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Optimization of air monitoring networks using chemical transport model and search algorithm

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Title Page

Manuscript title:

Optimization of Air Monitoring Networks Using Chemical Transport Model and Search

Algorithm

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29 Abstract

30 Air monitoring network design is a critical issue because monitoring stations should be
31 allocated properly so that they adequately represent the concentrations in the domain of interest.
32 Although the optimization methods using observations from existing monitoring networks are
33 often applied to a network with a considerable number of stations, they are difficult to be applied
34 to a sparse network or a network under development: there are too few observations to define an
35 optimization criterion and the high number of potential monitor location combinations cannot be
36 tested exhaustively. This paper develops a hybrid of genetic algorithm and simulated annealing to
37 combine their power to search a big space and to find local optima. The hybrid algorithm as well
38 as the two single algorithms are applied to optimize an air monitoring network of $\text{PM}_{2.5}$, NO_2 and
39 O_3 respectively, by minimization of the mean kriging variance derived from simulated values of a
40 chemical transport model instead of observations. The hybrid algorithm performs best among the
41 algorithms: kriging variance is on average about 4% better than for GA and variability between
42 trials is less than 30% compared to SA. The optimized networks for the three pollutants are
43 similar and maps interpolated from the simulated values at these locations are close to the
44 original simulations (RMSE below 9% relative to the range of the field). This also holds for
45 hourly and daily values although the networks are optimized for annual values. It is demonstrated

46 that the method using the hybrid algorithm and the model simulated values for the calculation of

47 the mean kriging variance is of benefit to the optimization of air monitoring networks.

48

49 **Keywords:** PM_{2.5}; NO₂; O₃; Genetic algorithm; Simulated annealing; Japan

50

51

1. Introduction

Air monitoring networks have been developed in various areas in the world for environmental, epidemiological, policy evaluation and/or emission surveillance purposes by national or local governments. These networks should be allocated properly so that they adequately represent the concentrations in the domain of interest to accomplish the purposes of the network. This issue is often referred to as a network design problem and has been widely discussed (e.g., Brus et al., 2007; Wu et al., 2011). The network design problem usually aims at minimization of a design criterion that may be based on observations or other information about the field of interest: to achieve this aim, subsets of potential monitor locations are selected by an algorithm.

A design criterion is often defined with the notion of entropy where a set of locations which maximize the entropy at the monitored sites is searched for (e.g., Zidek et al., 2000; Fuentes et al., 2007). Another popular criterion is defined with a geostatistical estimation method which is called kriging, where the theoretical interpolation error averaged over the region of interest, i.e. the mean kriging variance is minimized (e.g., Baume et al., 2011; Wu et al., 2011). When the mean kriging variance is used as a criterion, observations obtained from existing monitoring network are often used to construct a variogram for the calculation of the mean kriging variance. In these cases, it is assumed that the network represents the spatial distribution sufficiently, thus the network of interest is relatively dense where the efficiency of the network is focused, i.e.

70 reduction of stations. Therefore, this method is difficult to apply to a sparse network or a network
71 under development that insufficiently represents the spatial distribution of the pollutant of interest.

72 In the field of air quality study, the chemical transport model (CTM), that simulates physical
73 and chemical processes including emission, advection, photochemical reactions and deposition,
74 has been extensively used at various ranges of spatial and temporal scale, not only to obtain a
75 spatial distribution, but also to establish an effective strategy for the control of the concentrations
76 of air pollutants (e.g., Emmons et al., 2011; Chatani et al., 2014). Thus, simulated concentrations
77 from CTM with sufficiently high spatial resolution can be an alternative to observations to derive
78 a variogram to compute the mean kriging variance as a design criterion. Simulations have also
79 been used for sampling optimization by Kumral and Ozer (2013) in mine planning.

