https://doi.org/10.5194/amt-2023-173
Preprint. Discussion started: 13 September 2023

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Hybrid Instruments Network Optimization for Air Quality Monitoring

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Abstract The significance of air quality monitoring for analyzing the impact on public health is growing worldwide. A crucial part of smart city development includes deployment of suitable air pollution sensors at critical locations. Note that there are various air quality measurement instruments ranging from expensive reference stations that provide accurate data to low-cost sensors that provide reasonable air quality measurements. In this research, we use a combination of sensors and monitors, which we call as hybrid instruments and focus on optimal placement of such instruments across a region. The objective of the problem is to maximize a satisfaction function that quantifies the weighted closeness of different regions to the places where such hybrid instruments are placed (here weights for different regions are quantified in terms of the relative population density and relative $PM_{2.5}$ concentration). Note that there can be several constraints such as those on budget, minimum number of reference stations to be placed, set of important regions where at least one sensor should be placed and so on. We develop two algorithms to solve this problem. The first one is a genetic algorithm that is a metaheuristic and works on the principles of evolution. The second one is a greedy algorithm that selects locally best choice in each iteration. We test these algorithms on different regions from India with varying sizes and other characteristics such as population distribution, $PM_{2.5}$ concentration, budget available, etc. The insights obtained from this paper can be used to quantitatively place reference stations and sensors in large cities rather than using ad hoc procedures or rules of thumb.

1 Introduction

According to the World Health Organization (WHO), ambient air pollution is a significant threat to people's health, causing around 6.7 million premature deaths annually in 2019 (Fuller et al., 2022). Shockingly, 99% of the global population resides in areas that don't meet WHO's air quality guidelines, with 89% of these premature fatalities occurring in low or middle-income countries (WHO, 2022; Pandey et al., 2021). To address this issue, it's crucial to develop suitable sensor networks by putting the air pollution monitors or sensors at appropriate locations, meeting the requirements of various groups in the city, and providing the much-needed information. Air pollutant concentrations have traditionally been monitored using reference stations (we will refer to them as monitors in this paper) which are highly accurate but also very costly, limiting their widespread deployment (Lagerspetz et al., 2019). To achieve accurate air pollution monitoring within metropolitan regions,

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hundreds or even thousands of reference stations are required, which proves costly to maintain and operate (Zikova et al., 2017). However, the emergence of low-cost air quality sensors presents an opportunity for higher-density deployments and improved spatial resolution in monitoring (Spinelle et al., 2017; Castell et al., 2017). Low-cost sensors offer a cost-effective solution, reducing installation and maintenance expenses and facilitating broader spatial coverage, particularly in remote areas. Therefore, in order to balance the accuracy of monitoring along with costs involved in such instruments, we will consider deployment of both monitors and sensors in this paper.

Some studies focus on optimizing air quality monitoring networks (AQMNs) using different models: physical models (Araki et al., 2015; Hao and Xie, 2018) and learning-based models (Hsieh et al., 2015). However, the accuracy of these methods relies heavily on the precision of the air quality models, and both Hao and Xie (2018) and Hsieh et al. (2015) required existing air quality measurements as inputs for their prediction models which largely depend on the quality and completeness of input data. The studies by Li et al. (2017), Brenzia et al. (2015), and Zikova et al. (2017) discuss ad-hoc placement of air quality sensors in their respective study regions or using some rules of thumb. But this shows that the placement of sensors is not optimized under the budget constraints that might be present. To address these challenges, it becomes crucial to develop more strategic approaches for placing air quality sensors. Properly optimized sensor placement can lead to a more comprehensive and accurate understanding of air pollution patterns, facilitating targeted pollution control measures and ultimately improving public health and environmental management.

Lerner et al. (2019) presents a method for optimizing sensor placement based on sensor characteristics and land use analysis. Sun et al. (2019) also proposes an optimal sensor placement strategy based on population density without relying on air pollution data. Their study highlights that humans naturally depend on the closest station to observe and obtain relevant information regarding the environment when multiple stations are present in a city. The satisfaction regarding the information increases as one moves closer to the adjacent station. Unlike Lerner et al. (2019), Sun et al. (2019) represent the benefit of placing a sensor in a particular grid to the citizens not just living in that grid but also to those living the nearby grids. However, Sun et al. (2019) has limitations that it does not incorporate air pollution data as a parameter in optimization, which raises concerns about the accuracy and reliability of the obtained results. Furthermore, both Lerner et al. (2019) and Sun et al. (2019) only consider deployment of one type of sensor but as we discussed in the previous-to-previous paragraph, both monitors (that are very accurate) and sensors (that are not that accurate but much more economical than monitors) should together be considered for deployment.

