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APPLICATIONS OF INFORMATICS IN ENVIRONMENT ENGINEERING AND MEDICINE

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This book consist of the papers describing the applications of informatics in environment and health engineering and protection. Problems presented in the papers concern quality management of the surface waters and the atmosphere, application of the mathematical modeling in environmental engineering, and development of computer systems in health and environmental protection. In several papers results of the research projects financed by the Polish Ministry of Science and Information Society Technologies are presented.

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CHAPTER 1

Water and Air Quality Management

MINIMIZING COSTS OF EMISSION REDUCTION – A DYNAMIC PROGRAMMING APPROACH

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The paper deals with the problem of the efficient allocation of financial means to air pollution sources (mainly power and heating plants) located in a given region. The problem consists in minimization of the function, reflecting environmental losses due to air pollution, subject to costs constraints. Minimal value of the function can be achieved by optimal selection of the desulfurization technologies for each emission source, since the analysis is made on the example of sulfur oxides, which are the main air pollutants in Poland. Since both the number of emission sources and the number of desulfurization technologies are limited, the task belongs to a class of integer-type optimization problems. The full enumeration of all assignments of technologies to emission sources cannot be implemented due to the huge number of variables. The paper presents a dynamic programming method approach for solving the problem. The method was tested on the case of Silesia Region (Poland) with the set of major power plants, and the number of desulfurization technologies. Solving the relaxation of the integer problem, using the classical continuous-type gradient optimization algorithm, assesses the quality of solutions given by the dynamic programming method.

Keywords: Air pollution, emission reduction, dynamic programming.

1. Introduction

Some parts of Poland belong to areas with the most polluted air in Europe. The main reason for that is of historical nature. The heavy industry plants (power and heating stations, steel works etc.) were located close to coal and lignite mines. They use much amounts of these fossils for steel, electricity and heat production. The side effect of burning big amounts of coal is the emission of sulfur dioxides, due to content of sulfur in both coal and lignite. Moreover, most of the equipment in the plants is in a very poor condition. So, the renovation and modernization of this sector and thus emission reduction is one of the important environmental tasks to be done in the near future.

In order to modernize the industrial plants and to reduce emission one must spend means for it. The easiest approach is to distribute money for the emission reduction in all the plants proportionally to their current emission intensity. This solution, however, is not efficient. The impact of the source on the air quality is not only the function of its emission intensity, but also the function of its location and weather conditions. So, the cost-effectiveness of emission reduction must be taken into account. To solve the problem one must use optimization techniques.

The authors tried to elaborate the method for creating the regional-scale strategy for air pollution abatement. Regional-scale abatement strategy is dependent upon the criteria, how the environmental damage is evaluated. The main objective of the work consists in giving a decision-support tool that enables an analysis of cost-effectiveness and environmental impact related to emission reduction technologies.

2. Problem statement

We consider a region Ω with N controllable emission sources. We assume to have M technologies for emission reduction, to be assigned to each source. Each technology is defined by both the effectiveness and the unit cost (consisting of investment and operational cost). Our goal is to allocate emission reduction technologies to all the sources in such a way, that the value of certain environmental damage index (the objective function) will be minimal subject to constraints on total costs.

Let us denote:

$\Omega = L_x \times L_y$ – the area under consideration (rectangle),

N – number of sources,

M – number of available emission reduction technologies,

C – constraint on total (investment and operational), year averaged costs,

$\vec{u} = [u_1, u_2, \dots, u_N]$ – vector of emission volumes of controlled sources,

$\vec{e} = [e_1, e_2, \dots, u_M]$ – effectiveness vector of emission reduction technologies,

$F = \{f_{ij}\}, 1 \le i \le N, 1 \le j \le M$ – matrix of abatement cost per unit emission,

$X = \{x_{ij}\}, 1 \le i \le N, 1 \le j \le M$ – "0-1" matrix of technology assignment (matrix of decision variables) to the sources.

The environmental cost function has the form:

$$J(d) = \frac{1}{2}\int_{\Omega} w(x,y)[\max(0, d(x,y) - d_{ad})]^2 \, d\Omega\,, \qquad (1)$$

where

$w(x, y)$ – area sensitivity (weight) factor,

d_{ad} – admissible concentration level.

The concentration forecast used in (1) is calculated according to the formula

$$d(x,y) = d_0(x,y) + \sum_{i=1}^{N} A_i(x,y)\cdot u_i, \quad (x,y) \in \Omega \tag{2}$$

where

$d_0(x,y)$ – background concentration (impact of uncontrolled sources),

$A_i(x,y)$ – transfer matrix (relation emission → concentration) for the i-th source.