80 Once the criterion is defined, the network design problem can be treated as a combinatorial
81 optimization problem. When a network is small enough, complete enumeration of all possible
82 combinations is possible. For a large network, however, this will run into a combinatorial
83 explosion. To deal with this difficulty, search algorithms have been applied to the optimization of
84 large networks. For instance, Ruis-Cardenas et al. (2010) applied genetic algorithm (GA) for an
85 O₃ monitoring network with several hundred stations in the United States. Wu et al. (2011)
86 applied simulated annealing (SA) to the optimization of an O₃ monitoring network over France.
87 Given that the search space is huge when using simulated fields, superior ability both for a global

88 and a local search is required for a search algorithm to be applied. GA is able to search in a large
89 space, but is often not able to find the local optimal solution (Ruiz et. al., 2010). On the other
90 hand, SA is able to find locally optimal solutions, but is often trapped in regions far from the
91 global optimum (Ruiz et. al., 2010). Araki et al. (2015) developed a hybrid of GA and SA (HGS)
92 and successfully applied it to the optimization of a PM_{2.5} monitoring network using simulated
93 values obtained from CTM for the computation of the mean kriging variance. However, the
94 performance of HGS was not compared to those of other optimization algorithms in their study,
95 thus the advantages of HGS have not been demonstrated. In addition, HGS was applied only for a
96 PM_{2.5} monitoring network, and the possibility of application to other pollutants, that might have
97 different spatial distribution features, was not examined.

98 In this paper, CTM is used to generate spatial distributions of air pollutant concentrations to
99 derive variograms for the computation of the mean kriging variance as a design criterion, and
100 each of the algorithm including HGS, GA and SA is applied to PM_{2.5}, NO₂ and O₃ in the Kinki
101 region of Japan respectively, repeating each setting 30 times to capture random effects. The
102 performances of the algorithms are compared against each other in terms of the quality of the
103 solutions such as the mean and the standard deviation of the mean kriging variance of the
104 respective trials. Fields have been interpolated by ordinary kriging using the CTM simulated
105 values at the selected sites in the optimized networks, and the errors between the interpolated and

simulated fields are computed. The difference between the algorithms for each of the pollutants is discussed and the capability and the applicability of HGS are evaluated.

2 Methodology

2.1 Chemical Transport Model

The chemical transport model used in this study is the Community Multiscale Air Quality model (CMAQ) (Byun and Ching, 1999) version 5.0.1 which was driven with the Weather Research and Forecasting model (WRF) (Skamarock et al., 2009) version 3.5.1. Meteorological fields were produced using WRF configured with the same physics options as those used by Shimadera et al. (2014); also emission data for the air quality simulations was produced in a similar way. The other settings involved in the simulations and CMAQ configurations are detailed in Shimadera et al. (2015).

The WRF/CMAQ model was run from April 2010 to March 2011 (Japanese fiscal year 2010) with an initial spin-up period of 22-31 in March 2011. The horizontal domains consisted of three domains: domain 1 covering a wide area of Northeast Asia, domain 2 covering the main land of Japan, and domain 3 covering the area where the optimization algorithms are tested, which is shown as colored area in Figure 1. The horizontal resolution is 4 km and the number of grids is 68×72 for domain 3. The annual and daily values used for the network optimization are

computed by averaging the hourly CTM outputs over the corresponding time periods. This simulation is identical to that used in Araki et al. (2015).

