84/2007

Raport Badawczy

Research Report

RB/35/2007

Application of evolutionary algorithm technique in long-term analysis of emission reduction on a regional scale

J. Stańczak, P. Holnicki

Instytut Badań Systemowych
Polska Akademia Nauk

Systems Research Institute
Polish Academy of Sciences

POLSKA AKADEMIA NAUK

Instytut Badań Systemowych

ul. Newelska 6

01-447 Warszawa

tel.: (+48) (22) 3810100

fax: (+48) (22) 3810105

Kierownik Pracowni zgłaszający pracę:
prof. dr hab. inż. Zbigniew Nahorski

Warszawa 2007

Application of evolutionary algorithm technique in long-term analysis of emission reduction on a regional scale

Jarosław Stańczak [1], Piotr Holnicki [1]

Abstract

The paper deals with the problem as a long-term, cost-effective analysis of environmental quality related to air pollution and considered in a predefined time horizon. The problem is formally stated the optimal allocation of financial means for the long-term reduction of SO_2 concentration in a given region. The optimal choice of desulfurization technologies during a given time horizon, within the predefined set of the controlled power and heating plants is a difficult, integer-type optimization task. The paper presents solution of the basic task based on the evolutionary algorithm technique. The method has been implemented and tested on the real data for Silesia Region (Poland), with the set of the basic desulfurization technologies, which are to be allocated to the major power plants located in the region. Two alternative formulations of the optimization problem are discussed. The definition includes the measure of environmental damage related to air pollution and the cost of emission abatement strategy applied.

1. Introduction

Poland is one of the most polluted areas in the Central Europe. Air quality deterioration is, first of all, due to the sulfur oxides, emitted by a number of power and heating plants, industrial and domestic sources, transportation system. The most significant environmental damage is caused by the energy sector, since the dominating source of electricity production is coal (hard coal and lignite) combustion. The modernization of this sector and emission reduction is one of the fundamental environmental problems considered nowadays. In the paper the problem of a regional-scale strategy of SO_2 emission abatement is

[1] Systems Research Institute of the Polish Academy of Sciences, Newelska 6, PL-01447 Warsaw,
email: stanczak@ibspan.waw.pl, Internet: http://www.ibspan.waw.pl
email: holnicki@ibspan.waw.pl, Internet: http://www.ibspan.waw.pl

discussed. The main objective is to formulate decision-support algorithm for integrated analysis of cost-effectiveness and environmental impact related to the specific emission reduction strategy.

Regional-scale abatement policy depends on the criteria upon which the environmental damage is evaluated (compare Carlson et al. 2004; Cofała et al. 2004; Haurie et al. 2004). It is obvious, that the process of pollution reduction must be treated as a long-term, time-dependent one, due to high financial requirements and time needed to implement new technologies. This leads to formulation of the problem in terms of optimization techniques, based on cost-effectiveness analysis of emission reduction, taking into account the time factor. The problem is very difficult to solve using traditional optimization methods, thus an evolutionary algorithm has been applied (compare Stańczak et al. 2005).

Similar problem, but formulated as a static emission abatement task, was considered in the earlier papers, where some dedicated algorithms were applied. Compare (Holnicki and Kałuszko 2004 – heuristic method) and (Holnicki et al. 2004 – heuristic and evolutionary method) for details. In this paper the time factor related to the investments of desulfurization technologies is taken into account. The dynamics of this process is also taken into consideration in the evolutionary algorithm discussed in the sequel.

2. Formulation of the control problem

Assume that there are N controlled (modernized) emission sources in a given region Ω and there are M technologies of emission reduction available. Each technology has its effectiveness and the unit costs (consisting of investment cost and operational cost). The goal is to allocate emission reduction technology to each source in such a way, that the value of the assumed objective function minimized, subject to the set of constraints (environmental, technological or financial, depending on the problem formulation), considered in a predefined time horizon.