The unit transfer matrix $A_i(x,y)$ – represents the contribution of the i-th source, referred to the unit emission intensity. All the matrices $A_i(x,y)$; $(i = 1,\ldots,N)$, for controlled sources are calculated off-line by the forecasting model. In a similar way, the background pollution field $d_0(x,y)$ is computed for uncontrolled, background emissions, including the inflow from the neighboring regions. The current emission intensity of the i-th source depends on the initial emission value - u_i^0 and the efficiency of the abatement technology applied, as shown below

$$u_i = u_i^0 \sum_{j=1}^{M} (1 - e_j)\cdot x_{ij}, \quad \sum_{j=1}^{M} x_{ij} = 1, \quad x_{ij} \in \{0,1\}, \quad 1 \le i \le N \tag{3}$$

where

u_i – current emission intensity (volume) of the i-th source,

u_i^0 – initial intensity of the i-th source.

The cost of emission reduction in each source consists of two components: investment cost and operational cost. Both investment and operational costs depend on the chosen abatement technology and on the parameters of the energy installation where this technology is to be utilized. Here we use a simplified approach, where the investment cost of the j-th abatement technology applied to the i-th emission source is calculated as annual cost, averaged over the entire amortization period. Thus, the total emission abatement cost per year, calculated as a sum of reduction costs in all the plants, is used to formulate the cost constraint

$$\sum_{i=1}^{N} c_i = \sum_{i=1}^{N} u_i^0 \sum_{j=1}^{M} f_{ij}\cdot x_{ij} = \sum_{i=1}^{N} u_i^0 \sum_{j=1}^{M} (f_{ij}^1 + f_{ij}^2)\cdot x_{ij} \le C, \tag{4}$$

where

f_{ij} – averaged annual total cost of the of j-th technology applied to the i-th source,

f_{ij}^1 – averaged annual investment cost of the of j-th technology applied to the i-th source,

f_{ij}^2 – annual operational cost of the of j-th technology applied to the i-th source.

Now we can formulate the following problem of allocation of emission reduction technologies to emission sources

ALLOCATION PROBLEM (**AP**): *Determine the set of emission reduction technologies*

$$X^* = \{ x^*_{ij} \in \{0,1\} : \sum_{j=1}^{M} x^*_{ij} = 1, \ \ 1 \le i \le N, \ \ 1 \le j \le M \}$$

in such a way that the environmental cost function (1) is minimized

$$J(d(X^*)) \Rightarrow \min$$

subject to the total cost constraint

$$\sum_{i=1}^{N} c_i \le C$$

Since the decision variables x_{ij} in the above stated AP can take only binary $\{0,1\}$ values, the AP is of binary type. It is difficult to solve it by simple enumeration of the solutions, since there are M^N possible combinations of solutions.

3. Implementation of the dynamic programming method

The dynamic programming method, proposed by Bellman (Bellman, et al. 1962) is suitable for a certain class of problems. Its main assumption is that the objective function has the form

$$R(v_1, v_2, \ldots, v_p) = g_1(v_1) + g_2(v_2) + \ldots + g_n(vp) \tag{5}$$

subject to

$$\sum_{i=1}^{p} v_i = v \tag{6}$$

It means, that the function $R(v_1, v_2, \ldots, v_p)$ is additive over the arguments $v_1, v_2, \ldots, v_p$. This is, however, not the case of AP.

So, in order to use the dynamic programming method we must reformulate the original problem in such a way, that the new problem can be described as a minimization of the additive function. The first step is to define a new objective function

$$J_1(d) = \frac{1}{2}\int_{\Omega} w(x,y)d(x,y)d\Omega \tag{7}$$

Function J_I is additive over the decision variables x_{ij}, determining the concentrations $d(x,y)$, since the concentration $d(x,y)$ in the receptor element (site) (x,y) is simply the sum of the concentration contributions of each emission source.

Function J_I can be rewritten as

$$J_1(d) = \frac{1}{2}\sum_{i=1}^{N} \int_{\Omega} w(x,y)d_i(x,y)d\Omega \tag{8}$$

where

$$d_i(x,y) = d_0(x,y) + A_i(x,y)\cdot u_i, \quad (x,y)\in\Omega \qquad 1\le i\le N$$

is the share of the i-th source in the concentration in the site (x,y).

The algorithm used for minimizing the function J_I consists in the following steps.

STEP 1.
Divide the whole available resources (funds, which must be not greater than C) in $L+1$ levels, $0 = z_0 < z_1 < z_2 < \ldots < z_L = C$.

