POLISH ACADEMY OF SCIENCES
Systems Research Institute

MODELLING CONCEPTS AND DECISION SUPPORT IN ENVIRONMENTTAL SYSTEMS

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Polish Academy of Sciences • Systems Research Institute

Series: SYSTEMS RESEARCH
Vol. 45

Series Editor:

Prof. Jakub Gutenbaum

Warsaw 2006

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The purpose of the present publication is to popularize information tools and applications of informatics in environmental engineering and environment protection that have been investigated and developed in Poland and Germany for the last few years. The papers published in this book were presented during the workshop organized by the Leibniz-Institute of Freshwater Ecology and Inland Fisheries in Berlin in February 2006. The problems described in the papers concern the mathematical modeling, development and application of computer aided decision making systems in such environmental areas as groundwater and soils, rivers and lakes, water management and regional pollution. The editors of the book hope that it will support the closer research cooperation between Poland and Germany and when this intend succeeds then also next publications of the similar kind will be published.

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ISBN-10: 83-894-7505-7
ISBN-13: 978-83-894750-5-3
ISSN 0208-8029

CHAPTER 4

Water management and Decision support

APPLICATION OF POLLUTION DISPERSION MODELS IN AIR QUALITY MANAGEMENT

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Abstract: *The paper addresses possible applications of air pollution forecasting models for supporting decisions concerning optimal strategy of emission abatement or the real-time emission control. The approach is based on integration of dynamic forecasting model of air pollution dispersion with the respective optimization procedures. The first problem concentrates on selection of emission reduction technologies in a given set of power plants. Mathematically, this is a static, integer optimization task. The second problem is formulated as on-line minimization of an environmental cost function, by the respective modification of emission level in the controlled sources, according to the changing meteorological conditions. The objective function depends on the current level of SO_x concentration and the sensitivity of the area to this type of air pollution. In both tasks, dispersion of the atmospheric pollution is governed by a multi-layer, dynamic model of SO_x transport, which is the main forecasting tool used in the optimization algorithm. The test computations have been performed for a set of the major power plants in a selected industrial region of Poland.*

Keywords: air pollution transport, emission abatement strategy, emission control.

1. Air pollution transport model

The direct application of environmental models is forecasting of dispersion of pollutants. Air quality studies are also aimed at optimization, but numerous applications of optimization methods mainly occur in the design of monitoring networks. On the other hand, many important decisions in air pollution and environmental problems, which could be supported by the respective models, are directly made by decision makers. However, some optimization methods and environmental models give the possibility of implementation of air pollution control strategies.

For example, air pollution forecasting model was applied to evaluate the possible environmental consequences of the variant strategies of energy sector expansion in Poland (Holnicki, 2001). The problem of the regional-scale strategy for emission abatement in a set of the major power plants was discussed in (Holnicki, 2004; 2005). The solution of the last task is searched by the optimal selection of the desulphurization technologies for emission sources considered. From the viewpoint of the mathematical formulation, the above tasks are stated as static optimization problems.

Dynamic air pollution forecasting models can be used as a base for constructing the real-time emission control systems. In such a case, the optimal control problem is formulated as on-line minimization of an environmental cost function, by the respective modification of emission level in a set of the controlled sources, according to the changing meteorological conditions. The algorithms that solve such problems usually need certain procedure to evaluate the contribution of the controlled emission sources in the final environmental damage. This problem was discussed in (Holnicki, 2004).

It is assumed that the pollution transport process can be considered as distributed parameter system, governed by the transport equation. Implementation discussed in the sequel is sulfur-oriented, but the approach can be applied in a more general class of the forecasting models. The governing model generates short-term forecasts of air pollution related to a specified, complex emission field.

Computation of the transport of sulfur pollution is carried out by Lagrangian type, three-layer trajectory model (Holnicki, 1995). The mass balance for the pollutants is calculated for air parcels following the wind trajectories. The model takes into account two basic polluting components: primary – SO_2 and secondary – $SO_4^{=}$. Transport equations include chemical transformations $SO_2 \rightarrow SO_4^{=}$, dry deposition and the scavenging by precipitation.