In this paper, we propose deploying a combination of low-cost sensors (referred to as sensors) and reference stations (referred to as monitors), termed hybrid instruments, in a specific region. Note that Castell et al. (2017) also highlighted that sensors alone may not provide accurate air quality measurements as compared to reference instruments or monitors. Our proposed approach aims to leverage the strengths of both sensors and monitors to enhance air quality monitoring in a cost-effective

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manner. We refer to the combination of sensors and monitors as hybrid instruments. We propose to develop a framework for placing hybrid instruments with the objective of maximizing the public satisfaction by considering emission spread and population density as parameters (while considering the benefit of placing instruments in nearby grids also and not just the grids where they are placed). Also, several noble constraints such as having at least one sensor in a given set of important grids (like important residential or commercial areas), not having monitors in certain given grids (like places with sparse population, water bodies, etc.), having a minimum number of grids where monitors should be placed in the network, etc., have been proposed in the optimization formulation. Therefore, following are the contributions of our work:

- Our research focuses on optimal deployment of hybrid air-quality monitoring networks consisting of monitors and sensors where the goal is to maximize public satisfaction by providing accurate air quality information while considering several budget and other constraints.

- We propose a Genetic algorithm (GA) and a greedy algorithm (GrA) to solve the developed optimization problem.

- We test the developed algorithms on networks of varying sizes and geographic locations.

This paper's remaining sections are organized as follows: Section 2 describes the optimization problem and presents the algorithms for solving the problem. Next section provides the numerical results tested using different algorithms under different settings. The final section concludes our study and provides future directions.

2 Methodology

This section is divided into two parts. The first part describes the problem statement for optimization of hybrid instrument network. The second part describes the methods proposed to solve the optimization problem. The second part is further sub-divided into two sub parts: GA and GrA respectively.

2.1 Problem Statement

The approach focuses on the utility gain of placement of sensors as per people satisfaction. Realising that humans naturally depend on the closest station to observe and obtain relevant information regarding the environment when multiple stations are present in a city, we assume that an individual's satisfaction $g(d)$ with a sensor deployment system is a function of his or her distance to the closest sensor d (Sun et al., 2019). Intuitively, the satisfaction with the information increases as one moves closer to the adjacent station. Therefore, $g(d)$ must satisfy the following conditions as stated in Sun et al. (2019): (i) $g(d)$ be a strictly decreasing function, i.e., for any $d1 \leq d2$, $g(d1) \geq g(d2)$, (ii) for any $d \geq 0$, $g(d) \geq 0$ and $g(0) = 1$. The

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foremost condition corresponds to the relation of satisfaction function with distance, while the latter ones assure the fact that the $g \epsilon [0,1]$ and g is the highest when the distance is zero. The following exponentially decreasing function $g(d)$ readily satisfies the aforementioned conditions (Sun et al., 2019):

$$g(d) = \exp\left(-\frac{d}{\theta}\right), \tag{1}$$

where θ is an exponential decay constant. In accordance with the standard procedure for environmental monitoring (Krause et al., 2008, Hsieh et al., 2015), we divide the city into distinct, equal-sized square grids. Then, we place our hybrid instruments (sensors and monitors) in these fragmented grids. Let $V = \{a|a = 1, 2 \ldots, n\}$ represent a set of grids in the interested geographical area, in which $n = |V|$ represents the total number of grids. For each $a \in \{1, 2 \ldots, n\}$, let p_a represent the percentage of people living in grid a, e_a represents the percentage of $PM_{2.5}$ emissions in grid a and m_a denotes the average of p_a and e_a of grid a i.e., $m_a = \frac{p_a + e_a}{2}$. Note that both population density and $PM_{2.5}$ emission percentage are important factors while deciding the relative importance of various grids. Population density reflects the concentration of people residing in that grid, while the $PM_{2.5}$ emission indicates the level of fine particulate matter in the air in that grid. Averaging the corresponding percentage values of these parameters provides a single value that quantifies the importance of a particular grid and allows comparing between different grids.

