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Finding Optimal Stations Using Euclidean Distance and Adjustable Surrounding Sphere

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Abstract: Air quality monitoring network (AQMN) plays an important role in air pollution management. However, setting up an initial network in a city often lacks necessary information such as historical pollution and geographical data, which makes it challenging to establish an effective network. Meanwhile, cities with an existing one do not adequately represent spatial coverage of air pollution issues or face rapid urbanization where additional stations are needed. To resolve the two cases, we propose four methods for finding stations and constructing a network using Euclidean distance and the k-nearest neighbor algorithm, consisting of Euclidean Distance (ED), Fixed Surrounding Sphere (FSS), Euclidean Distance + Fixed Surrounding Sphere (ED + FSS), and Euclidean Distance + Adjustable Surrounding Sphere (ED + ASS). We introduce and apply a coverage percentage and weighted coverage degree for evaluating the results from our proposed methods. Our experiment result shows that ED + ASS is better than other methods for finding stations to enhance spatial coverage. In the case of setting up the initial networks, coverage percentages are improved up to 22%, 37%, and 56% compared with the existing network, and adding a station in the existing one improved up by 34%, 130%, and 39%, in Sejong, Bonn, and Bangkok cities, respectively. Our method depicts acceptable results and will be implemented as a guide for establishing a new network and can be a tool for improving spatial coverage of the existing network for future expansions in air monitoring.

Keywords: Euclidean Distance; spatial coverage; air quality monitoring network; sustainability monitoring

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1. Introduction

Air quality monitoring networks (AQMN) are established as tools that determine policies and strategies for achieving air quality standards. A plan for designing an AQMN depends on objectives such as urban planning, environmental policies, and budget. Generally, designing an AQMN is done by environmental authorities or governmental organizations based on empirical judgments. An expert group assesses various criteria to make their decisions, such as budget and population thresholds. These play a significant role in determining the required number and location of monitoring stations. For example, Thailand and South Korea set up air monitoring stations in government office areas to reduce the cost of installation, maintenance, and the safety of the devices [1,2]. Guidelines of the USA and Australia suggest installing new air quality monitoring stations based on population size [3,4]. In such cases, monitoring stations are often considered in an ad hoc fashion.

The critical issues in AQMN designing are separated into a setting up network for allocating optimum stations and optimizing the existing network to better reflect air quality in the area. There are different methods to design a new network, all of which must comply with the Environmental Protection Agency (EPA) guideline or local government regulations [5]. Furthermore, various studies mainly consider pollution data, population density, land-use regression, distance to major roads, and high-risk observation regions to identify new air quality monitoring stations [6–10]. Some studies investigated pollution indicators in the area surrounding stations [11–13]. Such a zone is called a sphere of influence (SOI) and the original algorithm was developed by Liu et al. in 1986. Their proposed method uses air pollution data to determine spatial coverage and the number of air monitoring stations [14].

Optimization, evaluation, and revision of existing AQMN to meet changing local area pollution levels has been an important research topic over the past few decades [15–18]. The main cause regarding the distribution of air pollution and emission source changed caused by urbanization. The rapid expansion of the urban areas in developing countries of Asia leads to air quality monitoring issues such as excessive numbers of stations in urban regions and a lack of adequate numbers of stations in rural areas [19]. Consequently, several approaches have suggested adding or removing stations by considering various constraints such as population density, historical pollution data, terrain conditions, budget, and health impact. They use statistical analytics, weight criteria, holistic approaches, data simulation, and pure measurement for AQMN optimization [20–22]. Moreover, some studies apply terrain maps, heat maps, gridded synthetic assessment, and graphical information systems (GIS) to show high pollution concentration areas. They analyze pollution criteria and combine them with spatial statistics to determine suitable areas to recommend for station location sites [23–27].

However, studies of optimal designs or revision of AQMN in less developed countries (LDCs) are relatively scarce. Such studies in the literature are mostly related to minimizing air pollution's health impact [28,29]. The LDCs have different issues than in developed countries, such as limited budgets to establish the stations, lack of historical pollution data, and requirements that demand air pollution monitoring cover vast areas. All of these constraints are critical factors for AQMN design [30]. Therefore, recommending the station location to cover a prospective land use expansion has an important key role for sustainable development of air pollution control and helps assess air pollution's spatial variability for better monitoring of air quality [31].

Previous studies attempted to design air monitoring networks by considering specific air pollution concentration, cost, population data, and other parameters, while spatial coverage was ignored. Such a design methodology causes station locations to have high density in some particular regions, especially in urban areas. It does not distribute coverage to rural areas with a sufficient number of stations. The incremental building of air quality monitoring in urban areas can make better monitoring of the specific areas. However, it leads to an increase in installation and maintenance costs, which is one of the main constraints for designing a dense air quality monitoring network. Furthermore, none of the methods in previous studies mentioned designing an AQMN without historical pollution data or city characteristics data. Furthermore, it is important to consider that the air monitoring networks designed are not only for use today but also for urban expansion in the future.

We organized the rest of the paper as follows. Problem formulation is introduced in Section 2. We describe the study areas in Section 3. In Section 4 proposes four methods for finding the best next station, which includes algorithms and equations. In Section 5, the evaluation criteria will be explained. The results of the proposed methods are compared and discussed in Section 6. Finally, Section 7 draws our conclusion and suggests possible future work.

2. Problem Formulation

The studied problem is based on finding the next stations to achieve maximum spatial coverage. We apply the concept of Euclidean Distance and the k-nearest neighbor algorithm (k-NN) to calculate the distance between station neighbors. The objectives are set up a network and improve an existing network. In the preparation process, we divide map of study areas into a square of a grid and identify latitude longitude pairs at the centroid of all grids. Such geographic coordinates are used to calculate the distance. Given only a study area map and a specified number of stations, how can one calculate and recommend the stations to achieve maximum spatial coverage? The objective is to find the stations which meet the following constraints:

(i) Achieve maximum spatial coverage while maintaining proper overlapped area between the nearest-neighbors' stations
(ii) Propose methods without using historical pollution and city characteristics data.

The proposed method was tested and demonstrated in three real cities and compared with existing network coverage. This study can provide recommendations for environmental authorities or city planners to select the stations for increasing spatial coverage of air quality monitoring.

3. Study Areas

This study used three cities—Sejong: South Korea, Bangkok: Thailand, and Bonn: Germany—as the primary research areas. The three cities are developed smart city prototypes facing urban expansion shortly. Another reason for our choices is that the three regions have different sizes and shapes. The sizes of the cities in ascending order are Bonn, Sejong, and Bangkok, respectively. Because the size of Sejong is in the middle, we chose Sejong city as the primary implementation, and the other two cities are used as test cases. Our study areas are described in this section.