The main output constitutes the concentrations of SO_2, averaged over the discretization element and the vertical layer height. The governing equation, considered in one vertical layer, has the following, general form

$$\frac{\partial c}{\partial t} + \vec{\upsilon}\nabla c - K_h \Delta c + \gamma c = Q + q \tag{1}$$

along with the boundary conditions

$$c = c_b \text{ on } S^{-} = \{\partial\Omega \times (0,T) \mid \vec{\upsilon}\cdot\vec{n} < 0\};$$

$$K_h \frac{\partial c}{\partial \vec{n}} = 0 \text{ on } S^{+} = \{\partial\Omega \times (0,T) \mid \vec{\upsilon}\cdot\vec{n} < 0\} \tag{1a}$$

and the initial condition

$$c(0) = c_0 \quad \text{in} \quad \Omega . \tag{1b}$$

Here Ω is the domain considered, T – time interval, c – pollution concentration, $\vec{\upsilon}$ – wind velocity vector, $\vec{n}$ – normal outward vector, K_h – horizontal diffusion coefficient, γ – scavenging factor. The emission field on the right side of (1) is composed of the background (uncontrolled) emission field $Q(x, y, t)$ and the emission field of the controlled sources – $q_i(x, y, t)$, which is defined as follows

$$q(x, y, t) = \sum_{i=1}^{N} \chi_i(x, y) \cdot q_i(t), \tag{2}$$

where

$q_i(t)$ - emission intensity of the i-th layer,

$\chi_i(x, y)$ - characteristic function of the i-th source (definition of the source location).

Numerical algorithm is based on the discrete- time, finite element spatial approximation, combined with the method of characteristics (Holnicki et al, 1993; Holnicki, 1995). The uniform space discretization step, $h = \Delta x = \Delta y$ is applied in the computational algorithm. The mass balance for the pollutants is calculated for air parcels following the wind trajectories. Points along the trajectory are determined at discrete time points, based on the predefined interval $-\tau$. The numerical algorithm developed for solving (1) – (2) is presented by Holnicki (1995).

2. Optimal strategy of emission abatement

This section presents an example of application of the forecasting model, as a decision support tool for environmental quality protection. Our goal is to find a method for allocation of emission reduction technologies in a set of emission sources. The method is based on minimizing the environmental cost function subject the constraint of the total cost of implementation of these technologies.

2.1. Statement of the problem

Assume that there are N controlled SO_2 emission sources in a region Ω, and M technologies for emission reduction. Each technology is characterized by the effectiveness and the unit cost (both for investment and operational costs). 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 minimized subject to constraints on investment and operational costs, in a given period T.

To state the optimization problem, the necessary notation must be introduced. We shall denote $\vec{u} = [u_1, u_2, \ldots, u_N]$ – emission vector of controlled sources,

$\vec{e}=[e_1,e_2,\dots,e_M]$ – effectiveness vector of desulphurization technologies applied, $F=\{f_{ij}\}$ – matrix of abatement cost per unit emission, $X=\{x_{ij}\}$ – "0-1" matrix of technology assignment.

Definition of the environmental criterion, which is to be minimized, depends on the objectives of the control strategy which is considered. We define here a global environmental cost function of the following form:

$$J(c)=\frac{1}{2}\int_{\Omega} w(x,y)\max{}^2(0,c(x,y)-c_{ad})\,d\Omega \tag{3}$$

where: $w(x,y)$ – area sensitivity (weight) function, c_{ad} – admissible concentration level.

The concentration forecast, considered as the solution to (1), is calculated as

$$c(x,y)=c_o(x,y)+\sum_{i=1}^{N}A_i(x,y)\cdot u_i,\quad (x,y)\in\Omega \tag{4}$$

where $c_o(x,y)$ – background concentration (impact of uncontrolled sources), $A_i(x,y)$ – transfer matrix (relation emission → concentration) of the i-th source.

The unit transfer matrices $A_i(x,y)$, $(i=1,\dots,N)$ for the controlled sources are preprocessed off-line by the respective forecasting model (Holnicki et al, 2001). In a similar way, the background pollution field, $c_o(x,y)$ 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^o and efficiency of the abatement technology applied, according to the formula

$$u_i(x,y)=u_i^o\sum_{j=1}^{M}(1-e_j)\cdot x_{ij},\quad \sum_{j=1}^{M}x_{ij}=1,\quad x_{ij}\in\{0,1\},\quad 1\le i\le N, \tag{5}$$

where u_i, u_i^o denote the current and the initial emission intensity of the i-th source, respectively.

Cost of emission abatement in each source consists of two components: investment cost and operational cost. Here a simplified approach is utilized, where the investment cost of the j-th abatement technology installed in the i-th emission source is calculated as annual cost, averaged over the entire amortization period.

Thus, the total emission abatement cost per year, considered as a sum of desulphurization costs in the respective plants, is calculated in the following form:

$$C_T = \sum_{i=1}^{N} c_i = \sum_{i=1}^{N} u_i^o \sum_{j=1}^{M} f_{ij} x_{ij} = \sum_{i=1}^{N} u_i^o \sum_{j=1}^{M} (f_{ij}^1 + f_{ij}^2) x_{ij}, \tag{6}$$

where the coefficients: f_{ij}^1, f_{ij}^2, f_{ij} denote here the averaged annual, investment, operational and total cost, respectively, of the j-th technology applied to the i-th emission source.