We will now introduce some variables to define the optimization formulation. Let S be a set of grids where instruments (sensors and monitors) are placed (i.e., set S consists of all grids a such that $z_a = 1$). The notations are summarized in Table 1 of appendix. For each $a \in \{1, 2 \ldots, n\}$, let x_a be equal to one, if a sensor is placed at grid a otherwise it is equal to zero, y_a be equal to one if a monitor is placed at grid a, otherwise it is equal to zero and z_a be equal to one if any instrument is placed at grid a, otherwise it is equal to zero. Let c be the cost of a sensor, c' be the cost of a monitor and P be the total available budget. Let B be the set of grids where at least one sensor should be placed. Let C be the set of grids where monitor cannot be placed. Let h be the minimum number of monitors that should be deployed. Let M be a very large positive number and m be a very small positive number. The formulation for optimally placing hybrid instruments is as follows:

$$\text{Max} \sum_{a=1}^{n} m_a . g(d(a)) \tag{2}$$

$$\text{s.t.} \sum_{a=1}^{n} (c x_a + c' y_a) \leq P \tag{3}$$

$$\sum_{a \, \epsilon \, B} x_a \geq 1 \tag{4}$$

$$\sum_{a \, \epsilon \, C} y_a = 0 \tag{5}$$

$$\sum_{a=1}^{n} y_a \geq h \tag{6}$$

$$M z_a + m \geq x_a + y_a, \forall \, a = 1,2, \ldots, n \tag{7}$$

$$x_a + y_a \geq z_a, \forall \, a = 1,2, \ldots, n \tag{8}$$

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where $d(a) = \min_{b \in V} \{z_b . d(a,b) + \overline{d}(a).(1 - z_b)\}$ and $\overline{d}(a) = \max_{b \in V} d(a,b)$.

The objective is to choose a subset of grids $S \subseteq V$ that maximizes the overall satisfaction percentage under given constraints. Here, $d(a)$ is the minimal distance between grid a and set S (assuming that S is not an empty set, which is the case because of the constraint in Equation (4)). The condition in Equation (3) is the budget constraint which states that the total cost of all instruments cannot exceed P. The condition in Equation (4) ensures that a sensor is placed in at least one of the grids belonging to the set B. Equation (5) ensures that no monitor is placed at any grid belonging to the set C (these grids can belong to locations like open areas, waterbodies, etc.). The condition in Equation (6) ensures that at least h number of monitors are deployed. Equations (7) and (8) are the definitional constraints for variable z_a. That is, they ensure that for each grid a, z_a is equal to one if $x_a + y_a \geq 1$ otherwise, z_a is equal to zero.

2.2 Methods

We will now present different algorithms to solve the proposed formulation. We will first introduce Genetic Algorithm (GA).

2.2.1 Genetic Algorithm

A Genetic Algorithm is a metaheuristic that is inspired by the natural selection process and genetics (Deb, 2001). It mimics the principles of survival of the fittest, crossover, and mutation to iteratively search for optimal solutions. The algorithm starts by creating an initial population of potential solutions, represented as strings or individuals. Consider a string comprising of $2n$ elements (n is the total number of grids), with the first n elements for the placement of sensors and the next n elements is for the placement of monitors. Each element in the string can take a value of either 0 or 1, where 1 indicates the presence of a sensor or monitor (depending on whether we are looking in the first n or last n elements) in the corresponding grid, and 0 indicates the absence. We now consider a modification of the above string where we remove the elements that correspond to monitors belonging to set C. The removed elements will always have value equal to zero due to the definition of set C (consequently, monitors will not be placed on the grids belonging to the C set) and thus they are separated so that the values of these elements do not change due different processes in GA. The aforementioned modified string is used in our problem. Each string encodes a set of decision variables, representing a candidate solution to the problem.