The performance of the model is detailed in Shimadera et al. (2015) and summarized as follows: the statistical measures obtained from the comparison between observed and simulated daily concentrations indicate that the model simulates the temporal and spatial variation patterns of $\text{PM}_{2.5}$, NO_2 and O_3 well with the Pearson's correlation coefficient being 0.76, 0.82, and 0.77 for $\text{PM}_{2.5}$, NO_2 and O_3 respectively. The scatter plots of the simulated and observed values of annual means for $\text{PM}_{2.5}$ and NO_2 , and annual means of daily maximum 8-hr mean concentrations for O_3 , which are used to derive variograms for the computation of the mean kriging variance, are presented in Figure 2 with root mean squared error (RMSE) and R^2 between the observed and simulated values. The number of observations for $\text{PM}_{2.5}$, NO_2 and O_3 is 8, 219 and 188 respectively. The reason for the limited number of observations for $\text{PM}_{2.5}$ is because the $\text{PM}_{2.5}$ network in Japan started to be developed since 2009, a year before the target year of this simulation. The concentrations of O_3 lie in a relatively narrow range, which results in low R^2 value for O_3 . However, RMSE of O_3 is approximately 10% of the mean values of O_3 . Therefore, these simulated concentrations have sufficient quality to derive variograms for the computation of the mean kriging variance as the optimization criterion. The spatial distributions of $\text{PM}_{2.5}$, NO_2 and O_3 are given in Figure 1. Both $\text{PM}_{2.5}$ and NO_2 show highest concentrations in densely

142 populated areas, where NO_2 is more concentrated to the agglomeration of Osaka. The higher and
143 lower concentration areas of $\text{PM}_{2.5}$ are generally distributed evenly. On the other hand, higher
144 concentrations of NO_2 are found in limited areas where megacities are located, while the lower
145 areas are widely distributed. The spatial distribution of O_3 is generally the reverse of that of NO_2 .
146 This is because the O_3 concentrations are affected by titration with NO_x , and higher NO_x
147 concentrations might cause lower O_3 concentrations in urban areas with relatively large
148 anthropogenic emissions. The histograms of the simulated values in the candidate areas i.e. in the
149 colored area in Figure 1 are given in Figure 3, which reflect the characteristics of the distribution
150 of each pollutant: $\text{PM}_{2.5}$ concentrations are approximately normally-distributed, the distribution
151 of NO_2 concentrations is skewed to zero and that of O_3 is relatively skewed to higher values.

152 **2.2 Design criterion**

153 The optimization criterion is minimizing the mean kriging variance, which has been used as a
154 design criterion in many previous studies (e.g., Van Groenigen, 2000; Brus et al., 2007; Wu et al.,
155 2010; Wu et al., 2011; Baume et al., 2011). A definition of a design criterion is an expression of a
156 purpose of a monitoring network. When minimization of the mean kriging variance is used as a
157 criterion, the purpose of the network can be seen to grasp the spatial distribution of a pollutant in
158 the whole region of interest well.

The simulated concentrations are transformed to a natural logarithmic scale before analysis, and back transformed after analysis so that the predicted concentrations are positive, which is not always the case without transformation (Beelen et al., 2009). The concentrations simulated by CTM are treated as point values at the grid cell centroids and an empirical variogram is computed from all the candidate points. A theoretical variogram is fitted to it with spherical model by weighted least-squares fitting. The derived variograms for the three pollutants are given in Figure 4. Although the ranges of the three variograms are slightly different, the variograms are generally similar, with nugget very close to zero.

The fitness value for a selected set of points is the mean kriging variance: kriging variance is computed in all points of the grid in the region of interest from the variograms and the selected set of points and averaged over the area; to avoid overestimation of the kriging variance at the boundaries, fifteen equally-spaced points at the margins of the region of interest (see Figure 1) are in addition regarded as selected.

2.3 Optimization algorithms

The optimal combination of points is searched for by the optimization algorithms. Each network configuration is given by a binary string, where each element represents a candidate location, with ones at gauged sites and zeros at ungauged sites. A subset of locations is selected from the candidate locations according to this binary string.

177 **2.3.1 Genetic algorithms**

178 The basic scheme of GA algorithm in this paper is similar to the standard GA which consists of
179 population, selection, crossover and mutation. The initial population is randomly generated and
180 the population size is 100. In the crossover operation, gauged sites in both parents are gauged in
181 the offspring, and ungauged sites in both parents are ungauged in the offspring. Half of the sites
182 that are gauged in one of the parents and not gauged in the other are randomly conversed. The
183 probability of crossover occurrence is set to 0.9. In the mutation operation, 5% of gauged sites are
184 randomly selected and swapped with the same number of randomly selected ungauged sites with
185 a mutation probability of 0.2. The solutions with the best 5% fitness, called elite, remain in the
186 next generation, while others are rejected in order to keep the population size unchanged. These
187 operations stop when the total number of generations reaches 500. The algorithm also stops when
188 the number of generations without any improvement in the fitness reaches 40.