STEP 2.
For the first source, determine the technology, which yields the best result, i.e. the minimal concentration in the whole region Ω, due to this source, for each level z_j, l=1, 2,..., L and save the results.

STEP 3.
If the list of the sources is completed – STOP. The best sequence obtained in step 4 is optimal. Otherwise, consider the next source.

STEP 4.
Take the sequential resource levels z_j, l= 0, 1, 2, ..., L and for each level create the list of all possible splits of the available resources: $(0, z_l)$, $(1, z_l\text{-}1)$, ... $(z_l, 0)$. For each split assign the left part to the current source and the right to sources already evaluated. For each level z_j choose the best sequence of technologies for all the sources already considered, including the current source. Save the results (sequences of technologies) for each resource level. Go to step 3.

The algorithm described above gives the minimal value of the function J_I. We must remember that our goal consists in minimizing the function J, and not J_I.

It is obvious, that for the function J_l meaningful is only the whole volume of the concentration in the region Ω, regardless how the concentration is distributed over the receptor points (x, y). This is not the case for the function J. It matters how the concentration is distributed. We pay more for the peaks, since the value of the function J is proportional to the 2nd power of concentration. This leads to the need of modification of the algorithm described above. The idea is to assign weights (importance coefficients) α to each emission source. The coefficient α_i for the i-th source is the sum of products of shares in the concentrations for the i-th source and the volumes of concentrations in the sites (x, y).

$$\alpha_i = \int_{\Omega} d_i(x, y) \cdot d(x, y)\, d\Omega \tag{9}$$

This modification, i.e. using the dynamic programming method with weighted sources allows us to take into account the peaks of concentrations and then to obtain results closer to those, when the function J is to be minimized.

4. Case study analysis

The dynamic programming method was applied in the real-data case for selection of desulfurization technologies in the major power plants of the industrial Upper Silesia Region. The region is characterized by high concentration of heavy industry and the energy sector installations.

The domain considered is a rectangle area 110 km x 76km. In this area 20 major power plants were selected and considered as the controlled sources. Moreover, certain number of medium and small industrial sources constitutes a background emission field.

In the example presented, 8 desulfurization technologies are taken into account (5 basic technologies and 3 combined). The technologies and the their emission reduction efficiencies are as follows:

- "do nothing" technology $(e = 0)$,
- low-sulfur fuel $(e \cong 0.30)$,
- dry desulfurization method $(e \cong 0.35)$,
- low-sulfur fuel + dry desulfurization method $(e \cong 0.545)$,
- half-dry desulfurization method $(e \cong 0.75)$,
- low-sulfur fuel + half-dry desulfurization method $(e \cong 0.825)$,
- MOWAP method $(e \cong 0.85)$,
- low-sulfur fuel + MOWAP method $(e \cong 0.895)$.

The annual unit concentration maps for the controlled sources (the transfer matrices $A_i(x,y)$, $i = 1,...,N$) are preprocessed off-line by the regional-scale forecasting model REGFOR3 defined in (Holnicki et all, 1994). This is a dynamical, single-layer model that uses the set of meteorological input data for the period of simulation (time-discretization step is 12 hrs). The same technique is used for generating a background concentration field for intermediate point and area sources. Computations were performed for one representative year, where a sequence of meteorological data with 12-hrs time resolution was applied.

The method was tested for three levels of the total cost constraint, with 50 different data sets each. In order to have a tool for assessment of the quality of the solutions given by the dynamic programming method, another approach was used. Its idea consists in formulation the main task as the respective continuous problem, where the decision variables can take continuous values $x_{ij} \in \langle 0,1 \rangle$. Such a continuous solution (Pshenitschny, 1983) is used as a reference base for evaluation of accuracy of the dynamic programming algorithm. The comparison of the achieved results (quality index shown in %), given as the ratio of value of the function J, obtained by the dynamic programming and the value of the function J obtained by the continuous method, is presented in Figures 1 – 3.

As one can observe in the figures, the dynamic programming method gives results, which quality varies from case to case and on the average are worse approximately 3.5 – 4% than those obtained via continuous method. Its main advantage is that the run time is proportional to the product of the 2nd power of the number of resource levels L and to the number of emission sources N.

The tests of the dynamic programming method, made on three data sets and the experience coming out of these tests, lead to conclusion, that the quality index of the solutions must be improved. It can be done by better calculation of the concentration coefficients α_I, what will be investigated as the next step of the research.