Sejong city is located almost the middle of Korea on a long, stretching mainly north to south. The population was about 350,000 in October 2020, and the size of Sejong city is 465.23 km^2. Sejong was specifically designed to be a smart city, so it serves as an example of the standard for the other cities experimenting with developing smart city infrastructure. Sejong city has four air quality monitoring stations, as shown with triangle symbols in Figure 1a. For this study, the whole area of the city is divided into 2024 grid cells of 500×500 m, as shown in Figure 1d.

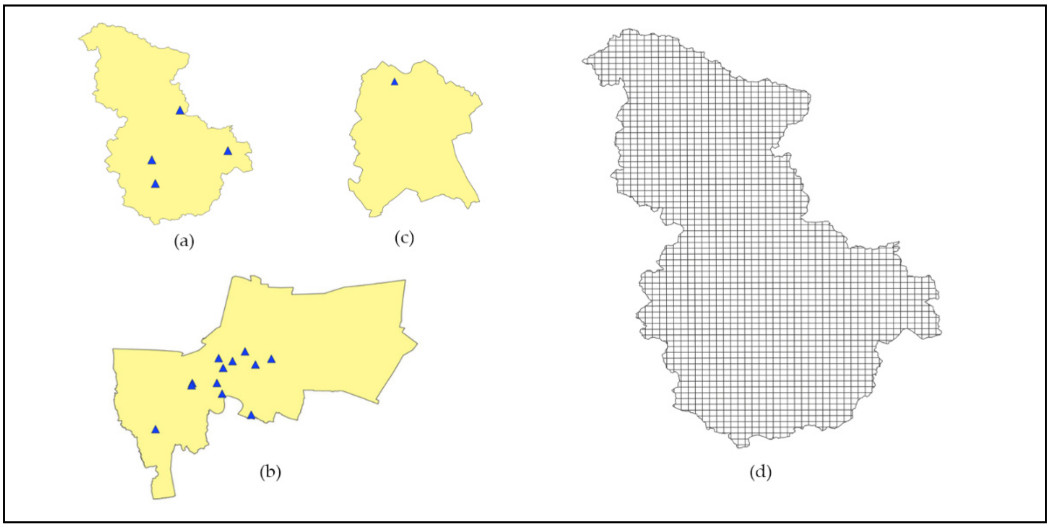


Figure 1. Study areas (**a**–**c**) show administrative boundaries, and triangle symbols show current stations. The map regions (**d**) divided into 2024 grid cells in Sejong city.

Bangkok is the capital city of Thailand. The city is located in almost the middle of Thailand and occupies 1568.7 km^2. Because this city has the highest population density in Thailand, Bangkok city has an air pollution problem from traffic and energy consumption. There are 12 air quality monitoring stations from the pollution control department, which are depicted with the triangle symbols, as shown in Figure 1b. Our experiment divided the area of Bangkok into 7010 grid cells of the same size as we used for Sejong city.

Bonn city is located in western Germany and occupies 141.06 km^2. This city is one of eight major smart cities studied and one of two cities that will now access their brand new 5G network. Bonn has only one air quality monitoring station, which is located in the north of the city. Figure 1c shows the map and location of the air quality monitoring station in Bonn. Furthermore, for our experiment, the whole area of the city is divided into 653 grid cells.

4. Proposed Methods

In this study, finding optimal stations' main target goal is achieving the maximum spatial coverage while still preserving appropriate overlapping areas. The maximum spatial coverage designed can be realized through the optimal placement of the stations in the city. Moreover, maintaining a relevant overlapped area can enhance effectiveness for more reliable and accurate data collection. Accordingly, in this section, we proposed finding the stations based on the Euclidean Distance and the k-nearest neighbor's algorithm (k-NN). The proposed methods framework consists of four main methods and two evaluation criteria, as shown in Figure 2.