The environmental cost function has the following form:

$$J(d) = \frac{1}{2}\sum_{t=1}^{T} \int_{\Omega} w(x,y)\left[\max(0, d_t(x,y) - d_{ad})\right]^2 d\Omega\ , \tag{1}$$

where:

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

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

T – assumed time horizon (in years),

t – current time (year), $t \in \{1,\ldots,T\}$,

d_{ad} – admissible concentration level,

$d_t(x, y)$ – the concentration (deposition) forecast, calculated according the formula

$$d_t(x,y) = d_0(x,y) + \sum_{i=1}^{N} A_i(x,y)\cdot u_{it}\ ,\ \ (x,y) \in \Omega \tag{2}$$

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

$A_i(x,y)$ – unit transfer matrix (relation emission to concentration) of the i-th source,

N – number of controlled sources,

u_{it} – current emission intensity of source i at the time stage t.

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 preprocessed off-line by the regional scale forecasting model (Holnicki et al. 2000). The computation was performed for the respective sequence of meteorological episodes, representing two-year period. In a similar way, the background pollution level $d_0(x, y)$ has been 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_{i0} and efficiency of the abatement technology applied during time T, according to the formula (3)

$$u_{it} = u_{i0}\,(1 - e_{s_{it}})\,, \tag{3}$$

where:

$e_{s_{it}}$ – efficiency of emission reduction technology applied for source i in the time step t,

s_{it} – index of applied technology for the i-th in the time step t,

u_{i0} – initial emission intensity of the i-th source.

The cost of emission abatement in each source consists of two components: the investment cost and the operational cost. Both components depend on the specific abatement technology applied as well as on the parameters of energy generation technology utilized in the plant considered. Some details related to the unit investment and operational costs can be found in (Holnicki and Kałuszko 2004; Holnicki et al. 2004). Thus, the total emission abatement cost per year, considered as a sum of reduction costs in the respective plants, can be formulated as follows:

$$C_t = \sum_{i=1}^{N} c_{it} = \sum_{i=1}^{N} u_{i0}\,(f_{s_{it}}^{1} + f_{s_{it}}^{2})\,, \tag{4}$$

where:

C_t – the total (investment and operational), annual costs in the control horizon,

c_{it} – total cost (investment and operational) of emission abatement in source i for year t,

$f_{s_{it}}^{1}$, $f_{s_{it}}^{2}$ – unit annual investment/operational cost of technology s applied to i-th source in year t.

Now the following, two alternative formulations of the problem related to the optimal allocation of emission reduction technologies to the predefined set of the modernized (controlled) emission sources can be considered.

Allocation problem (P1)

Determine the set of emission reduction technologies

$$S = \{\, s_{it} \in \{1,\ldots,N\}:\ 1 \le i \le N,\ 1 \le t \le T \}\,, \tag{5a}$$

such that the assumed environment quality standard is obtained

$$J(c(X_{ad})) \leq J_{MAX} \quad , \tag{5b}$$

at the minimum total annual cost of the operation

$$C_t \Rightarrow \min \ . \tag{5c}$$

Allocation problem (P2)

Determine the set of emission reduction technologies

$$S = \{ s_{it} \in \{1,\ldots,N\}: \ 1 \leq i \leq N, \ 1 \leq t \leq T \} \ , \tag{6a}$$

such that the environmental cost function is minimized

$$J(c(X_{ad})) \Rightarrow \min \ , \tag{6b}$$

subject to the total annual cost constraint

$$C_t = \sum_{i=1}^{N} c_i \leq C_{MAX} \ . \tag{6c}$$

The next section presents evolutionary algorithm technique applied for formulation and solving the above, integer-type optimization problems. Results of the test computations, performed for the real data case study, are presented in section 4.

3. Evolutionary algorithm

3.1 Solution encoding

The solutions obtained in the subsequent iterations of the algorithm are the population members. One population member is a quite complicated data structure (Figure 1). This data structure is used for both formulations of the optimization problem but with some modifications, described later in this paper.