We define a fitness metric that is used to assign a relative merit (fitness) to each solution based on the corresponding objective function value and constraint violations. The fitness, $F(H)$, of any string H is calculated as follows:

$$F(H) = \begin{cases} fn & if\ H\ is\ a\ feasible\ sol\ string \\ fn_{min} - D_1 - D_2 - D_3 & otherwise \end{cases} \tag{9}$$

$$\text{Where, } D_1 = \begin{cases} 0 & \sum_{a=1}^{n}(cx_a + c'y_a) \leq P \\ \sum_{a=1}^{n}(cx_a + c'y_a) - P & Otherwise \end{cases} \tag{10}$$

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$$D_2 = \begin{cases} 0 & \sum_{a \in B} x_a \geq 1 \\ 1 & Otherwise \end{cases} \tag{11}$$

$$D_3 = \begin{cases} 0 & \sum_{a=1}^{n} y_a \geq h \\ h - \sum_{a=1}^{n} y_a & Otherwise \end{cases} \tag{12}$$

Here, fn is the objective function value for string H as obtained by Equation (2), fn_{min} is the minimum value of objective function values over all the feasible solution strings in a given population of strings, and D_1, D_2 and D_3 are penalty values for violating constraints in Equation (3), (4) and (6), respectively. Note that there is no penalty value for violating the constraint in Equation (5) as that is automatically satisfied due to the way we define our strings (recall that we removed the elements corresponding to the grids of set C).

In each generation (or iteration) of GA, the Roulette Wheel Selection (RWS) is used to select solutions from a population based on their fitness values (Deb, 2001). RWS provides a proportional selection mechanism where fitter solutions have a higher probability of being selected, but it still allows weaker solutions to have some chance of being chosen. After the selection procedure, crossover procedure is followed where two strings are randomly selected from the mating pool, and a partial interchange from both strings is done to generate two new strings. We use the two-point crossover operator where two distinct crossover points divide the strings into three substrings and the middle substring is exchanged between the strings (Deb, 2001). After crossover, mutation procedure is carried where the mutation operator alters 1 to 0 or vice versa in each element of a string with probability P_m (referred to as the mutation probability). Note that mutation helps in maintaining diversity in the population. After applying the genetic operators, parent population and offspring population are combined, strings in the combined population are sorted in non-increasing order and the top half of the combined population is selected as the population for the next generation. This process is repeated over multiple iterations or generations until the termination criteria (to be specified next) is met. We now describe the termination criteria. Let the average fitness value of strings in the population of ith iteration or generation be k_i. Let N be the maximum number of iterations of GA that are allowed. Then, the algorithm stops at the end of the ith iteration if $\left|\frac{k_i - k_{i-1}}{k_{i-1}}\right| \leq \alpha$ (where α is a given value) or if i becomes equal to N.

2.2.2 Greedy Algorithm

The second method to solve the optimization problem from Section 2.1 is a Greedy Algorithm (GrA). A GrA iteratively comes up with a solution by making choices that are locally optimal in each iteration but it is not guaranteed to produce an optimal solution. In this algorithm, we first place a sensor at one of the locations from set B to satisfy Equation (4). This placement is done by selecting the grid with the highest m_a among the set B. Then, we find the placement location for h monitors to satisfy Equation (6) by ensuring that Equation (5) (which tells us about the grids where monitors can't be placed) is not violated. We

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now define grid location s^* with largest information gain as $s^* = \sum_{a=1}^{n} m_a \left(g\left(d'(a, K \cup s)\right) - g\left(d'(a, K)\right) \right)$ where K is the set of grids that have either a sensor or a monitor already placed (note that K is not an empty set because we have at least one grid belonging to set B that has a sensor placed) and $d'(a, K)$ represents the minimum distance between grid a and set K. The placement of h monitors is done by repeatedly choosing the grid location with largest information gain s^*. Let $P' = P$, where P' is the budget that remains after we reduce the cost of different instruments that are placed in different iterations of GrA. After the placement of one sensor plus h monitors, the available budget $P' = P - c - hc'$. After satisfying Equation (6), there is no benefit of placing more monitors that are costly and thus we target to place sensors. We keep placing sensors such that the grid location with the largest information gain s^* is selected while ensuring that P' is updated with every placement of sensor and budget constraint is satisfied.

3 Results

In this section, we will present results by testing our proposed algorithms in different settings. Our algorithms have been employed in two distinct areas within Surat and Mumbai cities. Both algorithms were implemented in MATLAB and executed on computer with Intel® Core™ i7-2600 processor and 8 GB RAM.

3.1 Surat City

We first consider a portion of Surat which a major city in the state of Gujarat, India, for optimal placement of air quality instruments. In this study, we take a pilot project area of 5 km x 5 km in Surat and divide it into 25 grids (thus each grid is of the size 1 km x 1 km). For calculating the optimal locations for hybrid instruments, we use the average percentage of population density (World Bank provides population density data at a spatial resolution of 1 km x 1 km) and $PM_{2.5}$ emission data (The Energy and Resources Institute (TERI) provides $PM_{2.5}$ emission data for Surat city at a spatial resolution of 1 km x 1 km) for the part of Surat city that we focus.