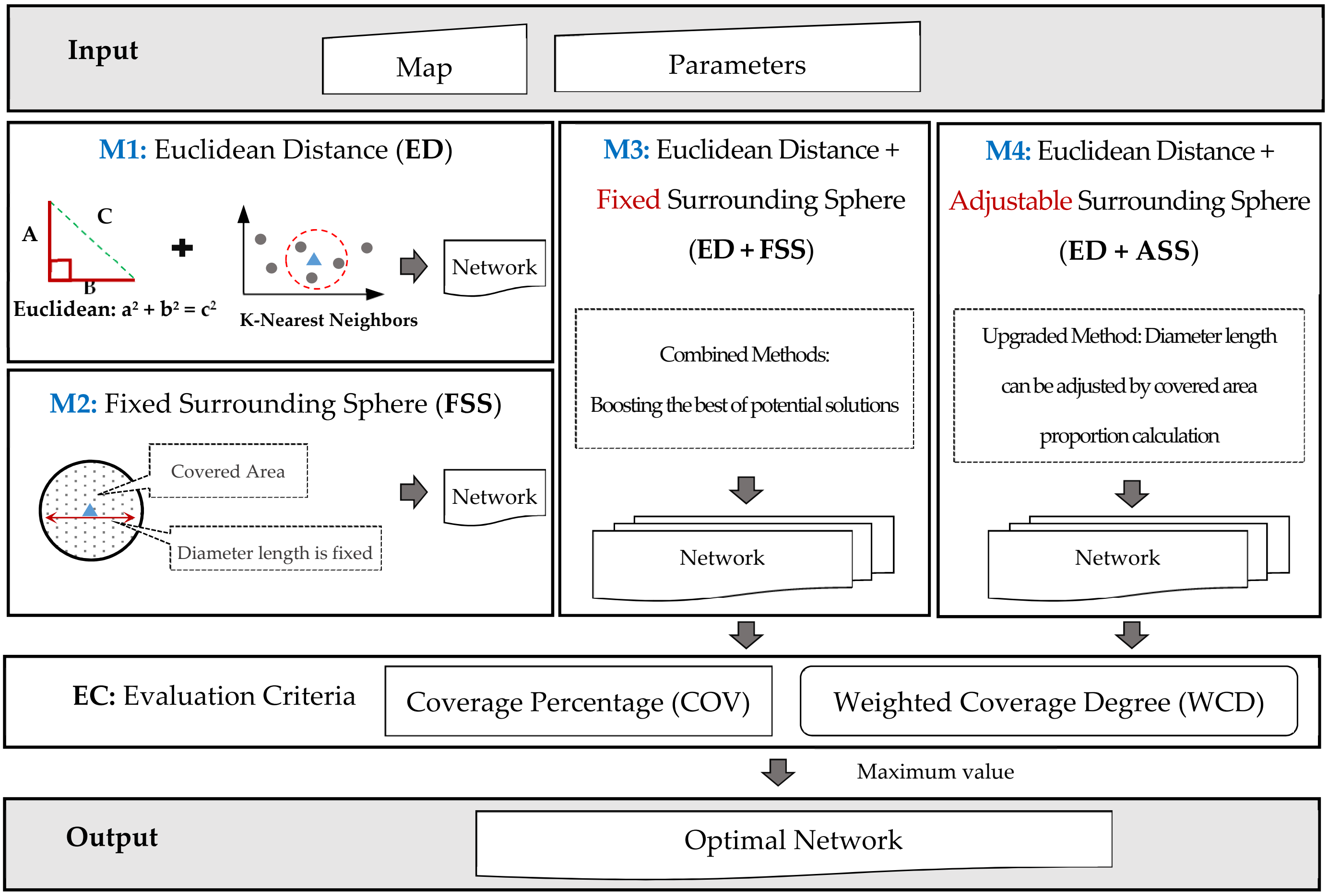


Figure 2. The framework of proposed methods.

In the proposed framework, our input consists of a map and parameters. The map of the study area is divided into a square of continue grid. A centroid of each square grid is a point that consists of latitude-longitude coordinates. For simple understanding throughout this paper, we use the term "location" (L_i), $i = 1 \ldots N$ to represent the centroid of a grid. The parameters consisted of (i) a grid index at the center of the map, (ii) a specified number of stations, and (iii) the diameter length of the surrounding sphere of each station as described in Section 6.1. Next, we give stations in area A, which consist of η stations. The value $S = \{S_j, \ldots, S_\eta\}$ is a list of stations. Each station S_j, $j = 1 \ldots \eta$ is at a location in our study area. All of the input will use to calculate by our proposed methods.

M1: Euclidean Distance (ED) and M2: Fixed Surrounding Sphere are the initial method for finding the next stations. The M3 method is a combination of previous methods. The M4 is an upgraded version of M3. Our evaluation criteria, coverage percentage (COV), and weighted coverage degree (WCD) are used to evaluate the results from the methods then return the optimal network. The comprehensive methods are described in the following sections.

4.1. Euclidean Distance (ED)

In this study, we apply the Euclidean Distance function to calculate distance from location (L_i) to three nearest neighbor stations $\{NS_1, NS_2, NS_3\}$, as illustrated in Figure 3. We use k-NN (k = 3) because the nearby stations can exchange data reliability with existing stations. Let NS_1, NS_2, and NS_3 be members of the set of nearest neighboring stations of L_i, where L_i is a position to calculate ED_i. We calculate the Euclidean Distance (ED_i) at any L_i as:

$$ED_i = \sqrt{\left(D_{L_i,\ NS_1}\right)^2 + \left(D_{L_i,NS_2}\right)^2 + \left(D_{L_i,NS_3}\right)^2} \tag{1}$$

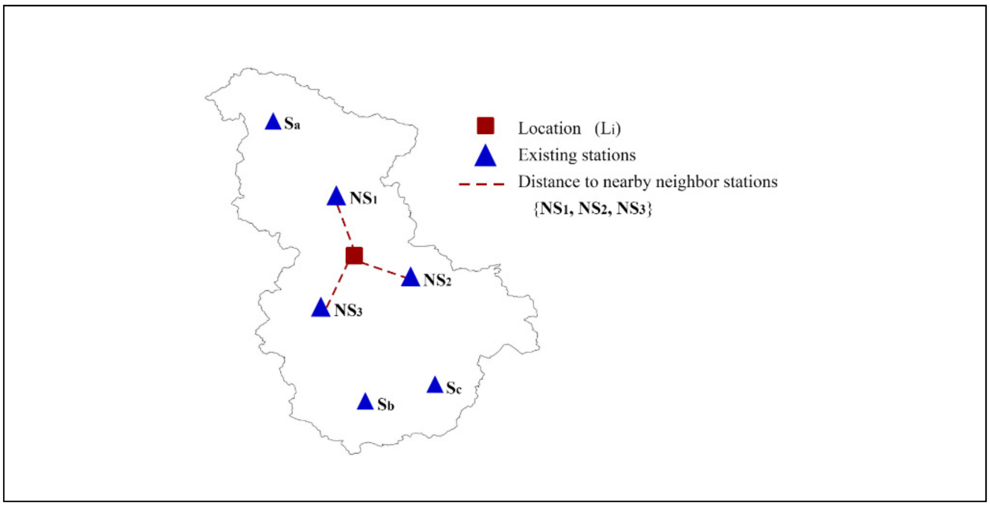


Figure 3. The location of L_i and its nearest neighbor stations NS_1, NS_2, and NS_3.

ED_i denotes Euclidean Distance at L_i, where i is an index of the location, and each parenthesized value is the distance from L_i to NS_1, NS_2, and NS_3, respectively. If $k < 3$, then we adapt the equation by using only existing stations. For example, if $k = 2$, then D_{L_i,NS_3} is equal to zero. Thus, ED_i is calculated using only D_{L_i,NS_1} and D_{L_i,NS_2}.

In order to calculate and find the next station, the following definitions are used. Let S denote a list of stations in a network and let L_t be a candidate station to be evaluated for the possibility of it being the next station. Thus, the current station network is $S + L_t$. Here, we calculate ED_i according to Equation (1). Subsequently, we sum ED_i values as:

$$TED_{L_t} = \sum_{i=0}^{N} ED_i \tag{2}$$

TED_{Lt} denotes the total of ED_i, where L_t is a candidate for the next station, and N is the number of locations. The candidate with the lowest TED_{Lt} will be defined as the additional station.

4.2. Fixed Surrounding Sphere (FSS)

The fixed surrounding sphere (FSS) method was inspired by the original sphere of influence (SOI) [12]. We applied such an idea for determining the area surrounding each station without using pollution concentration data. The constant value is identified to a diameter length of FSS with reference to city air quality monitoring network designing in Seoul city [2]. In Seoul's existing air monitoring network, the 25 stations are located approximately 5 km away from each other. They are not located close to the road, high emission concentration sources, or high-density population areas. On the other hand, these stations are distributed throughout the city. Consequently, we predefined a fixed diameter (dm_s) of FSS to divide the covered and non-covered areas under stations. As shown in Figure 4, the triangle symbols represent stations. The surrounding covered area of the stations is illustrated as a circle shape in Figure 4a and a pie shape in Figure 4b by determining a diameter length. The areas outside represent the non-covered areas. The shapes depend on the position of stations on the map. However, such areas are defined as covered areas, although the shapes of the areas are different.

