as air quality is not an “event” to detect, but a dynamic character of the environment one wishes to monitor constantly, and in the entire region, this method will not be suitable. Similarly, Chakrabarty et. al. (2002) presented a scheme for surveillance and target location (over a grid), with support for different sensor types. However, again, no regard is given to the characterristics of the deployment region besides distances between grid points. This is a crucial topic when examining a chemophysical phenomenon as air pollution, with various sources and environmental pathways.

This paper describes a new, general approach to optimally deploy a WDESN composed of various types of MSUs in an urban area, based only on MSU characteristics and land use analysis of the defined region, with no prior knowledge on pollutant concentrations. Solving this optimization problem results in a detailed map of deployment locations. The problem definition is flexible and enable customization based on the defined region, to better comply with specific conditions. Using the suggested method to choose deployment locations leads to a fruitful deployment, where the best possible monitoring results are obtained under a set of given premises.

2. Materials and Methods

2.1. Instrumentation

In this study, two types of MSUs were used: (1) GeoTech’s AQMesh pods (AQMesh, 2017); and (2) Perkin Elmer’s ELM units (Perkin-Elmer, 2017). These two MSUs present different capabilities in monitoring urban air pollution. The ELM unit is weather resistant, AC powered MSU, which consists of two semiconducting metal-oxide gas sensors, measuring O_3 and NO_2, sampling for every 20 seconds. O_3 data is averaged over 60 seconds, before transmission to a remote server. These units also measure atmospheric pressure (AP), local temperature and total suspended particles. The ELM MSU was reported to present accurate O_3 measurement that capture well intra-neighborhood spatiotemporal variability (Lerner et al., 2015; Moltchanov et al., 2015).

The second set of the sensors is the battery-powered, GeoTech’s AQmesh. Here, the sensing pods are electrochemical, measuring NO, NO_2 and O_3, along with AP and temperature, where sampling is taken every 15 minutes before data is transmitted back. Some of the AQmesh units also include an optical counter for particulate matter ($PM_{2.5}$ and PM_{10}). The AQmesh units were reported to accurately measure NO ambient levels and correctly report PM spatial patterns (Fishbain et. al., 2017).

The ELM MSU measures O_3 at a relatively high accuracy, however it lacks in its ability to correctly indicate levels of NO_2. Thus, it is less suited to monitor traffic-related pollution at its source (i.e. near major roads or busy commercial areas), and better suited to be placed in Near-Residential Open Spaces (NROSs), to monitor secondary pollutants levels. On the Other hand, the AQMesh MSU presents relatively accurate NO and CO measurements, also measuring PM, and thus it should be placed near major roads or combustion-related pollution sources (i.e. roads, industrial centers, dense residential districts, etc.), hence, Traffic-Residential Regions (TRRs).

2.2. Study Regions

Two regions were chosen to test the suggested method. The first is an area in the city of Hadera, in the central costal plane of Israel (see Figure 1a and zoomed in section in Figure 1b). This area composes of a combination of TRRs, including two major highways, NROSs, and also a hospital and a power plant. Thus, it demonstrates various pollution sources and vast deployment options. This makes this area an interesting site to monitor the behavior of air pollution emitted from those sources, and a good testing ground for our algorithm. Few combinations of the formulation parameters and constraints are explored so the best approach for an optimal solution is found.

The other case study is Citi Sense project (CITI-SENSE Project, 2017) air pollution sensors deployment in the city of Haifa. Haifa is a port city, which resides on the northern part of the Israeli coast of the Mediterranean Sea (Figure 1c). Currently, a few dozen MSUs are deployed at Neve Sha’anan, a residential neighborhood, located on a relatively leveled region of the Carmel Ridge, about 200 m Above Sea Level. The neighborhood is roughly divided by a major road (Trumpeldor Ave.), which also serves as the main commercial center for the residents of this area. Haifa region deployment was solved under several configurations, starting with the entire region (all theoretical optional locations, OLs) and zeroing into the current deployment sites. This approach aims at comparing the optimal solution to that obtained by trial and error, or human decisions. The complete process is described in the results section.