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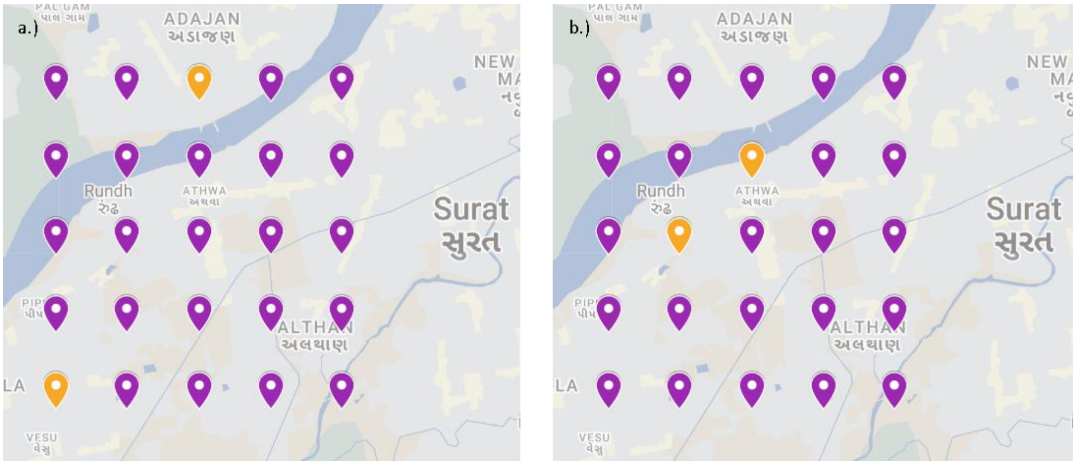

Fig 1. Hybrid sensor placement obtained by GA (left) and GrA (right) for the Surat network with budget value of \$313000. © Google Maps 2023.

Figure 1 displays the placement locations of sensors (purple points) and monitors (orange points) in Surat city as obtained by Genetic algorithm (left) and Greedy algorithm (right). The parameter values that are used in this placement are as follows: cost of a sensor (c) is \$3000, cost of a monitor (c') is \$122000, total available budget (P) is \$313000, value of θ and h are 1 and 2 respectively. The GA parameters that are used are as follows: population size is equal to 1000, mutation probability (P_m) is equal to 0.1, maximum number of iterations or generations is 500 and value of α is 10^{-5}.

Figure 2 shows the values obtained and computational time for the two algorithms, considering different total available budgets (i.e., P). The minimum budget that is considered is \$253,000, which is equal to the cost of three sensors plus h monitors. The maximum budget in Figure 2 is \$313,000, which allows for the placement of 2 monitors and 23 sensors, covering the entire portion area (as there are a total of 25 grids) under minimum possible budget as at least 2 monitors need to be placed by Equation (6).

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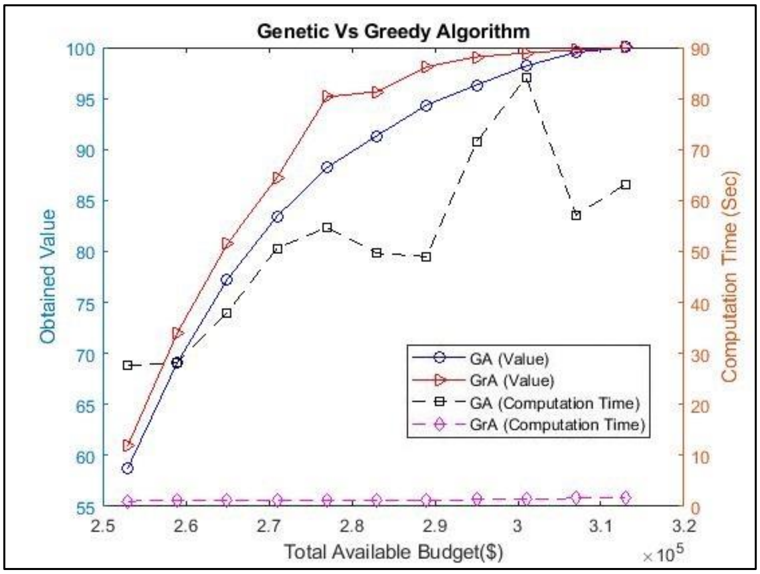

Fig 2. Plot comparing genetic vs greedy algorithms for varying total available budget values.