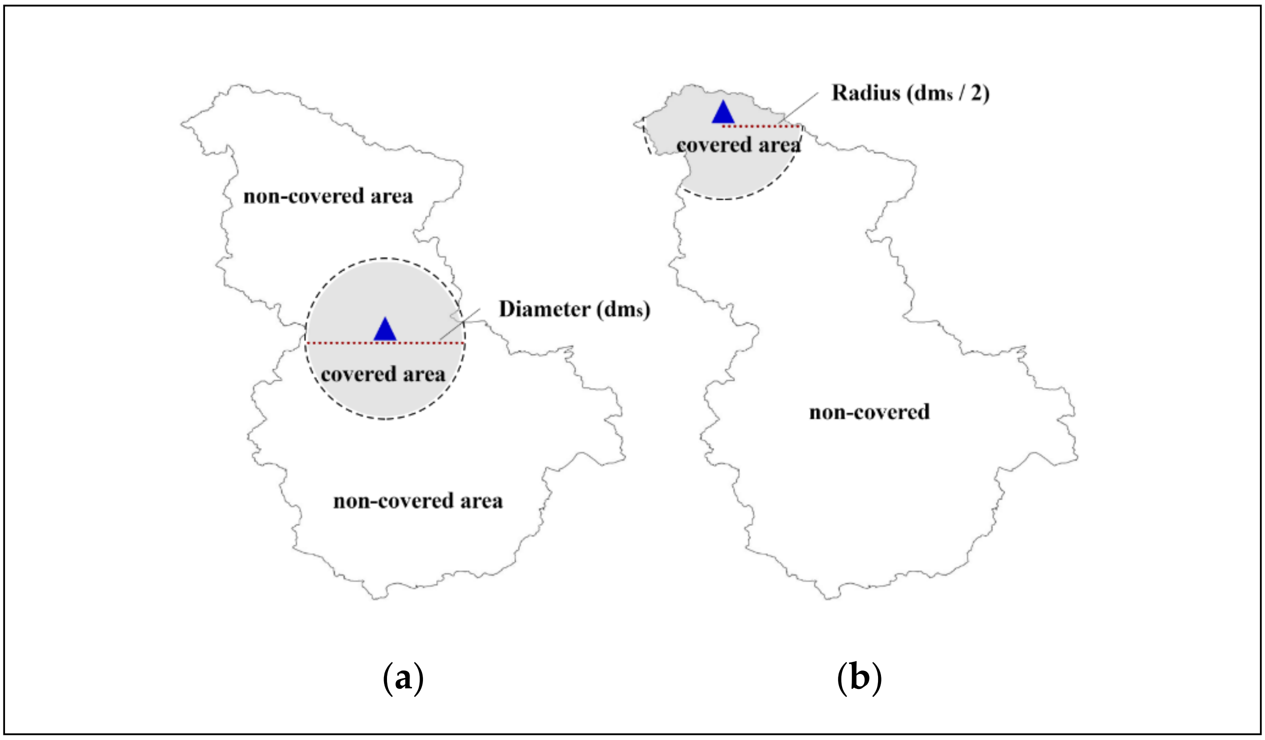


Figure 4. The (**a**) circle and (**b**) pie shapes indicate the covered areas by stations at the different positions on the map by determining a diameter length.

The procedure to classify the covered and non-covered areas under a station are described in this subsection. Let station S_j be a location of station and the diameter of S_j be equal to dm_s. The location (L_i) is covered (monitored) by a station S_j when the distance from L_i to S_j is less than $\frac{dm_s}{2}$ and also such L_i will be members of all covered areas for A_{sj}. Equation (3) represents the probability p(L_i,S_j) that a location is covered by station S_j.

$$\mathrm{p}(L_i,\ S_j) = \begin{cases} 1: \text{“covered area”},\ if\ distance(L_i, S_j)\ \leq\ \frac{dm_s}{2} \\ 0: \text{“non} - \text{covered area”},\ otherwise \end{cases} \in\ A_{Sj} \quad (3)$$

i is the index of location from 0 to $N-1$, where N represents the number of locations in area A, and j provides an index of stations in S.

The Algorithm 1 Fixed Surrounding Sphere (FSS) can be described as follows:

Algorithm 1. Fixed Surrounding Sphere (FSS)

Input: Map; a specified number of stations; index of center of map;
Identify the first station at center of map and insert into station list $S = \{S1\}$.
  while a specified number of stations is not satisfied **do**
    while all L_t in the non-covered area have not been tried **do**
      Select candidate station (L_t) and we temporarily append L_t to the station list S.
      Classify covered and non-covered areas of S with Equation (3).
      Calculate the total of the non-covered area and pass value to the #poor variable.
      Remove the temporarily added L_t from S.
    end while
    #poor values are compared.
    The L_t with the smallest value of #poor will be chosen as the next location of station.
    L_t is permanently appended to the station list S.
  end while
return List of stations S. *# The output is a list of stations with the first station at S1. For examples:*
 # $S = \{S1, L_a, L_b, \ldots, L_\eta\}$

4.3. Euclidean Distance + Fixed Surrounding Sphere (ED + FSS)

This method combines the concepts Euclidean Distance (ED) and Fixed Surrounding Sphere (FSS). However, the difference between this method and the previous one is the location of the first station. For ED and FSS, the first stations are set at the center of the map, while for ED + FSS, all map locations are tried as a first station. The output of this method is a multi-list of stations in which the first stations are different. Consequently, further evaluation criteria have been introduced to evaluate the best network with a maximum of spatial coverage.