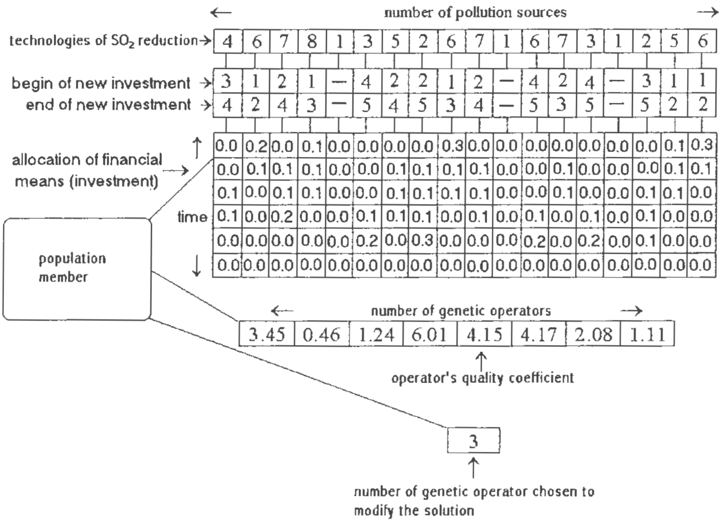

Figure 1. The population member for both problem formulations.

The main part of it is a vector of the length equal N (number of emission sources) with possible one of M different values on each position (number of abatement technology[2]). Each of N positions (emission source) has also two data fields for beginning and completion time of new investment. Time of beginning of new investment and the number of technology chosen for execution are generated by evolutionary operators. The time of investment completion of new technology is computed by the evaluation function using factors of financial means allocation. These factors are also modified by evolutionary operators and denote how financial means for new investments are divided among emission sources. It must be noticed that these financial factors have slightly different meaning for both considered problems. In the problem with cost minimization (P1), these are the direct values of financial means spent on pollution abatement for one year. In the problem (P2) their meaning is more complicated, because money for current exploitation is the most important and investments are made only if there is a financial surplus. Thus, values of allocation factors are percents of this surplus allocated for investments to emission sources for one year.

Moreover, the member of the population contains several more data including: the vector of real numbers, which describe its knowledge about genetic operators and the number of the operator chosen for current iteration - more related details will be given later in this paper.

3.2 Fitness function

In the case of the first problem formulation (P1), where constraints are imposed on the level of environmental cost function, the optimized by evolutionary algorithm fitness function bases on the objective function (5c) and a penalty function for constraints violation (5b) and is formulated as follows:

$$Q = \min_{e_{s_{it}}} \left(\sum_{t=1}^{T} \left(\sum_{i=1}^{N} c_{it} + \max(0, J_t(d) - J_{MAX}) \right) \right), \tag{7}$$

where:

$$J_t(d) = \frac{1}{2} \int_{\Omega} w(x,y)[\max(0, d_t(x,y) - d_{ad})]^2 \, d\Omega \,, \tag{7a}$$

it is a small modification of the formula (1), while J_{MAX}- represents the admissible level of environmental damage cost function for each year of the considered time horizon.

The fitness function for the problem with cost constraints (P2) bases on the objective function (6b) and a cost constraint (6c) violation (a penalty function)

---

[2] Technology number 1 is a basic one and it means that no investment is applied. It is assumed that till the moment of new investment completion, all pollution sources use technology 1.

$$Q = \min_{e_{s_{it}}} \left(J(d) + 10000 \cdot \sqrt[8]{\sum_{t=1}^{T} \max(0, \sum_{i=1}^{N} c_{it} - C_{MAX})} \right). \quad (8)$$

It is the weighted sum of two elements, with the experimentally tuned values of coefficients (cost constraint violation is significantly less than the values of environmental damage function, thus this specific form of the penalty function is applied). In the conducted simulations we assumed that new technology is ready to use in the next year, after all financial means for investment are granted.