Basing on the above notation, we can formulate optimization problem, aimed at selection of emission abatement technologies. Depending on the criterion function and the constraints – the following two complementary problems can be considered

Formal statement of the optimization task is presented by Holnicki and Kaluszko (2004). Mathematically, the problem can be classified as integer programming optimization.

Discrete problem (DP) of optimal selection of emission abatement technologies

Determine the set of emission reduction technologies

$$X_{ad} = \{x_{ij} \in \{0,1\} : u_i = u_i^o \sum_{j=1}^{M} (1 - e_j) x_{ij}, \ \sum_{j=1}^{M} x_{ij} = 1, \ 1 \le i \le N, \ 1 \le j \le M\}, \tag{7}$$

in such a way that the environmental cost function (3) is minimized

$$J(c(X_{ad})) \Rightarrow \min \tag{7a}$$

subject to the total cost constraint

$$C_T = \sum_{i=1}^{N} c_i \le C_{MAX} \tag{7b}$$

Since the decision variables x_{ij} in (DP) can take only binary $\{0,1\}$ values, the problem is of binary type. Several numerical algorithms have been developed for solving (DP) problem and tested on the real-data case. These implementations are:

a) the heuristic algorithm (Holnicki and Kaluszko, 2004), computationally efficient, but with relatively low accuracy of the optimal solution,
b) an algorithm based on the evolutionary methods (genetic algorithm) (Stanczak et al, 2006), which is accurate, but very time-consuming,
c) an algorithm based on the continuous approximation of the original, integer type problem (DP). The algorithm - due to the respective definition of the set of admissible solutions - generates solutions of integer-type, which exactly correspond to the genetic algorithm results (Holnicki, 2005). Comparing with the previous two methods, this implementation is fast and computationally effective.

The last method gives the best solution, from the point of view of the objective function reduction. For this reason it was used for evaluation of the other methods accuracy. The next paragraph presents computational results obtained for the real-data case study, performed for the selected set of power plants.

2.2. A case study of application

Optimization methods were tested on the real data in the industrial region of Upper Silesia in Poland. The area is characterized by a high concentration of heavy industry and energy sector, controlled installations. The domain, with 20 major power plants considered as the controlled sources. Figure 1(a) shows the map of SO_2 initial concentration in the area with the marked location of major power plants.

As the emission reduction methods, 8 desulphurization technologies are taken into account (5 basic and 3 combined technologies). The technologies and the respective emission reduction efficiencies are:

-- "do nothing" technology $(e=0)$,

-- low-sulfur fuel $(e\cong 0.3)$,

-- dry desulphurization method $(e\cong 0.35)$,

-- low-sulfur fuel + dry de desulphurization method $(e\cong 0.545)$,

-- half-dry desulphurization method $(e\cong 0.75)$,

-- low-sulfur fuel + half-dry desulphurization n 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 $A_i(x,y)$; $i=1,\dots,N$) are preprocessed off-line by the regional scale forecasting model, discussed in Section 1. Then, these matrices are used in the optimization algorithm, to calculate the overall concentration map according to formula (4).

Application of the optimization algorithm to minimization of the environmental cost for a given cost constraint generates the optimal solution as assignment of the selected abatement technologies to each emission source. Table 1 presents an example of integer-type, optimal solution, obtained by evolutionary method for the total cost constraint, $C = 150$ mil. PLN/y. The selected -- for a given power plant -- abatement technology is indicated by "1" in the respective column.

Table 1. The optimal solution obtained for the cost constraint 150 ml PLN/year.

source	initial emis-sion	abatement cost = **150.00** ml PLN/year								final emission
		abatement technology								
		1	2	3	4	5	6	7	8	
1	303.20	0	0	0	0	0	0	**1**	0	45.48
2	225.30	**1**	0	0	0	0	0	0	0	225.30
3	104.00	0	0	0	**1**	0	0	0	0	47.32
4	91.80	0	0	0	**1**	0	0	0	0	41.77
5	90.10	0	0	0	0	0	**1**	0	0	15.77
6	78.00	0	**1**	0	0	0	0	0	0	54.60
7	65.00	0	**1**	0	0	0	0	0	0	45.50
8	52.00	**1**	0	0	0	0	0	0	0	52.00
9	52.00	0	**1**	0	0	0	0	0	0	36.40
10	45.10	0	**1**	0	0	0	0	0	0	31.57
11	34.70	0	0	0	0	0	0	**1**	0	5.21
12	33.80	0	0	0	0	0	0	0	**1**	3.55
13	29.90	0	0	0	0	0	0	**1**	0	4.49
14	25.10	0	0	0	0	0	0	**1**	0	3.77
15	26.00	0	0	0	1	0	0	0	0	11.83
16	18.70	0	0	0	**1**	0	0	0	0	8.51
17	16.90	0	**1**	0	0	0	0	0	0	11.83
18	15.10	0	0	0	**1**	0	0	0	0	6.87
19	12.30	**1**	0	0	0	0	0	0	0	12.30
20	11.60	0	0	0	**1**	0	0	0	0	5.28