189 **2.3.2 Simulated annealing**

190 SA is an iterative search algorithm which starts with a randomly selected initial solution and the
191 fitness value is computed. A new potential solution is created by exchanging a randomly selected
192 gauged site for a randomly selected ungauged site in the pre-defined search window of the
193 selected gauged site. The fitness value is then computed for the new potential solution and
194 compared to that of the current solution. The new potential solution is accepted when the fitness

value improves. Even when the fitness value degrades, the new potential solution is accepted with a certain probability, which is given by

$$p = \exp\left(\frac{-\Delta f}{T}\right), \quad (1)$$

where Δf is the amount of degradation of the fitness value and T is a control parameter (Brus et al., 2007). T is gradually decreased with iterations by

$$T_{k+1} = \alpha T_k, \quad (2)$$

where α is 0.9 and k is a number of iterations. The initial T (i.e., T_I) is set so that the average p in the equation (1) equals to 0.8 (Brus et al., 2007).

The size of the search window is fixed in the first 500 iterations at 18 km (approximately equals to 7×7 cells window). Then it is decreased after 500 iterations down to 12 km (5×5 window), and 6 km (3×3 window) from 1,000 iterations and onward. The total number of iterations for each run is set to 50,000. The algorithm also stops when the number of iterations with no progress in the fitness value reaches 4000.

2.3.3 Hybrid algorithm

HGS algorithm is identical to that applied in Araki et al. (2015) and summarized as follows. The basic scheme of HGS is similar to GA. The initial population of the size of 100 is randomly generated and GA is applied for 75 iterations. After 75th generation, SA is applied to each of the 15% best solutions for 30 iterations with the fixed search window size of 7×7 . The rest 85%

solutions are kept unchanged and combined with the solutions obtained from SA. GA is then applied to this set of solutions i.e. population for 1 iteration, and the next generation is obtained. Again, SA is applied to the best 15% solutions for 30 iterations in the generation and the solutions are combined to the rest 85% solutions. The next generation is obtained by the application of 1 iteration of GA to the set of solutions. The parameters of HGS in the first 75 generations are identical to GA algorithm described above. After 75 generations, the crossover and mutation probability is set to 0.3 and 0 respectively. After the 100th generation, the search window size is reduced to 5×5 . This window size is again decreased to 3×3 after 125th generation and is keep unchanged. The total number of iterations is set to 155, but the algorithm also stops when the number of generations with no progress in the fitness value reaches 8 after 75th generation. The flowchart of HGS is presented in Figure 5.

2.4 Application of the algorithms

The algorithms are tested in the area that includes the Kinki region in Japan ($134.2^{\circ}\text{E} - 136.5^{\circ}\text{E}$, $33.4^{\circ}\text{N} - 35.8^{\circ}\text{N}$) that consists of six prefectures, and its contiguous areas, which equals to the colored area in Figure 1. Only land areas are considered for the potential locations of the monitoring stations. The number of the candidate locations is 1984. Megacities such as Osaka, Kyoto and Kobe are located in this region. The number of monitoring stations for NO_2 and O_3 in the study area is 221 and 187 respectively in the year 2011, which has remained almost

231 unchanged in recent years, while that of $PM_{2.5}$ is increasing rapidly from 57 stations in the year
232 2011 to 117 in the year 2013. This is because the national air quality standard for $PM_{2.5}$ in Japan
233 was set in the year 2009 and the monitoring network was initially developed by placing
234 continuous monitors at existing stations.