3.3 Genetic operators

There were several different genetic operators used:

- **mutation I** - random change of reduction method,
- **mutation II** – random modification of begin of investment time,
- **mutation III** – random modification of coefficients of financial means allocation,
- **transposition** - exchange of methods between two solutions on randomly chosen positions,
- **crossover** - exchange of fragments of solutions between two population members,
- **inversion** - inversion of a fragment of solution,
- **"intelligent" mutation** – on the randomly chosen position a method that gives best possible result is introduced (operator computes values of fitness function for tested cases).

Application of specialized genetic operators requires utilizing some method of sampling them in all iterations of the algorithm. In the used approach (Stańczak 1999, 2000) it is assumed that an operator that generates good results should have bigger probability and more frequently affects the population. But it is very likely that the operator, that is good for one individual, gives worse effects for another, for instance because of its location in the domain of possible solutions. Thus every individual may have its own preferences. Every individual has a vector of floating point numbers, beside encoded solution. Each number corresponds to one genetic operation. It is a measure of quality of the genetic operator (a quality factor). The higher the factor is, the higher is the probability of the operator. The ranking of qualities becomes a base to compute the probabilities of appearance and execution of genetic operators. This set of probabilities is also a base of experience of every individual and, according to it, an operator is chosen in each epoch of the algorithm. Due to the gathered experience one can maximize chances of its offspring to survive.

The method of quality factors computing is based on reinforcement learning (one of algorithms used in machine learning, Cichosz 2000). An individual is treated as an agent which role is to select and call one of the evolutionary operators. When the selected i-th operator is applied it can be regarded, as an agent's action a_i leading to a new state s_i that in this case is a new solution. Agent (genetic operator) receives reward or penalty respectively to the quality of the new state (solution). The aim of the agent is to perform the actions which give the highest long term discounted cumulative reward V^*.

$$V^* = \max_{\Pi}\left(V^{\Pi}\right), \qquad V^{\Pi} = E_{\Pi}\left\{\sum_{k=0}^{\infty} \gamma^k r_{t+k+1}\right\}, \tag{9}$$

where

Π – strategy of the agent,

V^{Π} – discounted cumulative reward obtained using strategy Π,

E_{Π} – expected value of reward using strategy Π,

k – index of the following time steps,

t – index of the current time step.

The following formula can be derived from (9) and is used for the evaluation purposes:

$$V(s_{t+1}) = V(s_t) + \alpha\left[r_{t+1} + \gamma V^*(s_{t+1}) - V(s_t)\right] \quad , \tag{10}$$

where

$V(s_t)$ – is a quality factor or discounted cumulative reward,

r_{t+1} – represents the reward for the best action, which is equal to the improvement of the quality of a solution after execution of the evolutionary operator,

α - a learning factor,

γ - a discount factor.

In the presented experiments the values of α and γ were set to 0.1 and 0.2, respectively. The quality coefficients can be easily converted into a vector of probabilities of evolutionary operators' execution using normalization of its elements.

3.4 Selection method

The applied mixed selection method (Stańczak 1999, 2003) consists of two methods with different properties: a histogram selection (increases the diversity of the population) and a deterministic roulette (strongly promotes best individuals).

These methods are selected in random during the execution of the algorithm. The probability of executing of the selection method is obtained from the formula (11). If individuals in the population are described by too small standard deviation of the fitness function ($\sigma(F(t))$) with respect to the extent of this function ($max(F_{av}(t)- F_{min}(t), F_{max}(t)- F_{av}(t))$), then it is desirable to increase the probability of appearance of the histogram selection. On the contrary the probability of the deterministic roulette selection is increased. As far as parameters of the population are located in some range, considered as profitable we may keep approximately the same probabilities of appearance for both methods of selection. It is important that always $p_{his}(t)+p_{det}(t)=1$ - it means that some method of selection must be executed.