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, discussed in Section 1. Then, these matrices are used in the optimization algorithm, to calculate the overall concentration map according to formula (4).

Application of the optimization algorithm to minimization of the environmental cost for a given cost constraint generates the optimal solution as assignment of the selected abatement technologies to each emission source. Table 1 presents an example of integer-type, optimal solution, obtained by evolutionary method for the total cost constraint, C = 150 mil. PLN/y. The selected - for a given power plant - abatement technology is indicated by "1" in the respective column.

Repeating the optimization algorithm for selected levels of cost constraints, one can obtain the respective set of the optimal solutions. Calculations were performed for the cost constraints 100 ml PLN/y, 150 ml PLN/y and 250 ml PLN/y, respectively. The higher funds available, the more effective technologies can be applied and the better environmental quality improvement is be obtained. The solutions are also reflected in the final pollution concentration maps. Figure 1 presents the respective SO_2 concentration maps, obtained for the above cost limits.

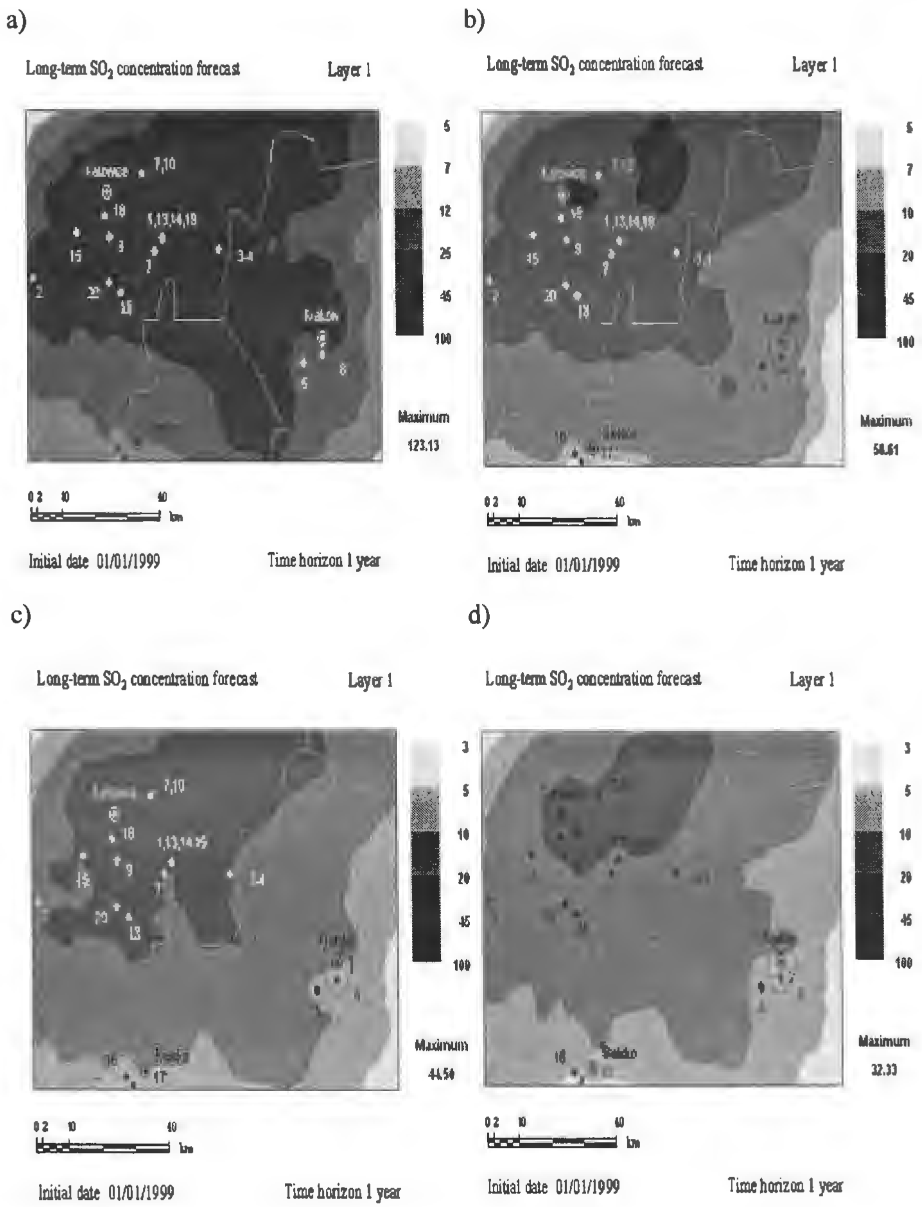


Figure 1. Maps of SO_2 concentration, depending on the total cost of emission reduction: a) initial; b) cost constraint 100 mil. PLN/y; c) cost constraint 150 mil. PLN/y; d) cost constraint 200 mil. PLN/y

3. The real-time emission control

3.1. Statement of the problem

The general idea of control consists in minimizing a predefined environmental cost function, according to the changing meteorological conditions, by redistribution of energy production (emission intensity) within the set of the selected emission sources (controlled sources). Certain economic and technological constrains are also taken into account.

To formally state the optimal control problem, we below define the basic conditions. Assume that in a given domain Ω there are N controlled emission sources described by certain spatial and temporal characteristics – $\chi_i(x,y)$ and $q_i(t)$, respectively. There is also a set of uncontrolled emission sources Q that form the background pollution field.

State equation. We consider a concentration of the polluting factor $c(x,y,t)$, which satisfies the following transport equation