235 GA, SA and HGS algorithms were applied to three different network sizes; 1) 57 stations,
236 which is consistent with the number of stations of $PM_{2.5}$ in the year 2011, 2) 117 stations,
237 consistent with that in the year 2013, 3) 150 stations, which is approximately 3 times as much as
238 the first case. It should be noted that the locations of the existing stations were not considered
239 because the application of the observation-free method is focused. Each of the algorithms are
240 applied to each pollutant combined with each network size respectively, repeating each of these
241 27 settings 30 times to capture random effects. The performances are compared in terms of the
242 mean and the standard deviation (SD) of the fitness values of the respective 30 trials. The
243 stopping parameters of iterations for GA, SA and HGS are set so that the total effort of all the
244 three algorithms is similar for a fair comparison.

245 Data analysis was carried out using R statistical software 3.1.2 (R Core Team, 2014) with the
246 package GA (Scrucca, 2013) for the basic scheme of GA algorithm, the package gstat (Pebesma,
247 2004) for kriging.

248

249 **3. Results and discussion**

250 **3.1 Performance of the algorithms**

251 The mean and standard deviation (SD) of the fitness values obtained from 30 random trials of
252 each algorithm for the three network sizes and the three pollutants are presented in Figure 6.
253 Regarding the comparison between the performance of GA and SA, SA gives smaller means in
254 all the cases. However, SD of GA is consistently smaller than that of SA. In the case of the
255 network size of $n=117$ for $PM_{2.5}$, for instance, SD of GA is as small as 36 % of that of SA. These
256 results indicate that SA is able to find a better solution but is not as stable as GA.

257 The mean of HGS is between 95 and 96% of the means of GA in all the cases and SD is 26 -
258 47% of that of GA. When compared to the results of SA, HGS gives smaller means than those of
259 SA and the SD is as small as 13 - 29% of that of SA. This indicates that HGS outperforms GA
260 and SA with a better search capability and stability.

261 The best network placements out of the 30 trials for each network size and pollutant obtained
262 by HGS are presented in Figure 7. The selected sites in the best network designs are generally
263 placed homogeneously. Although the distributions of the simulated values for the three pollutants
264 have unique characteristics, the difference in the optimized network between the pollutants is
265 small.

266 **3.2 Spatial characteristics of the resulting best networks**

As shown in Figure 7, there seems to be few differences between the optimal networks for the different pollutants. For a quantitative comparison, the fitness value of each pollutant is calculated using the optimized network obtained by HGS for all the pollutants. For instance, fitness values of $PM_{2.5}$ are calculated using optimized network for NO_2 and O_3 , which in turn are compared to that obtained using $PM_{2.5}$ -optimized network. The fitness value is computed for each solution of 30 trials. The obtained results are presented in Figure 8.

The fitness values for each pollutant generally lie in the same range, no matter which pollutant is used in the optimization. Thus, the network optimized for one pollutant also result in good fitness for the other pollutants, and the relative goodness of a network compared to others does not change between the pollutants.

As shown in Figure 4, the variograms of all said three pollutants used for the optimization are generally similar, spherical model with nugget very close to zero. Van Groenigen (2000) showed that the optimized networks obtained for linear, exponential and spherical variograms with a relatively low nugget were similar. The results in this study agree with this previous study.

3.3 Interpolation error

The monitoring network can be evaluated by how well it represents the spatial distribution of the concentrations in the domain of interest. More specifically, the concentration field is generated by ordinary kriging using the CTM simulated values at the selected sites in the

285 optimized network. The variogram is constructed using simulated values at the selected sites.

286 Fifteen equally-spaced points on the outer side of the study area are included in the same way as

287 described in the Section 2.2. The resulting map is compared to the CTM simulated field.