We divide ED + FSS into two processes: (i) finding the next stations and (ii) evaluating a maximum coverage percentage while still preserving an appropriate overlapped area for the network. The first process, finding the next stations, is described with Algorithm 2 Euclidean Distance + Fixed Surrounding Sphere (ED + FSS) as follows:

Algorithm 2. Euclidean Distance + Fixed Surrounding Sphere (ED + FSS)

Input: Map; a specified number of stations;
For each L_i in map **do**
  select L_i and insert into station list, $S = \{L_i\}$.
  while a specified number of stations is not satisfied **do**
    while all L_t in the non-covered area have not been tried **do**
      Select candidate station (L_t) and we temporarily append L_t to the station list S.
      Classify covered and non-covered areas of S with Equation (3).
      Calculates TED_{Lt} with Equation (2) and stores the current TED_{Lt} value in a list.
      Remove the temporarily added L_t from S.
    end while
    Compare TED_{Lt} value in a list
    The L_t with the smallest value of TED_{Lt} will be chosen as the next location of station.
    L_t is permanently appended to the station list S.
  end while
  Store station list S into multi-list
end for
return Multi-list of stations.
 # The output is multi-list of stations. For examples:
$\{S_i = \{L_i, L_a, L_b, \ldots, L_\eta\}, S_{i+1} = \{L_{i+1}, L_c, L_d, \ldots, L_\eta\}, \ldots, S_N = \{L_N, L_e, L_f, \ldots, L_\eta\}\}$

After we obtain a multi-list of stations, the next process is to evaluate the maximum coverage percentages of all S_x. The ED + FSS will use two criteria, Coverage Percentage (COV) and Weighted Coverage Degree (WCD), for selecting the best network. The descriptions of COV and WCD criteria are outlined in Section 5.

4.4. Euclidean Distance + Adjustable Surrounding Sphere (ED + ASS)

This method is an upgrade from ED + FSS. We change from using a fixed diameter to an adjustable diameter, which depends on a station's covered area proportion. Our proposed method considers economic benefits based on deployment costs and station location with the highest spatial coverage for a specified number of economically feasible stations. The covered area proportion can be adjusted as needed. For example, if the environmental authority has a budget limit for establishing monitoring stations, an arbitrary ratio can be predefined as 50% or 70%. On the other hand, if they require high spatial resolution monitoring or an unlimited budget, the ratio can be predefined as 10% or 30%.

As a warmup to ED + ASS, we select a station at the center of the map (S_{center}) for calculating the length of the diameter. Next, we calculate ED_i from all locations (L_i) on map to the S_{center} with Equation (1). We pass all the ED_i values into a list. Subsequently, we sort the obtained list in ascending order, which means that locations closer to the station with lower ED_i values will be at the beginning of the list. The cut off position corresponds to an arbitrary ratio, as mentioned above. We calculate the cut off position value with Equation (4).

$$Cut\ off\ position = round(ratio \times length\ (list)) \tag{4}$$

ratio is predefined covered area proportion of the station, length (list) is equal N where N represents the total number of locations in area.

In the sorted list, we access the index of the list at the cut off position and get the value of that ED_i value. The value of ED_i is multiplied by two and defined as a diameter length of the ED + ASS method. Once, we have obtained the diameter length, and then we can continue the procedure of establishing the station network and evaluating the global maximum coverage of the station network in the same way as we did with ED + FSS.

5. Evaluation Criteria

In ED + FSS and ED + ASS, there is a multi-list of station networks with different first locations that must be processed to evaluate the maximum coverage percentage. Consequently, in order to find the best station network, the evaluation criteria are designed and described next.

5.1. Coverage Percentage (COV)

The covered area of stations (A_S) can be determined using Equation (3). Given the list of stations S located in a study area, we can assess the k-coverage when a location is covered by at least k different stations. The parameter k is called Coverage Degree. It means at least k stations cover each location in the study area. There are previous studies of wireless network coverage that have discussed the required k value of a network. Such studies explain a proper value of k that depends on the application. For example, an application requires $k = 1$ in a monitoring environment in which fault tolerance is not important. Meanwhile, $k > 1$ should be used when stronger monitoring is required, such as in an industrial or dangerous chemical region. Furthermore, in cases requiring fault tolerance, $k \geq 3$ is required. Therefore, it is clear that the station networks with higher k-coverage are more reliable [32,33].

Suppose that there are four stations. The circle shapes represent covered areas of a station and $\times$ symbols represent L_i for coverage degree assessment. If $\times$ symbols are within the covered areas of one station, then we define such L_i as a C1. If $\times$ symbol lies within the covered areas of two, three, and four stations, then it is denoted by C2, C3, and C4 as shown in Figure 5a–d, respectively. The area outside the circle is defined as a C0, which means it is a non-covered area.

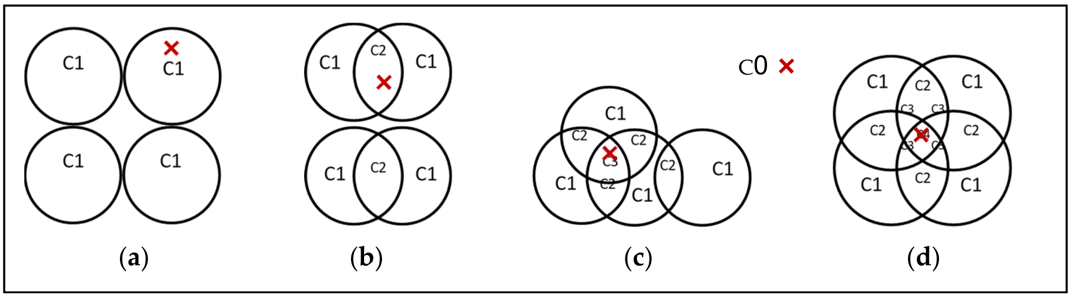


Figure 5. The example of coverage degree, (**a**–**d**) indicate the covered areas by one, two, three, and four stations.

We calculate the coverage percentage using the count L_i in each of the coverage degrees. The coverage percentage (COV) is used to evaluate results in our proposed methods and can be calculated with Equation (5).

$$COV_{percentage} = 100 \times \frac{\sum_{i=1}^{k} C_i}{N} \tag{5}$$

C_i denotes the summation of L_i in coverage degree, i is k-coverage number, k indicates a number of stations in the network, and N is total number of locations in study area A.

5.2. Weighted Coverage Degree (WCD)

Weighted coverage degree (WCD) is an additional criterion. It is used whenever COV cannot give a unique answer to the best network. The WCD corresponds to number of stations and k-coverage. For example, if the study area has four stations, here the k-coverage k = 4 (coverage degree: C0, C1, C2, C3, C4) and the weight has five values of coverage degree. We calculate the weight value by employing the Divide and Conquer concept. The $\sum W_i$ is a value equal to one. The W_k is calculated from $\sum W_i$ divided by two. The next weight value at $W_{k\text{-}i}$ will decrease from the previous by half, which means $W_{k\text{-}i} = W_k$ divided by two. The weight calculation is done continuously until the last weight at W_0 is set equal to W_1. Table 1 is an example of weight value generation when the coverage degree is equal to 4. The WCD can be calculated by coverage degree weighting with Equation (6).

$$WCD = 100 \times \frac{\sum_{i=0}^{k} W_i C_i}{N} \tag{6}$$

Table 1. Example of weight generation.