$$\frac{\partial c}{\partial t} + \vec{\upsilon}\,\nabla c - K_h \Delta c + \gamma c = Q + \sum_{i=1}^{N} q_i \quad \text{in } \Omega \times (0,T) \tag{8}$$

with the boundary and initial conditions (1a-b). Emission characteristics of the controlled sources are represented by the product

$$q_i(x,y,t) = \chi_i(x,y) F_i(u_i(t)) \quad \text{for} \quad i = 1,\dots,N, \tag{8a}$$

where $F_i(u_i(t))$ is the temporal characteristics of emission intensity. Vector function $\vec{u} = [u_1,\dots,u_N]$ denotes here the control and represents production level (e.g. energy production of the power plant). Functions F_i, $(i = 1,\dots,N)$ relate energy production level of the respective plant, to the emission intensity, which is the right side of the state equation.

Cost functional to be minimized consists of two components: environmental cost function (air quality damage) and cost of the control. It is defined as follows

$$J(\vec{u}) = \frac{\alpha_1}{2} \int_0^T \int_\Omega w[\max(0,\, c(\vec{u}) - c_{ad})]\, d\Omega\, dt + \\ + \frac{\alpha_2}{2} \int_0^T \sum_{i=1}^{N} \beta_i (u_i(t) - u_i^*) \tag{9}$$

Here the coefficients α_1, α_2, β_i, $(i = 1,\ldots,N)$ are given constants, where $\alpha_1 \geq 0$, $\alpha_2 \geq 0$, $\beta_i > 0$. The area sensitivity function in (9) satisfies the inequality $0 \leq w(x,y) \leq 1$ and c_{ad} is an admissible concentration, u_i^*, $(i = 1,\ldots,N)$ - the nominal production of the sources.

Constraints imposed on the production level of the controlled emission sources represent some technological and economic requirements, and are as follows:

$$\underline{u}_i \leq u_i(t) \leq \overline{u}_i \quad \text{for} \quad i = 1,\ldots,N, \tag{10a}$$

$$\sum_{i=1}^{N} \delta_i u_i(t) \geq d. \tag{10b}$$

Inequalities (10a) define the lower and upper technological limits on the real production level of the plant under consideration. Condition (10b) represent constraints of total energy demand, which is imposed on the j-th subset of plants, with some coefficients δ_{ij}.

We denote by $U_{ad} \subset H^1(0,T;R^N)$ the set of admissible controls defined by (10). It is known (Lions, 1971) that the state equation (8) has a unique solution $c = c(\vec{u})$ determined for a given $\vec{u} \in H^1(0,T;R^N)$ and for fixed, constant parameters K_h and γ, where $K_h > 0$.