From Figure 2, it can be observed that, for most budget points, the obtained value is higher for GrA compared to GA, except for the $313,000 budget where both algorithms yield the same value. Also, note that the obtained values for both the algorithms increase with the increase in budget because it is possible to place more instruments with the increase in budget and that results in increase in the overall satisfaction function value. Note that the computation time of GA is significantly larger than that of GrA because GA samples through a set of possible solutions and iteratively applies various operators such as selection, crossover and mutation whereas GrA is a deterministic algorithm that comes up with a single solution.

3.2 Mumbai City

We now present the results that we tested for portions of the Mumbai, which is the financial hub of India. In this case, we only considered the contribution of population in the objective function (i.e., $m_a = p_a$) due to unavailability of $PM_{2.5}$ emission data for Mumbai city. However, the aforementioned change does not have any significant issue on the results that we present as we plan to test the effect of varying the budget (as in the last section) and the effect of varying the size of the network (i.e., the number of grids). All the parameter values for the algorithm's execution were maintained consistently as above in Surat city, except for the variable θ, which has now been set to 5 (note that θ has been increased now because we have larger number of grids in Mumbai network as compared to Surat, resulting in higher average distances between the grids for the Mumbai network and thus we need to update θ for better normalization). Consider a region of size 10 km x 10 km in Mumbai City that has been divided into 100 grids (i.e., each grid is of the size 1 km x 1 km). Figure 3 shows the variation of values obtained and

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computation time with total available budget for GA and GrA for this region. The solid lines represent the obtained values and dashed lines are used to represent the computation time in seconds for different algorithms. It can be seen that the genetic algorithm (GA) provides higher value as compared to the greedy algorithm (GrA) for most of the cases, which is opposite to that observed in the previous section. Thus, it highlights the importance of GA in obtaining values that are closer to the optimal as compared to GrA when the network size increased (however this advantage comes at the high computational cost of GA as compared to GrA).

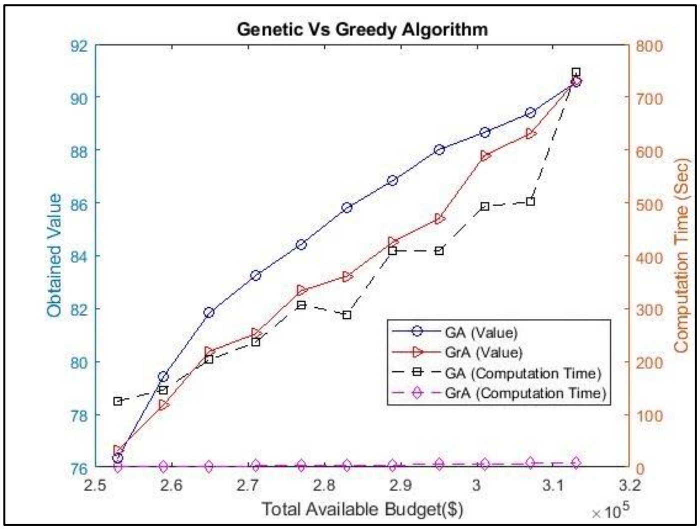

Fig 3. Plot comparing genetic vs greedy algorithm for varying total available budget values.

Figure 4 shows us the placement of hybrid instruments obtained for the two algorithms (GA and GrA) when the budget is equal to $283000 when we have all the parameters the same as that in Figure 3. The blue and orange points represent the placement of sensors and monitors, respectively. From Figure 4b that represents the hybrid sensor placement by GA, it is evident that sensors and monitors are mainly concentrated in the bottom-leftmost region. In contrast, Figure 4a shows a more diverse or scattered distribution of sensors and monitors. It is because GA samples through various solutions to procced towards a solution is closer to the optimal whereas GrA is a deterministic algorithm and may get stuck near a locally optimal solution.