Coverage Degree	**C4**	**C3**	**C2**	**C1**	**C0**	**C4**
Weight, $\sum W_i = 1$	W4 = 0.5	W3 = 0.25	W2 = 0.125	W1 = 0.0625	W0 = 0.0625	W4 = 0.5

W_i is a weight value and $\sum W_i = 1$, $i \in \{0, 1, 2, \ldots, k\}$, k indicates a number of stations in the network, and the weights are associated to Coverage Degree (C_i).

6. Results and Discussion

This section explains the parameters used in the experiment and compares each method's pros and cons. In scenario 1, setting up a network by considering four cases as following, (i) spatial coverage, (ii) performance of coverage percentage versus the number of the stations added incrementally, (iii) coverage percentage versus a specified number of stations, and (iv) flexibility to apply our methods to different cities. In scenario 2, finding an additional station to improve the current network is evaluated.

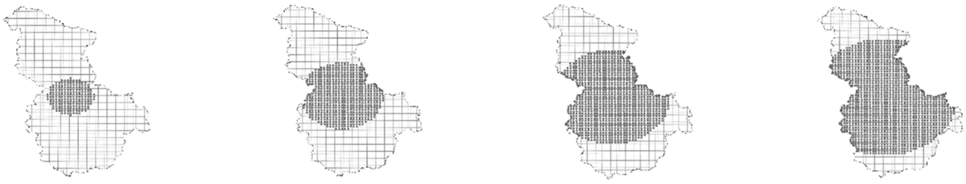
6.1. Experimental Parameter Settings

The parameter settings are shown in Table 2. The area size (A) is the number of locations in study areas. The centers of the maps are located at indices 1056, 3516, and 218 for Sejong, Bangkok, and Bonn. The specified number of stations is equal to the existing stations in the cities. The diameter length of the M3: ED + FSS is a fixed value of ten kilometers and the M4: ED + ASS is predetermined. We consider the proportion of covered area from reasonable based on the number of existing stations, as shown in Figure 6. Finally, we determined that 30% is a proper value for our experiment.

Table 2. Experiment Parameter Setting.

Parameters	**Sejong**	**Bangkok**	**Bonn**
Area size (A)	2024	7010	653
Index of the center of the map	1056	3516	218
Number of stations	4	12	1
Diameter length of FSS (dm_s)	10 km.	10 km.	10 km.
Diameter [1] length of ASS (dm_s)	14.2 km.	25.4 km.	8.6 km.

[1] Diameter calculation is based on proportion with a covered area of 30% for the cities.



(**a**) 10% (**b**) 30% (**c**) 50% (**d**) 70%

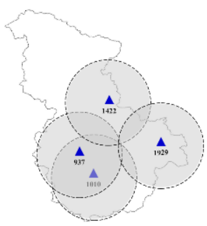
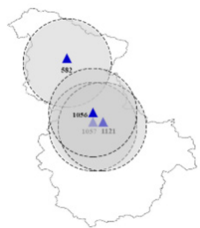
Figure 6. Depicts the proportion of covered area in 10%, 30%, 50%, and 70% (**a**–**d**), respectively.

6.2. Assessment of Scenario 1: Setting Up a Network

6.2.1. Spatial Coverage

Table 3 shows M1: ED, M2: FSS and compares them with the existing stations in Sejong city. In Table 3, triangle symbols depict existing stations, and circles represent the spatial coverage. Let us consider a result in M1: ED, where we defined the first station at the center and used four stations as input parameters. The output from M1: ED is shown in Table 3 (b). Three stations are located near each other, but one station is located far away from its neighbors. We found significant inefficient spatial coverage in that case because almost all covered areas overlap. The COV of M1: ED is 57%, which is a 16% decrease in the current value, and WCD shows a value of 12.58, which increased 48% when compared with the current value. Next, consider the result in M2: FSS; we used the input parameters as same as M1: ED except adding a fixed diameter of ten kilometers to be used in the calculation. The result shows that most stations are located apart from the first station at the center, as shown in Table 3 (c). As a result, M2: FSS achieves the best coverage percentage up to 91% and an increase of 34% compared to the current value. On the other hand, the WCD value shows 7.44, which decreased by 13%.

Table 3. The existing stations and the results of stations, coverage percentage, and weighted coverage degree of two methods: M1: ED and M2: FSS.

	Current		**M1: ED**		**M2: FSS**	
Map of Sejong city and Stations	 (a)		 (b)		 (c)	
1. Coverage Degree & Weight	C0: 655 C1: 774 C2: 527 C3: 67 C4: 1	W0: 0.0625 W1: 0.0625 W2: 0.125 W3: 0.25 W4: 0.5	C0: 877 C1: 526 C2: 44 C3: 508 C4: 69	W0: 0.0625 W1: 0.0625 W2: 0.125 W3: 0.25 W4: 0.5	C0: 183 C1: 1513 C2: 299 C3: 29 C4: 0	W0: 0.0625 W1: 0.0625 W2: 0.125 W3: 0.25 W4: 0.5
2. Coverage Percentage (COV)	68%		57% (−16%)		91% (+34%)	
3. Weighted Coverage Degree (WCD) value	8.52		12.58 (+48%)		7.44 (−13%)	

The M1: ED shows large overlapping areas which make a strengthened area with neighboring stations. The area of overlap can make data more reliable in case of data verification between neighboring stations and also produce a network which is fault tolerant. We denominate such overlap areas as confidence areas because they can enhance data reliability. However, this method shows spatial coverage weaknesses. In contrast, M2: FSS shows achieving good spatial coverage which can cover an area up to 91% in the case of four stations in Sejong city. For the spatial coverage assessment, it is possible to conclude that M2: FSS is better than M1: ED.

6.2.2. Performance of Coverage Percentage Versus the Number of Stations Added Incrementally

Our previous result when establishing four stations using M2: FSS shows a high coverage percentage of about 91%, which is better than M1: ED. In this case, we compared the performance of M2: FSS and M3: ED + FSS in terms of coverage percentage versus the number of stations added incrementally. The specified number of stations is seven. In Figure 7, the plot graph shows a comparison coverage percentage (COV) as the number of stations increases. The dashed line with square symbols indicates M2: FSS that shows coverage percentage increasing sharply and degrading from stations numbered 4 to 7. In contrast, the dotted line with triangle symbols indicates M3: ED + FSS and offers a relatively stable increasing trend from stations numbered 1 to 7. We conclude that M3: ED + FSS shows a coverage increasing trend better than that of M2: FSS.