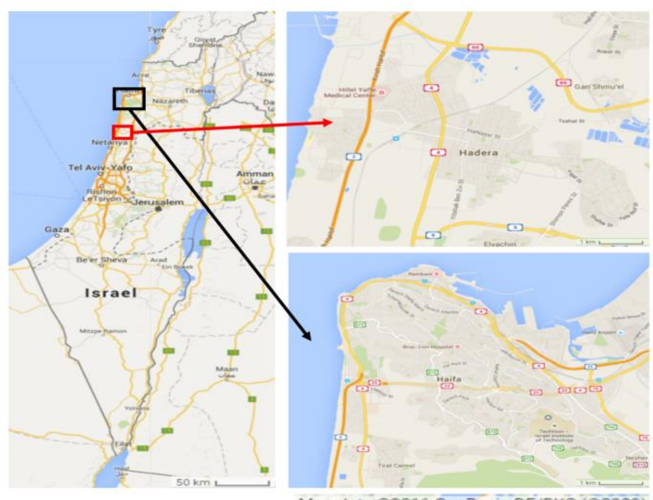

Figure 1. The study regions.

2.3. Problem Definition

2.3.1. Deployment Considerations

Previous studies that aimed at optimally deploy air quality monitors, defined the study area as a continuous surface (e.g. Kanaroglou et al., 2005), and calculated the optimal deployment locations as a grid of nodes in pre-defined distance from one another. Here, we took a different approach; after choosing our deployment region, we define the set Ω, which consists of *n* catchments or “Optional Locations” (henceforth termed OLs), where an MSU can be placed. As the deployment region, can vary in size or shape, the defined OLs are flexible in their relative locations throughout the region.

The OLs in the study region differ in their characteristics; these include their relative position on the grid (i.e. peripheral vs central location) and their function (i.e. land-use, is there a road in that location or an open area). As described earlier, the two types of MSUs used in this study demonstrate different characteristics; An ELM unit is better suited for Near-Residential Open Spaces (NROSs), while AQMesh is preferable in Traffic-Residential Regions (TRRs). These differences are expressed in our design as the Suitability (S) of placing each MSU type at a given OL, due to its advantages (or disadvantages). The suitability is defined on a scale of zero to one, where zero indicates that the MSU is completely ineffective or not required at that location, while one will be given to a location best suited for the specific type of MSU. The suitability measure is a representation of the OLs land-use, and its implication on MSU placement. Figure 2a demonstrates a sample suitability matrix for an AQMesh MSU, at a sample region map. For the sake of simplicity, all OLs in this example are spread as a square grid of n OLs, with an equal distance between two neighboring locations. Each position on the 2D-grid is described by a single coordinate, termed i, where $i \in \{1, 2, \ldots, n\}$. This region includes several major highways (routes 2, 4 and 65), a NROS and some residential centers. As the AQMesh MSU is better suited for measuring pollutants originating from TRRs, the suitability is higher along the major roads and lower between them.

In addition to the suitability, two other sets of parameters are defined for any OL. The first parameter is the rank (r), indicating the number of neighboring OLs this location has. Assuming that the correlation between two adjacent OLs is relatively high (Moltchanov et al., 2015), a single MSU may cover more than its close surroundings, and thus, a more central location will provide accurate monitoring for a wider area. To illustrate, in the example of Figure 2, an OL located in the corner of the grid has 3 neighboring locations, while a central one has 8. These values are normalized to the scale of zero to one, to match that of the suitability, as demonstrated in Figure 2b.

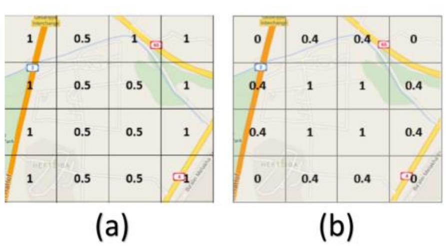

Figure 2. Utility (U) composing matrices of a sample region; (a) Suitability (S) matrix, for a traffic-oriented MSU; (b) rank (r) (normalized number of neighboring OLs).

2.3.2. Decision Variables and Objective Function

The problem at hand is solved by defining an objective function, aimed at maximizing the utility of the deployed MSUs. To this end, each OL is represented by two (or more if there are more types of sensors) binary decision variables, x_i and y_i, that indicate whether an MSU of a given type (x or y, representing AQMesh and ELM, respectively) is located in that OL. For example, $x_1 = 1$ indicates that an AQMesh MSU is placed in catchment number 1. If $x_1 = 0$ then an AQMesh sensor should not be placed in that catchment.