Optimal control problem (P). *Find the element* $\vec{u}^0(t)$ *which minimizes the cost functional (9) over the set of admissible controls*

$$J(\vec{u}^0) = \inf_{\vec{u} \in U_{ad}} J(c(\vec{u}))$$

where $c(\vec{u})$ *satisfies the state equation (8).*

It can be shown (Lions, 1971; Martchuk, 1995), that the solution of (P) can be characterized by the system of the optimality conditions, including the state equation (8) and the adjoint equation (Holnicki, 2004; Lions, 1971). These conditions, including the adjoint variable -- p^0, can be utilized as a base for construction of a gradient optimization algorithm, which contains the following steps: i) solve the state equation (8), ii) solve the respective adjoint equation, to determine p^0, iii) calculate components of the gradient vector – $J'(\vec{u})$, according to the left side of (13). The gradient of the objective functional, in this case has, a form (Lions, 1971)

$$J'(\vec{u}) = \alpha_1 \int_0^T \int_\Omega \chi_i F'(u_i^o) p^o \, d\Omega \, dt \; + \alpha_2 \int_0^T \beta_i (u_i^o - u_i^*) dt \quad \text{for } (i = 1,\dots,N). \quad (11)$$

According to the main optimal control problem (P) defined before, the following calculations are performed in the consecutive iteration of the algorithm:

- Solving of the state equation in the interval $(0,T)$,
- Calculation of the objective function $J(\vec{u})$,
- Solving of the adjoined equation for the reversed time,
- Calculation of the components of the gradient $J'(\vec{u})$,
- Calculation of the optimization direction
- Performing of the optimization step.

The next paragraph presents an example of the real-data application of the above techniques.

3.2. Case study analysis

The general approach presented in Section 3.1 has been implemented and tested on a real data case. The test calculations have been performed for the selected region of Upper Silesia (Poland) and the set of the major power plants, considered as the controlled emission sources.

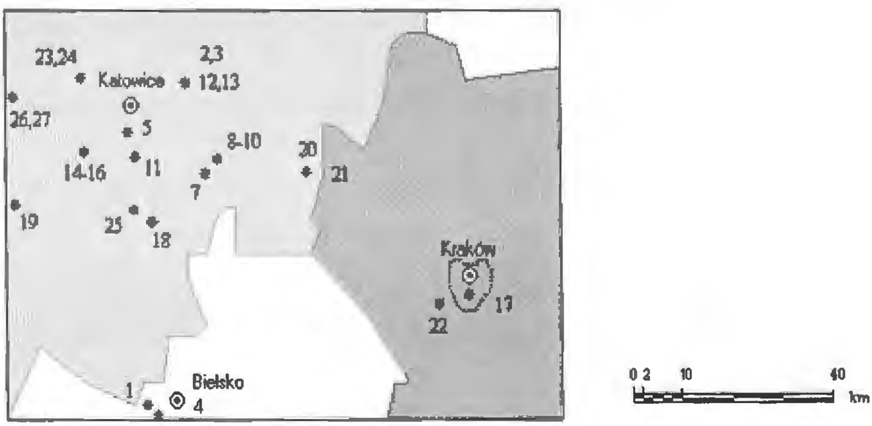


Figure 2. Computational domain and location of the controlled emission sources.

Figure 2 presents the computational domain and the location of emission sources. We assume for simplicity that function that relates emission to production level is identity, i.e. $F_i(u_i) = u_i$ for $i = 1,\dots,N$.

The computational domain 110x74 km^2 shown in Figure 2 was discretized with the homogeneous grid (discretization step, $h = 2$ km). The computations were performed for the set of 27 the dominating power plants located in the industrial region of Upper Silesia. Computational results shown below represent the real-time emission control for one 12-h time interval and for a selected meteorological scenario. The nominal emissions of the controlled sources refer to the winter season values, as presented in Table 2.

The area weight function $w(x,y)$, which spatially characterizes sensitivity of the area to sulfur-type air pollution in the objective function (9), defines surroundings of Krakow as the protected area and is as follows:

$$w(x,y) = \begin{cases} 1 & \text{for } (x,y) \text{ within Krakow area,} \\ 0 & \text{for } (x,y) \text{ outside this domain.} \end{cases} \tag{12}$$

Numerical algorithm used for analysis of the state and adjoint equations (Holnicki, 2004) is based on the regional scale forecasting model URFOR3 (Holnicki et al, 1993). The finite dimensional approximation scheme of the transport equation is based on a combination of the method of characteristics and the finite element spatial approximation (Holnicki et al, 1993). As discussed in (Holnicki, 1995), the algorithm is computationally efficient and it guarantees good shape-preserving properties and gives the respective accuracy of the finite solution.

Numerical implementation of the optimization algorithm is based on the method of linearization by Pshenitchny (1971), where the gradient of the objective function as well as the constraints are utilized. Results of test computations related to this approach can also be found in (Holnicki, 2004).