288 RMSE and R^2 between the simulated values and kriged values for each set of trials are

289 computed. The obtained RMSE is given in Figure 9. RMSE is less than $0.6 \text{ (}\mu\text{g m}^{-3}\text{)}$ for all the

290 three algorithms for $\text{PM}_{2.5}$, less than 1.7 (ppb) for NO_2 and less than 1.8 (ppb) for O_3 . These

291 RMSE values are 6, 8 and 9% relative to the ranges of the simulated values of $\text{PM}_{2.5}$, NO_2 and O_3

292 respectively. The difference in RMSE between the three algorithms is minute for each network

293 size and pollutant. R^2 is generally higher than 0.62 for all the cases and the difference in R^2

294 between the algorithms is also marginal (not shown here).

295 In addition, the kriged fields generated by the optimization result of the three algorithms for the

296 same size and pollutant are similar to each other and generally capture the feature of the

297 corresponding simulated fields. As an example, the error maps between the simulated and kriged

298 fields obtained from the result of HGS for the size of $n=57$ and for the three pollutants are given

299 in Figure 10, where positive values represent overestimates and negative values represent

300 underestimates. The errors for $\text{PM}_{2.5}$ are close to zero, between -3.6 and $1.6 \text{ (}\mu\text{g m}^{-3}\text{)}$, over the

301 region of interest. On the other hand, underestimates for NO_2 and overestimates for O_3 are found

302 in limited areas such as agglomeration of Osaka. These areas correspond to the areas of the

303 highest concentrations of NO₂ or the lowest concentrations of O₃. These under/overestimates are
304 due to the lack of the selected site in such limited areas of high/low concentrations. However,
305 under/overestimates are not significant for most of the region except for the limited areas. These
306 results indicate that the optimized networks obtained by the three algorithms represent the spatial
307 distribution of the concentrations in the region of interest sufficiently.

308 **3.4 Evaluation of the optimized network for daily and hourly values**

309 The monitoring networks should map not only annual mean concentrations but also daily or
310 hourly mean concentrations well. In order to evaluate the optimized network versus daily and
311 hourly means, interpolation errors (RMSE) between the simulated and kriged fields for each day
312 and hour of the whole year are computed in the same way as described in the section 3.3.
313 Variograms are derived in an automated way using package automap (Hiemstra et al., 2009),
314 because manually constructing variograms for every single day or hour of the entire year would
315 be too time consuming.

316 The resulted RMSE are given in Table 1. The finer the temporal scale is, the larger RMSE
317 becomes, which may be due to less homogeneous spatial distribution of pollutants at a finer
318 temporal scale. However, RMSE of all the pollutants for all network sizes are relatively small
319 compared to the ranges of the simulated daily or hourly means of the corresponding pollutants.
320 Although not every daily or hourly result is checked manually, these results demonstrates that the

optimized network obtained using the annual mean is also optimal, at least to some extent, to produce maps of daily or hourly mean concentrations.

4. Conclusions

In this paper, the performance and the applicability of HGS that is a hybrid of GA and SA is evaluated and compared to the single GA and SA using CTM simulated values to derive variograms for the computation of the mean kriging variance as a design criterion for $PM_{2.5}$, NO_2 and O_3 in the Kinki region of Japan for three network sizes. HGS consistently outperforms the rest of the two algorithms for all the network sizes and pollutants. This demonstrates that HGS successfully combines the advantages of GA and SA. The optimized network for one pollutant is optimal for other pollutants and the relative goodness of a network compared to others does not change between the pollutants. This is because the variograms of the pollutants are similar. This implies that only one pollutant might be necessary to be considered when a network with multiple pollutants of similar variograms is optimized simultaneously. The concentration fields are generated by ordinary kriging using the simulated values at the selected sites in the optimized networks obtained by GA, SA and HGS respectively, and compared to the simulated fields to obtain interpolation errors. The difference between the algorithms is minute and the optimized networks obtained by the three algorithms represent the spatial distribution of the concentrations

339 in the region of interest sufficiently. The optimized network to well map the annual mean is
340 optimal, to some extent, to produce maps of daily or hourly mean concentrations.