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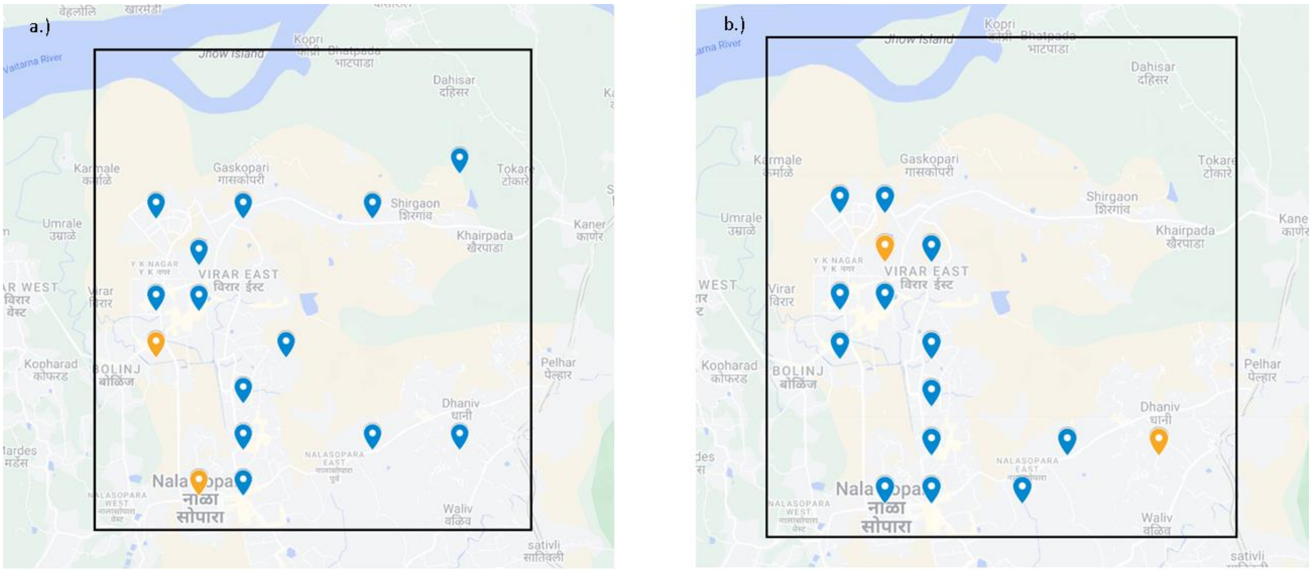

Fig 4. Sensor placement obtained by GA (left) and GrA (right) for 10 km x 10 km (100 grids) region in Mumbai when the budget is equal to $283000. © Google Maps 2023.

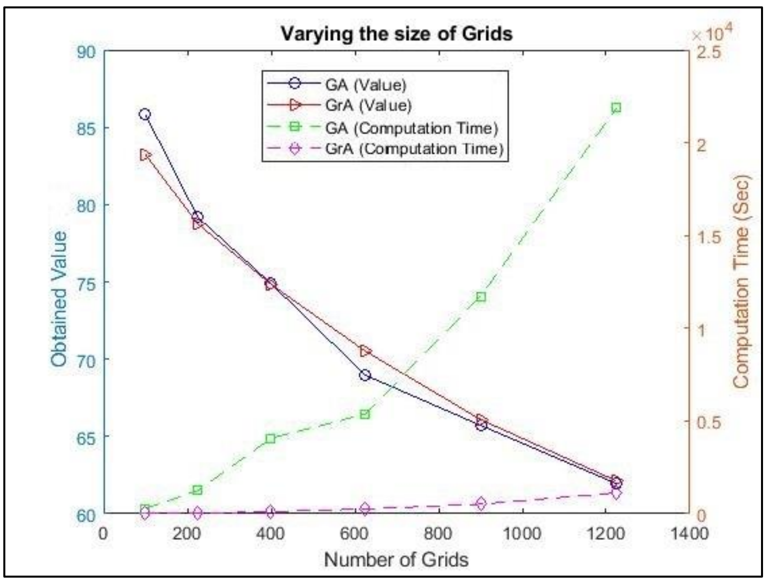

Fig 5. Plot comparing genetic and greedy algorithms for varying number of grids.