Let S_i^x and S_i^y be the *suitability* of a given OL in Ω, for the MSU of type X and Y, respectively, and r_i the *rank* of the same OL, then the contribution of having any MSU in that location will be defined by $r_i S_i^x \mathrm{x}_i + r_i S_i^y y_i$. Summing for all OLs in Ω, we get the following term, describing the complete contribution of all deployed MSUs:

$$\sum_{i\in\Omega} r_i S_i^x \mathrm{x}_i + \sum_{i\in\Omega} r_i S_i^y \mathrm{y}_i \tag{1}$$

Constraints. We define here that each OL can support at most one MSU. This might arise from physical limitations (e.g. placing the MSU on a street light with minimal space), limited budget or other reasons. Thus, for the entire grid, we define that at each location, only one decision variable might be equal 1:

$$x_i + y_i \leq 1, \forall\, i \tag{2}$$

In addition, there are locations where an MSU cannot be deployed (e.g. ocean, restricted access areas, etc.), and others where a mandatory deployment is in order (declared fixed positions). For this end, these specific cases are represented in the constraints as $x_i = 1, \mathrm{y}_i = 0$, or vice versa.

There is also a budget constraint, and to solve that we limit the number of MSU deployed, by assigning a cost of a single MSU of any type to the parameters C^x and C^y for the AQMesh and ELM units respectively. The total cost is then limited by the following constraint:

$$\sum_{i\in\Omega} C^x x_i + \sum_{i\in\Omega} C^y y_i \leq \textit{total available budget} \tag{3}$$

Quite often the budget constraint is not in the form of monetary terms, but in the form of available sensors. The latter may be the case, for example, when one has a set of sensors and he seeks for an optimal deployment for this set. To accommodate for this, the budget constraint of Equation (3) can be replaced with a set of constraints limiting the maximum number from each sensor type:

$$\sum_{i\in\Omega} x_i \leq \textit{maximum}_x \tag{4-1}$$

$$\sum_{i\in\Omega} y_i \leq \textit{maximum}_y \tag{4-2}$$

Table 1. Definitions of Mathematical Symbols Used throughout Equations (1) to (6)

Symbol	Definition
Ω	Set of catchments (OL's) compromising deployment area
ω ($\omega_l \in \Omega$)	Subsection of set Ω
$\{S_i^x\}$, $\{S_i^y\}$ ϵ {0..1}	Suitability of OL_i for MSU of type X or Y, respectively, based on land-use
r_i ϵ {0..1}	Rank of OL_i, indicating normalized number of neighboring OLs
$\{x_i\}$, $\{y_i\}$ ϵ {0..1}	Indicates presence of MSU of type x or y, respectively, in OL_i
C^x and C^y	Cost of MSUs of types x and y
x_a and y_a (where a ϵ ω_l)	Indicates presence of MSU of type x or y, respectively, in any OL_i (i ϵ a) within a defined subsection of Ω. Used to calculate the Occupancy measure.

It is important to note that the constraints of Equation (3) and Equation (4) can be applied concurrently, where any subset of Equation (4) can be applied independently from the others, i.e. limiting the number of sensors of a single type.

To enhance the flexibility of the algorithm, we tested several options to influence the scattering of the solution's chosen OLs, by applying optional constraints on the deployment. The first is the use of Anchor sites (A_s). These anchors are intended to force the algorithm to deploy several MSUs at fixed positions on the grid, regardless of the utility. These anchors are defined using the terminology set by Equation (2). Anchor locations can also be used for a functional purpose (A_f) and not just for scattering, e.g. a location where we want a sensor to be deployed. A good example is a known pollution source, where we want to place an MSU that measures the released pollutant. Another example is an area of high interest, a hospital for example, where exposure analysis is most important for the well-being of the patients (Jerrett et al., 2007).

An alternative approach for governing the scattering patterns of deployed MSUs is to define an *occupancy* (O) function, which mandates the presence of MSUs in any given subsection of Ω. To this end, let us define a set of subsections $\{\omega\} \subset \Omega$, which may intersect, i.e. for arbitrary ω_a and ω_b in Ω, the intersection, $\omega_a \cap \omega_b$, may not be the empty set. Using these notation, the constraint is formulated as follows:

$$\sum_{a \in \omega_l} x_a \geq 1,\ \forall\ \omega_l \subset \Omega \qquad (5\text{-}1)$$

$$\sum_{a \in \omega_l} y_a \geq 1,\ \forall\ \omega_l \subset \Omega \qquad (5\text{-}2)$$

Figure 3 illustrates this concept, where Ω is divided into squared grid and ω_l are all 3 × 3 neighborhoods, within Ω.