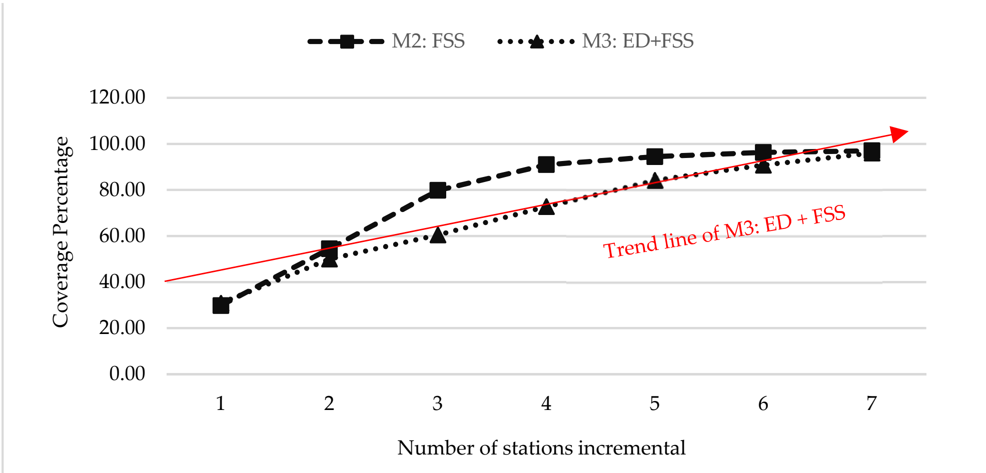
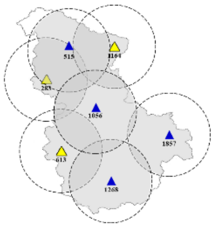
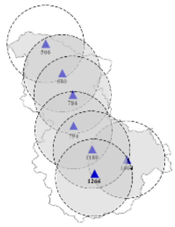


Figure 7. Plot of historical coverage percentage versus number of stations in Sejong.

Next, we investigated the additional stations of M2: FSS. As shown in Table 4 (a), light color of triangle symbols indicated the three additional stations which are located close to the border.

Although the M2: FSS achieves excellent spatial coverage (98%) nonetheless, the additional stations cause loss of area coverage, which shows the transparent area inside circles. On the other hand, all seven stations from the M3: ED + FSS method are located inside the city. These stations provide both sufficient spatial coverage (94%) and right overlapping area, as clearly shown in Table 4 (b). According to the result, we can assert a performance of M3: ED + FSS in achieving spatial coverage without loss of area coverage while still preserving the overlapped areas. The nearby stations can enhance strength to neighboring stations, which makes the network more robust and its data more reliable.

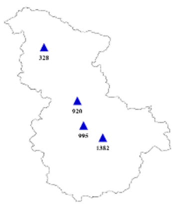
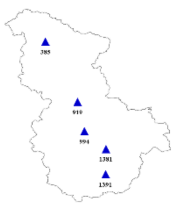
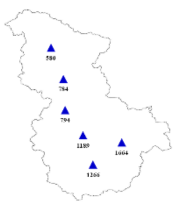
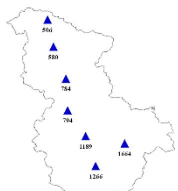
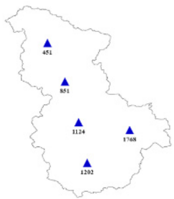
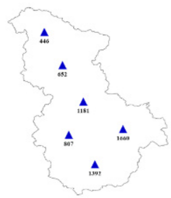
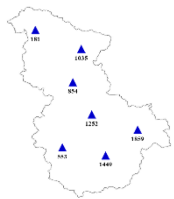
Table 4. The results of stations, coverage percentages, and weighted coverage degrees of two methods: M2: FSS and M3: ED + FSS.

	M2: FSS		M3: ED + FSS	
Map of Sejong city and Stations	 (a)		 (b)	
1. Coverage Degree & Weighted	C0: 49 C1: 767 C2: 856 C3: 290 C4: 62 C5: 0 C6: 0 C7: 0	W1: 0.0078125 W1: 0.0078125 W2: 0.015625 W3: 0.03125 W4: 0.0625 W5: 0.125 W6: 0.25 W7: 0.5	C0: 121 C1: 520 C2: 757 C3: 584 C4: 42 C5: 0 C6: 0 C7: 0	W1: 0.0078125 W1: 0.0078125 W2: 0.015625 W3: 0.03125 W4: 0.0625 W5: 0.125 W6: 0.25 W7: 0.5
2. Coverage Percentage (COV)	98%		94%	
3. Weighted Coverage Degree (WCD) value	1.61		1.86	

6.2.3. Coverage Percentage Versus a Specified Number of Stations

In this experimental case, we compared the performance of M3: ED + FSS and M4: ED + ASS concerning coverage percentage versus a specified number of stations. The location of station results from two methods is shown in Table 5. This part of our experiment aims to consider the flexibility of finding stations when we predefine the number of stations.

Table 5. Location of stations within the cities and coverage percentage.

	4 Stations	**5 Stations**	**6 Stations**	**7 Stations**
M3: ED + FSS	 COV: 76%	 COV: 87%	 COV: 91%	 COV: 94%
M4: ED + ASS	 COV: 83%	 COV: 93%	 COV: 97%	 COV: 99%

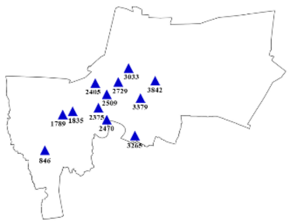
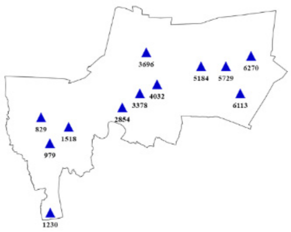
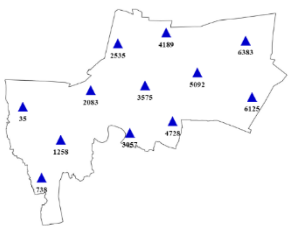
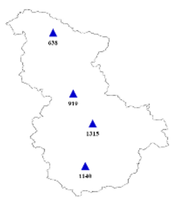
We will evaluate the coverage percentage and distribution of the stations in the study area. The results based on M3: ED + FSS show that the stations in similar aligned positions seem like a straight line in all four cases. On the other hand, results for M4: ED + ASS show a better balance of stations. The stations are readjusted whenever the number of stations changes. Furthermore, in four cases of a specified number of stations, the M4: ED + ASS has a higher coverage percentage and is better than M3: ED + FSS. Clearly, M4: ED + ASS is better than M3: ED + FSS to better cover the percentage and balance of stations.