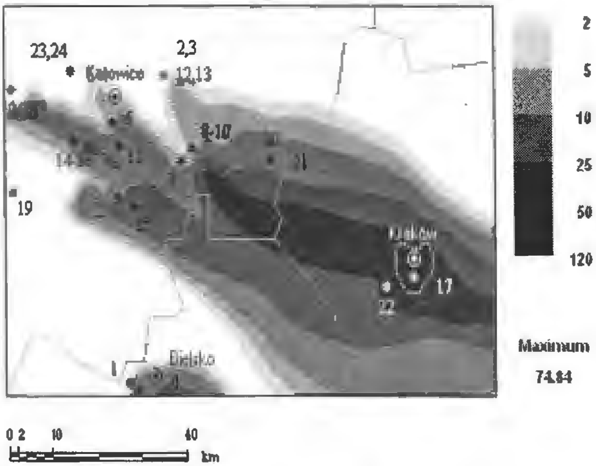
The test calculations were performed for selected 12-h time intervals of the Winter season emission level of the controlled sources, listed in Table 2. The final results presented in the sequel refer to the selected meteorological episode: the moderate N-W wind and the neutral atmospheric stability conditions. Performance of the algorithm strongly depends on the initial emissions of the sources and the meteorological forecast. For the scenario considered, computation process of the optimal control procedure completes in 4 iterations, while the computing time does not exceed 1 min. The quantitative optimization results are shown in Table 2 (the last column).

The quantitative results of the optimal control, related to modifications in the emission sources, are presented in Table 2 in a form of relative changes of the initial emission intensity in the controlled sources. As the result of the optimization procedure -- the sources No. 9, 10, 13, 20, 21 have the emissions reduced, while 11, 14, 19, 22 – the emission respectively increased, to satisfy the energy demand constraint (10-b). The corresponding results are presented in a graphical form in Figures 3 – 4, where the respective maps of distributions of the state variable - c^o (or SO_2 concentration) and the adjoint variable - p^o are shown.

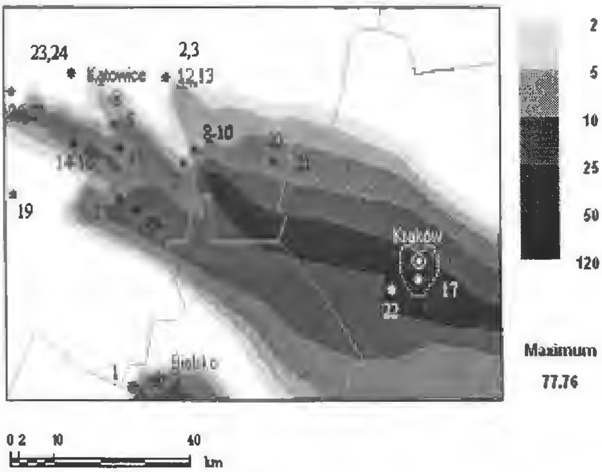
Table 2. Emission parameters of the controlled sources. Optimization results.

No	source name	source coord.	stack [m]	emission [kg/h]	control action
1	Bielsko Biała	(14,2)	160	426.91	1.00
2	Będzin A	(18,31)	95	94.89	1.00
3	Będzin B	(18,31)	135	132.82	1.00
4	Bielsko-Kom.	(15,1)	250	426.9	1.00
5	Chorzów	(12,27)	100	363.66	1.00
6	Halemba	(8,25)	110	569.24	1.00
7	Jaworzno I	(20,23)	152	284.61	1.00
8.	JaworznoIIA	(21,24)	100	573.60	1.00
9	JaworznoIIB	(21,24)	120	664.08	0.80
10	Jaworzno III	(15,1)	300	6324.60	0.80
11	Katowice	(18,31)	95	1106.81	1.10
12	Łagisza A	(18,31)	160	948.69	1.00
13	Łagisza B	(18,31)	200	1359.79	0.90
14	Łaziska I	(8,20)	200	1660.21	1.10
15	Łaziska II	(8,20)	160	758.95	1.00
16	Łaziska III	(8,20)	100	727.95	1.00
17	Łęg	(46,12)	260	1106.81	1.10
18	Miechowice	(14,17)	68	161.28	1.00
19	Rybnik	(1,20)	300	4711.83	1.25
20	Siersza A	(30,231)	150	1929.00	0.80
21	Siersza B	(30,23)	260	2055.49	0.80
22	Skawina	(43,11)	120	1992.25	1.10
23	Szombierki A	(9,31)	110	164.44	1.00
24	Szombierki B	(9,31)	120	170.76	1.00
25	Tychy	(13,19)	120	110.68	1.00
26	Zabrze A	(2,29)	60	205.55	1.00
27	Zabrze B	(2,29)	120	221.36	1.00