2.3.3. Mathematical Formulation

Summarizing the sections above, using the notation summarized in **Table 1**, the complete problem is formulated as follows:

$$\text{Max}\, DS = \sum_{i \in \Omega} r_i S_i^x \mathrm{x}_i + \sum_{i \in \Omega}^{n} r_i S_i^y \mathrm{y}_i \qquad (6\text{-}1)$$

$s.t.$

$$\sum_{i \in \Omega} C^x x_i + \sum_{i \in \Omega} C^y y_i \leq total\ available\, budget \qquad (6\text{-}2)$$

$$\sum_{i \in \Omega} x_i \leq maximum_x \qquad (6\text{-}3)$$

$$\sum_{i \in \Omega} y_i \leq maximum_y \qquad (6\text{-}4)$$

$$\{x_i\},\{y_i\} \in \{0,1\} \qquad (6\text{-}5)$$

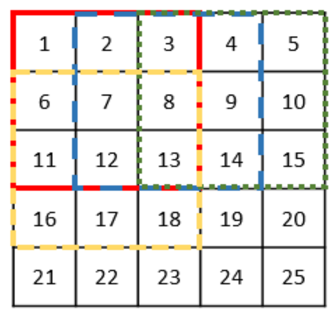

Figure 3. Occupancy measure; Four 3 × 3 sub-grids of a 5 × 5 grid (out of 9 available).

Examining the above DS problem (Equation (6)), it is clear that one can characterize the MSUs by cost and utility, and the deployment area by its constraints. Thus, the DS problem is essentially the knapsack problem (Kellerer et al., 2004), with binary decision variables and linear constraints. The knapsack problem is NP-Complete (Karp, 1972), thus there isn't a known method to solve the problem efficiently.

Here the DS problem is solved as a Mixed-Integer Linear Problem (Mixed-ILP). To this end, Matlab® and IBM CPLEX OPTIMIZER (IBM, 2015; MathWorks, 2015) were used. CPLEX solves this type of problems using a heuristic approach, combining simplex (to identify optimal solution) and Branch & Bound to find the binary values (Lima, 2010). Hardware used was a self-assembled PC with Windows 7®OS, running an Intel Multi-core processor and 16 GB RAM.

3. Results and Discussion

3.1. Hadera Case Study

For the city of Hadera, *utility* matrices were defined for both aforementioned MSU types (Figure 4):

(a) (b)

Figure 4. Suitability (S) matrices for theoretical study region (Hadera, Israel). (a) ELM MSU; (b) AQMesh MSU.

First, the problem is solved using solely the occupancy measure to avoid extreme centrality of the result. As seen in Figure 5a, this resulted in a deployment, which takes into account the highway that crosses this region, and covers the NROS's. The problem was solved in less than a minute. It is also clear that the AQMesh and ELM units are placed correctly in TRR and NROS area respectively. There is still one noticeable problem, sea areas, which are not feasible location, have been included in Ω and two MSUs (one of each type) were actually placed in the Mediterranean Sea. This problem can be solved either by forcing the decision variable of placing a sensor in a sea region to have a zero, i.e. no sensor, value, or by removing this location from Ω. It is important to note that these two solutions differ as the latter solution also alters the occupancy measures. Figure 5b illustrates, the former, where the functionality of Equation (2), which forces the decision variables in sea areas to be zero. Indeed, the deployment of Figure 5b presents good coverage and adequacy of MSUs to land-use characteristics. Computation time for both solutions was less than 1 second.

3.2. Haifa Case Study

Next, the suggested approach is tested in the city of Haifa, where an actual deployment exists. Figure 6a depicts an aerial photo of the deployment region, which is 1.6 × 1.6 km in size (1 squared mile). The region is divided into 10 × 10 grid of equal sized OLs (Figure 6b). Utility matrices are created for both types of MSUs. The problem is solved, limiting the maximum amount of MSUs available (Equation (4)); This was designed to represent the actual inventory. As seen in Figure 7, the solutions do cover the region efficiently, providing a good adaptation of the different types of MSUs to the land use characters.

Increasing the maximum number of available units (from 12 in Figure 7a, to 15, 20 and 25 in Figures 7b to 7d, respectively), do improve the coverage while maintaining the basic principles: more AQmesh units along major roads and in residential areas while ELM units are concentrated in the less densely populated domains.

(a) (b)

Figure 5. Optimal deployment in Hadera, entire region. Blue crosses: ELM units; red x: GT units. (a) S, r, O, Af; (b) S, r, O, Af, no_sensors_at_sea.