6.2.4. Flexibility to Apply Our Methods for Different Cities

The M4: ED + ASS shows good spatial coverage and balance of stations based on a specified number of stations. For this section, we compared our method's capability to apply to different sizes of cities and evaluated balancing and distribution of the stations in cities. We used M3: ED + FSS and M4: ED + ASS in Bangkok, Sejong, and Bonn. The cities in that list are in descending order by size.

Table 6 (bkk-1), (sj-1), and (bo-1) shows the existing stations and current coverage percentages. There are twelve stations in Bangkok, four stations in Sejong, and one station in Bonn. The result of M3: ED + FSS in Table 6 (bkk-2) shows an imbalance of stations. On the other hand, the stations from M4: ED + ASS in Table 6 (bkk-3) are evenly distributed over the city. One benefit of balancing locations and overlapping areas is that the network can better support the future urban expansion and provide better air pollution monitoring. Although in Table 6, (sj-3) and (bo-3) cannot clearly show the balancing of stations when compared with Table 6 (sj-2) and (bo-2), the COV values of M4: ED + ASS are higher than M3: ED + FSS and show significantly increased rates of 56%, 22%, and 37%, in Bangkok, Sejong, and Bonn, respectively. These results allow us to conclude that our M4: ED + ASS is more flexible than M3: ED + FSS for designing new station networks in any city size.

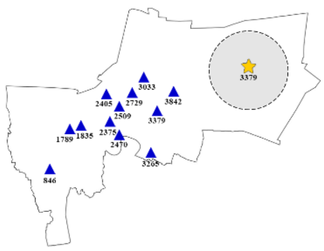
Table 6. Locations of stations within the cities and coverage percentages: (bkk-1), (sj-1), (bo-1) depict current stations, (bkk-2), (sj-2), (bo-2) depict station networks using M3: ED + FSS, and (bkk-3), (sj-3), (bo-3) depict station networks improved using M4: ED + ASS, in Bangkok, Sejong, and Bonn, respectively.

Country/Methods	Bangkok, Thailand (1568.7 km^2)	Sejong, Korea (465.23 km^2)	Bonn, Germany (141.06 km^2)
Current	 (bkk-1) COV: 64%	 (sj-1) COV: 68%	 (bo-1) COV: 27%
M3: ED + FSS	 (bkk-2) COV: 99% (+55%)	 (sj-2) COV: 76% (+12%)	 (bo-2) COV: 33% (+22%)
M4: ED + ASS	 (bkk-3) COV: 100% (+56%)	 (sj-3) COV: 83% (+22%)	 (bo-3) COV: 37% (+37%)

6.3. Assessment of Scenario 2: Finding Additional Stations to Improve the Current Network

For this section, we applied M4: ED + ASS to add one station into the network. Then, we evaluated the results with our proposed criteria: COV and WCD. In Table 7, triangle symbols indicate the existing stations, and star symbol indicates the additional station. The additional stations show the performance of our proposed method and evaluation criteria. They can improve coverage percentages by 39%, 34%, and 130% in Bangkok, Sejong, and Bonn.

Table 7. Location of an additional station and resulting coverage percentages in Bangkok, Sejong, and Bonn.

Bangkok, Thailand	Sejong, Korea	Bonn, Germany
		
COV: 89% (+39%)	COV: 91% (+34%)	COV: 62% (+130%)

One of the key limitations of our study is the appropriate ratio of spatial coverage satisfaction versus confidence area. As shown in Figure 8, the dashed line plot graph compares coverage percentage and the number of stations. The 6th stations show the most coverage percentage of 90%. Increasing the number of stations from 7 up to 12 does not significantly increase coverage. Thus in future work, a change of strategy is needed after achieving the spatial coverage to increase the overlapped regions.

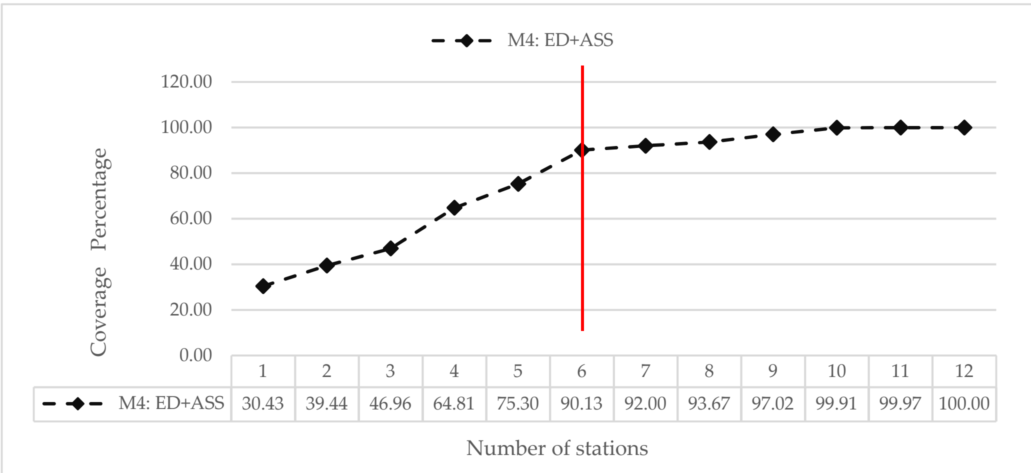


Figure 8. Plot of coverage percentage versus number of stations in Bangkok.

7. Conclusions

Increasing spatial coverage of AQMN gives effective environmental management. Especially in setting up a network in cities that lack historical pollution data, adding stations in cities with an existing network that face urbanization can make it challenging to design adequate spatial coverage and effective AQMN. Our experimental results proved the ability of the proposed method to provide maximum spatial coverage based on a given number of stations. The results showed that ED + ASS achieved effectiveness both in enhance spatial coverage and proper confidence area. In setting up a network in the cities, such a method suggested a balance of station locations and achieved maximum spatial coverage. The stations are neither located close to the border, nor are they close together. However, they are evenly distributed over the city. These results indicated that if the city planner considers economic benefits and the investment costs for constructing a network, the proposed method can give an excellent. In adding stations in cities, the results showed an optimal for the next station and enhanced the spatial coverage. Our proposed method showed effectiveness for expanding the existing networks as well as setting up AQMN.

In future work, we will consider the ratio of spatial coverage satisfaction versus confidence area as we mentioned in our experiment. We will modify our methods by changing strategies after achieving the spatial coverage to increase the overlapped regions of confidence areas. Moreover, we will integrate the historical pollution information, the city characteristics data, and land-use to find stations for better air pollution monitoring.

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