Figure 3 indicates the differences in the distribution of SO_2 concentration for the reference emission field (according to Table 2) and for the emission control strategy suggested by the optimization procedure (the last column of Table 2).



a) Reference emission field



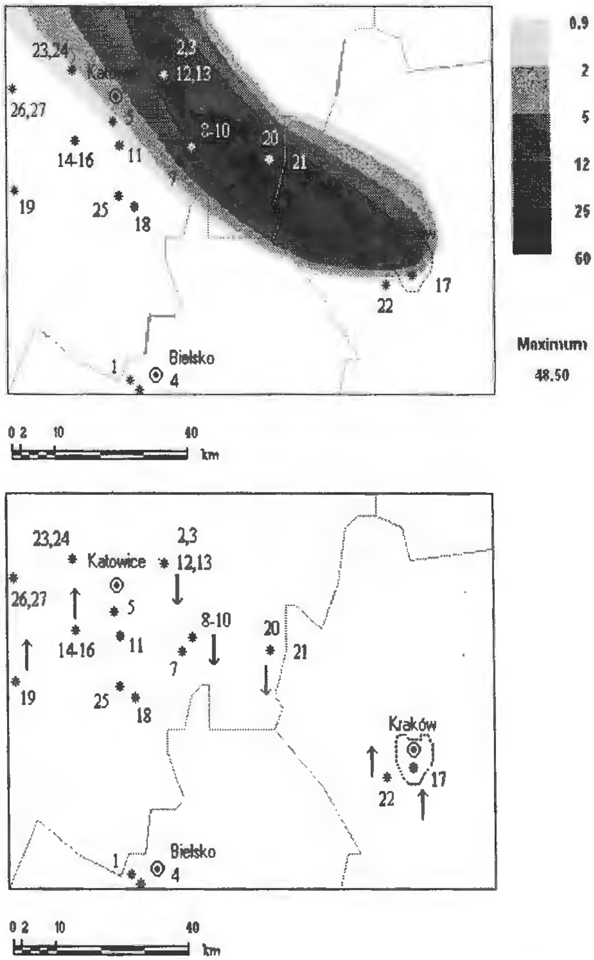
b) Emission control strategy

$$\frac{J_{opt}}{J_{ref}} = 0.85$$

Figure 3. Maps of SO_2 concentration: initial (a), and -- for the optimal emission control (b).

Some differences in concentration field can be observed within the high sensitivity area, according to the definition of the area sensitivity function (12) and the Fig. 1. The respective reduction of the objective functional is 0.85 for the considered scenario (see Fig. 3).

The correlation between the distribution of the adjoint variable and the location of the dominating controlled sources are shown in Figure 4. The area of high values of the adjoint variable (Fig. 4a) coincides with locations of the sources, which significantly contribute to the overall environmental cost function (compare Table 2), for the current meteorological conditions (e.g. wind direction).



a) distribution of adjoint variable

b) modification of emission intensity

Figure 4. Distribution of the adjoint variable (a) and modifications of the controlled sources (b)

These sources have the emissions respectively reduced, as the result of the optimization algorithm (compare Table 2). The related changes of the emission intensities are shown in Fig. 4b. On the other hand, to satisfy the energy demand constraints (10) - the production level (and emission) in some sources must be risen. These are the sources located outside the area of high influence, which do not contribute to the quality functional for this particular meteorological situation.

The obtained results confirm the possibility of the effective utilizing of air pollution transport models and the discussed above technique in the real-time emission control. The accuracy and performance of the computer implementation of the model is satisfactory from the point of view of the possible future applications of this approach.

The applications of the technique discussed in the paper concentrate on the problem of the real-time emission control. Presented results show, that some elements of the technique can also be utilized in long-term analysis of regional scale sustainable development. The remark refers to the adjoined variable, which indicates the area which is the most influencing from environmental perspective. Thus, in long-term analysis, distribution of this variable can also be an important factor in supporting decisions of the planned energy sector investments and their location within the region.

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MODELLING CONCEPTS AND DECISION SUPPORT IN ENYIRONMENTAL SYSTEMs

This book presents the papers that describe the most interesting results of the research that have been obtained during the last few years in the area of environmental engineering and environment protection at the Systems Research Institute of the Polish Academy of Sciences in Warsaw and the Leibniz-Institute of Freshwater Ecology and Inland Fisheries in Berlin (IGB). The papers were presented during the First Joint Workshop organized at the IGB in February 2006. They deal with mathematical modeling, development and application of computer aided decision making systems in the areas of the environmental engineering concerning groundwater and soil, rivers and lakes, water management and regional pollution.

ISBN-10: 83-894-7505-7
ISBN-13: 978-83-894750-5-3
ISSN 0208-8029