341 It is demonstrated that HGS is a valid and feasible method for the optimization of an air
342 monitoring network. The combination of HGS and CTM simulation to derive a variogram for a
343 criterion calculation is of benefit especially when a network with a limited number of stations or
344 network under development is considered, and provide information of vital use on the air
345 monitoring network optimization.

346

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349

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407 **Figure Captions**

408 Figure 1. The area of interest and the spatial distribution of PM_{2.5}, NO₂ and O₃ concentrations
409 obtained by CTM for the Japanese fiscal year 2010. The values for PM_{2.5} and NO₂ are annual
410 means and that for O₃ is annual mean of daily maximum 8-hr means. The circles represent the 15
411 extra points used to derive variograms. Units are $\mu\text{g m}^{-3}$ for PM_{2.5} and ppb for NO₂ and O₃.

412

413 Figure 2. The scatter plots of the simulated and observed values for annual means of PM_{2.5} and
414 NO₂, and annual means of daily maximum 8-hr mean concentrations for O₃. Units are $\mu\text{g m}^{-3}$ for
415 PM_{2.5} and ppb for NO₂ and O₃.

416

417 Figure 3. Histograms of the simulated values for PM_{2.5}, NO₂ and O₃. Units are $\mu\text{g m}^{-3}$ for PM_{2.5}
418 and ppb for NO₂ and O₃.

419

420 Figure 4. The variograms derived for PM_{2.5}, NO₂ and O₃.

421

422 Figure 5. The flowchart of the HGS algorithm.

423

Figure 6. The mean fitness values obtained from 30 random trials of each algorithm for PM_{2.5} (in the left row panels), NO₂ (in the middle row panels) and O₃ (in the right row panels) for the network size of n=57 (in the upper column panels), n=117 (in the middle column panels) and n=150 (in the lower column panel). The fitness values are normalized by the mean values of GA of the corresponding network size and pollutant. The error bars represent SD.

Figure 7. The optimized network by HGS for PM_{2.5} (in the left row panels), NO₂ (in the middle row panels) and O₃ (in the right row panels) for the network size of n=57 (in the upper column panels), n=117 (in the middle column panels) and n=150 (in the lower column panel). The crosses represent the selected sites. The circles represent the 15 extra points used to derive variograms.

Figure 8. The mean fitness values of a set of 30 trials for PM_{2.5} (in the left row panels), NO₂ (in the middle row panels) and O₃ (in the right row panels) obtained using the network optimized for each pollutant for the network size of n=57 (in the upper column panels), n=117 (in the middle column panels) and n=150 (in the lower column panel). The top legend refers to the pollutant for which fitness value is computed using the optimized network of the three pollutants and the bottom legend refers to the pollutant for which the network is optimized for. The shaded areas

442 indicate that the fitness values are calculated for a pollutant using the optimized network of the
443 same pollutant. The fitness values in each panel are normalized by mean values of PM_{2.5}-
444 optimized network in the same panel. The error bars represent SD.

445

446 Figure 9. RMSE between CTM simulated field and kriged field with the simulated values at the
447 selected sites of the optimized network of each set of 30 trials by GA, SA and HGS for the
448 network size of n=57, 117 and 150, and for PM_{2.5}, NO₂ and O₃. The error bars represent SD.

449 Units of RMSE for PM_{2.5} are $\mu\text{g m}^{-3}$ and ppb for NO₂ and O₃.

450

451 Figure 10. The error map between the CTM simulated fields and the kriged fields with the
452 simulated values at the selected sites of the optimized network of a) PM_{2.5}, b) NO₂ and c) O₃ by
453 HGS for the network size of n=57. The positive values represent overestimates and the negative
454 values represent underestimates. The crosses represent the selected sites. The circles represent the
455 15 extra points used to derive variograms. Units of concentrations are $\mu\text{g m}^{-3}$ for PM_{2.5} and ppb
456 for NO₂ and O₃.

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