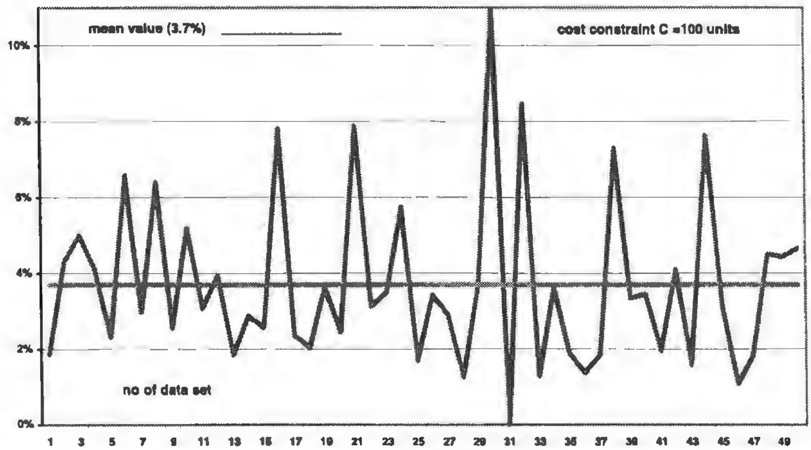

Figure 1. Quality index of the dynamic programming method for the cost constraint level 100 units.

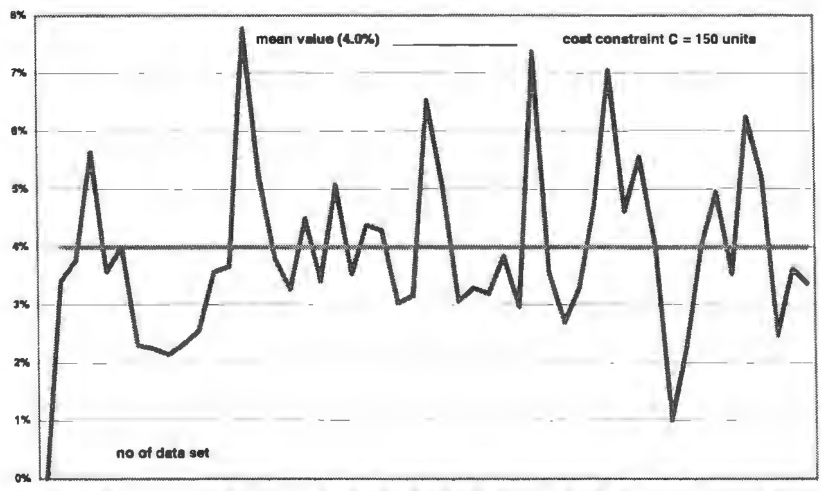

Figure 2. Quality index of the dynamic programming method for the cost constraint level 150 units.

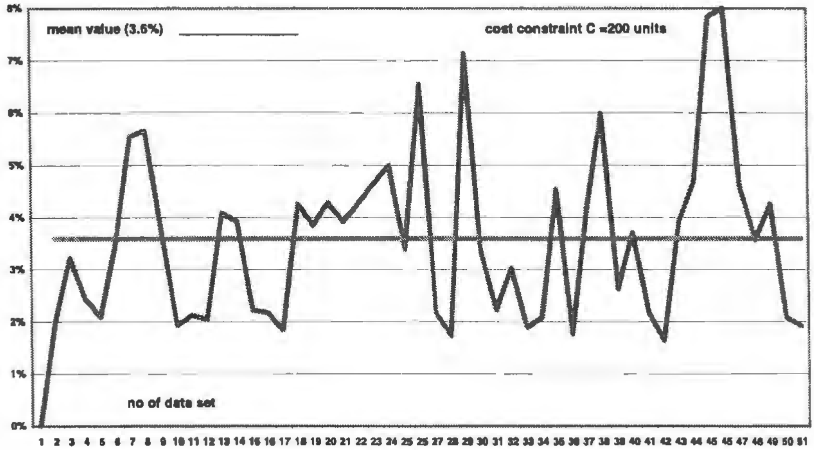

Figure 3. Quality index of the dynamic programming method for the cost constraint level 200 units.

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The purpose of the present publication is to popularize applications of informatics in environment and health engineering and protection. Runned papers are thematically chosen from the works presented during the conference *Multiaccessible Computer Systems* (*Komputerowe Systemy Wielodostępne*) that has been organized by the Systems Research Institute and University of Technology and Agriculture of Bydgoszcz for several years in Ciechocinek. Problems described in the papers concern quality management of the surface waters and the atmosphere, application of the mathematical modelling in environmental engineering, and development of computer systems in health and environmental protection. In several papers results of the research projects financed by the Polish Ministry of Science and Information Society Technologies are presented.

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