Figure 5 shows the comparison between GA and GrA with varying number of grids for the budget value of $283000. The solid lines represent the obtained values in percentage for different algorithms and dashed lines are used to represent the computation time in seconds for different algorithms. As the number of grids increases, there is a noticeable decline in citizen satisfaction

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(i.e., the obtained values) because the budget P remains the same and thus the satisfaction averaged across all the grids reduces as it gets distributed across the total region (note that the percentage of population in each grid also reduces as the number of grids increase and thus that also contributed to the observed trend). Also, the values obtained by GA and GrA are similar and in some cases GA outperforms GrA whereas the reverse happens in other cases. Note that the computation time required for GA increases rapidly with the increase in the number of grids because with the increase in the number of grids, the size of each string in GA increases and it takes more iterations before the termination criterion is reached in GA (as the number of feasible solutions increase with the increase in grid size). However, the increase in the computational time of GrA is not that high as it is a polynomial-time algorithm (Cormen et al., 2022), i.e., the computational time increases polynomially with respect to the increase in the problem size (i.e., the number of grids in our problem).

4 Conclusions

This research paper proposed an optimization formulation for placement of hybrid instruments (sensors and monitors). The objective of the problem is to maximize the satisfaction function while satisfying various constraints for the placement. To solve this formulation, we proposed two algorithms: a genetic algorithm (GA) which is a metaheuristic that works using the principles of evolution and a greedy algorithm (GrA) that makes choices that are locally optimal in each iteration. We tested the placement solutions generated by these algorithms on networks from different locations (Surat and Mumbai) that differed over sizes and characteristics (population distribution, budget and $PM_{2.5}$ distribution). We observed that as the total available budget increased, the obtained values from the two algorithms also increased as it became possible to place more instruments (sensors and monitors). We found that GrA is very computationally efficient as compared to GA, but we found that both GrA and GA provided close values when the number of grids were large (in some cases GA outperformed GrA whereas in other cases the reverse happened). Note that since GA searches through a set of solutions over multiple iterations and uses operators like mutation it has a better likelihood of getting towards the optimal solutions whereas GrA may get stuck near a local optimum in some cases. These findings suggest that if time is not constrained (i.e., we have a few days to decide the placement solution) it might be better to use GA and GrA together (i.e., use the best solution out of the two algorithms) to place the instruments whereas in scenarios where there is scarcity of time, it is advised to use GrA. Our research aims to provide valuable insights for future government decision-making processes regarding the optimal deployment of hybrid instruments in cities lacking an existing sensor network. But there are several interesting future extensions of this work that are possible. For instance, we assumed a particular form of the satisfaction function (consisting of exponential terms) but other forms can also be tested. Similarly, other factors apart from population density and $PM_{2.5}$ concentration such as socio-economic disparities across various grids can also be factored while determining the satisfaction function.

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Appendix

Table 1

Notations	Description
V	Set of all grids
n	Total number of grids
S	Set of grids selected for deploying hybrid instruments
$g(d)$	A function of d
θ	Exponential decay parameter
p_a	Percentage of population living in grid a
e_a	Percentage of concentration of $PM_{2.5}$ in grid a
m_a	Average of p_a and e_a
c	Cost of each sensor
c'	Cost of each monitor
P	Total available budget
h	Minimum number of monitors to be deployed
z_a	Binary variable signifying whether a sensor or a monitor is placed at grid a or not
x_a	Binary variable signifying whether a sensor is placed at grid a or not
y_a	Binary variable signifying whether a monitor is placed at grid a or not
B	Set of grids where at least one sensor is to be placed
C	Set of grids where monitors cannot be placed
M	A very large positive number
m	A very small positive number
P_m	Mutation probability
N	Maximum number of iterations of GA that are allowed
$d(a)$	Minimum distance between grid a and the grids containing hybrid instruments
$d(a,b)$	Distance between grid a and grid b
$\overline{d}(a)$	Maximum distance between grid a and any other grid of set V
$d'(a,K)$	Minimum distance between grid a and set K

Author Contribution

HG and SNT led the conceptualization of this work. NA did the data curation. HG proposed the methodology. NA performed 290 the coding and software part. HG and SNT supervised this work. NA prepared the original draft. All the authors contributed to review and editing.

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Competing Interests

The contact author has declared that none of the authors has any competing interests.

Data availability

The data shown in the paper are available upon a reasonable request from the corresponding authors.

Acknowledgements

The authors would also like to acknowledge the support of Centre of Excellence (ATMAN) approved by the office of the Principal Scientific Officer to the Government of India. The CoE is supported by philanthropies including Bloomberg Philanthropies, the Children's Investment Fund Foundation (CIFF), the Open Philanthropy and the Clean Air Fund and author SNT also acknowledges J C Bose award (JCB/2020/000044).

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