To show the flexibility of the method, the solution of Figure 7 is repeated, where the placement of a sensor is restricted to OLs where an MSU is currently deployed. The current deployment was designed based on various considerations, both physical and demographic, thus it might be sub-optimal. Solving for the same number of OLs enables a comparison to the suggested optimal solution of our algorithm. When comparing the actual and optimal deployments, the difference is clearly noticeable. The optimal solution distributes the MSUs based on their contribution to the total monitoring quality (Figure 8a), where the different types match the region's characters. However, the actual deployment didn't take these considerations into account, thus placing the MSUs in a manner that might lead to erroneous measurements and a less accurate exposure assessment (Figure 8b). Moreover, when removing the limitation on MSU number, we see that we better place an uneven number of units, 18 AQmesh and 12 ELM in total, to maximize the monitoring quality (Figure 8c). Computation time for all solutions was less than 1 second, each.

Figure 6. Case study region (Haifa, Israel). (A) region only; (B) OLs, 10 × 10 grid.

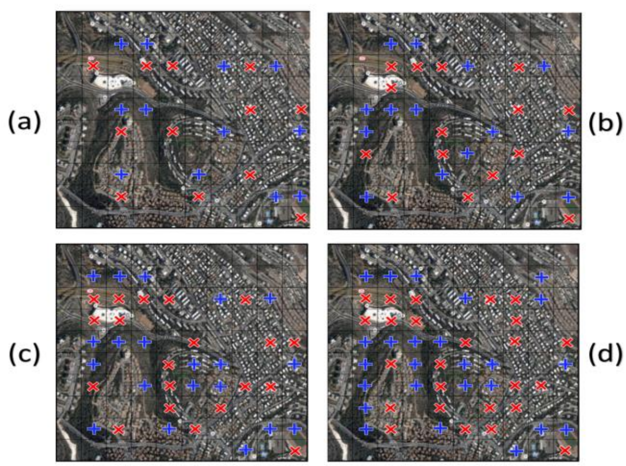

Figure 7. Optimal deployment in Haifa case study. Blue crosses: ELM units; red x: GT units; Maximum MSUs (per type): (a) 12; (b) 15; (c) 20 (d) 25.

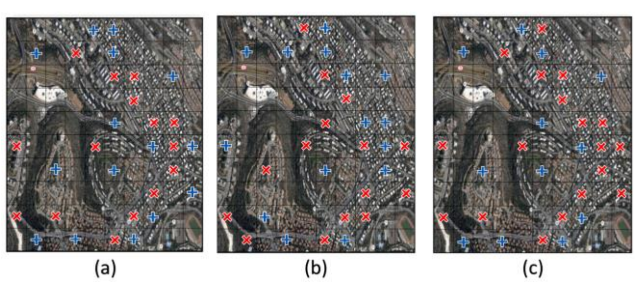

Figure 8. Optimal vs. actual deployment in Haifa case study. Blue crosses: ELM units; red x: GT units. (a) 15 MSUs of each type, optimal; (b) 15 MSUs of each type, actual; (c) Optimal deployment, no limitations.

4. Conclusions

The new algorithm, presented here, aims at finding the best deployment locations for air quality micro sensing units, deployed in a mixed residential or open area region. With the increasing number of air-quality monitoring networks deployed globally, arises the need to properly choose deployment locations to increase the WDESN monitoring potential. Previous attempts aimed at this goal didn't regard the unique characteristics of MSUs, when compared to standard AQM stations, thus leading to a limited solution.

As demonstrated here, both in the theoretical sense and when compared to a real case study of a functioning monitoring network, the above algorithm supplies an extremely fast, flexible solution, easily implemented in different regions and with a wide array of possible limitations and setups. This approach might also be extended for a 3-dimensional deployment scheme (Chakrabarty et al., 2002; Carter and Ragade, 2009), for the purpose of air-quality monitoring near high buildings and dense populated areas. This is a complex deployment scenario that is usually solvable using complex Computational Fluid Dynamics (CFD) models and limited sensor deployments (Woo et al., 2016).

Using this method, one can design the best possible deployment based on existing knowledge (available MSU types, cost, land use data of the desired region, etc.), and use this solution to avoid logistical problems throughout his deployment. Thus, this approach saves time, money, while maximizing the efficiency of the final, deployed WDESN.

Once a WDESN is deployed based on this approach, further techniques might be used to verify how well MSUs locations fit the deployment region (i.e. how efficient is the coverage, and does it represent the entire region), for example, by a random placement of MSUs in un-assigned locations, and comparison of the measured results with adjacent, assigned MSUs. This analysis can be performed using common methods for spatiotemporal correlation analysis in WSNs (e.g. Vuran et al., 2004; Pham et al., 2010; Villas et al., 2013; Almeida et al., 2017).

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