$$p_{his}(t+1)=\begin{cases} p_{his}(t)*(1-a) \text{ for } R(t)>3*\sigma(F(t)) \\ p_{his}(t)*(1-a)+0.5*a \text{ for } R(t)\geq 0.5*\sigma(F(t)) \wedge R(t)\leq 3*\sigma(F(t)) \\ p_{his}(t)*(1-a)+a \text{ for } R(t)<0.5*\sigma\ldots(F(t)) \end{cases} \tag{11}$$

$$R(t)=\max\,(F_{av}(t)-F_{\min}(t), F_{\max}(t)-F_{av}(t))$$

where

$p_{his}(t+1)$, $p_{his}(t)$ - probability of histogram selection appearance in following iterations ($1-p_{his}(t)$ is a probability of deterministic roulette method $p_{det}(t)$),

$F_{av}(t)$, $F_{min}(t)$, $F_{max}(t)$ - average, minimal and maximal values of fitness function in the population,

$\sigma(F(t))$ - standard deviation of fitness function ($F(t)$) in the population of solutions,

a - a small value to change probability $p_{his}(t)$, in simulations (a=0.05).

The method of deterministic roulette consists in setting the number of children of the population member according to formula

$$N_i = round\left(\frac{Q_i}{Q_{ave}}\cdot NPM\right), \tag{12}$$

where:

N_i - number of offspring of the i-th population member,

NPM - number of population members,

Q_i – value of the fitness function for the i-th population member,

Q_{ave} – averaged value of the fitness function for all population members.

In the histogram selection, the list of individuals of different values of the fitness function is created (this list resembles a histogram). The length of this list is usually shorter than the number of individuals in the population, due to elimination of repetitions. Next, a mean value of the fitness function is calculated, but using only once each value from the list, no matter how many individuals is connected with this value. Each individual (or rather value from the list) passes to the offspring population an adequate number of individuals

$$N_i = round\left(\frac{Q_i}{Q_{ave\_l}} \cdot NPM\right) \tag{13}$$

where:

N_i - number of children of the *i-th* member of the list,

NPM - number of population members,

Q_i – value of the fitness function for the *i-th* list member,

Q_{ave_l} – averaged value of the fitness function for all list members.

In the case when calculated number is lower than the size of base population (for both selection methods), an appropriate number of best creatures that were rejected in the first phase are added to the population. On contrary some worst are eliminated.

4. Results of test computation

The emission data represents the industrial Upper Silesia Region, which is characterized by high concentration of heavy industry and the energy sector installations. The domain considered is a rectangle area 110 km x 76 km. In this area 20 major power plants were selected and considered as the controlled sources (compare Holnicki and Kałuszko (2004) for technological details). Moreover, certain number of medium and small industrial sources constitutes the background emission field.

Test computations consider 8 desulfurization technologies, characterized by the unit cost and effectiveness of emission reduction (5 basic technologies and 3 combined). The technologies and the respective emission abatement effectiveness are as follows:

1. "do nothing" technology $e = 0.0$,
2. low-sulfur fuel $e \cong 0.30$,
3. dry desulfurization method $e \cong 0.35$,
4. low-sulfur fuel + dry desulfurization method $e \cong 0.545$,

5. half-dry desulfurization method $e \cong 0.75$,

6. low-sulfur fuel + half-dry desulfurization method $e \cong 0.825$,

7. MOWAP method $e \cong 0.85$,

8. low-sulfur fuel + MOWAP method $e \cong 0.895$.

Computer simulation results for the environmental cost constraints problem (P1)

Table 1A: Values of imposed constraints (J_{MAX}*10^6), the obtained costs (c_t) and environmental objective function ($J(d) * 10^6$) in the consecutive time stages.

t	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
J_{MAX}	2.0	2.0	2.0	2.0	2.0	2.0	2.0	2.0	2.0	2.0	2.0	2.0	2.0	2.0	2.0	2.0	2.0	2.0	2.0	2.0
c_t	0.0	1.48	20.3	30.7	30.7	30.7	30.7	30.7	30.7	30.7	30.7	30.7	30.7	30.7	30.7	30.7	30.7	30.7	30.7	30.7
$J(d)$	3.24	3.24	1.99	1.71	1.71	1.71	1.71	1.71	1.71	1.71	1.71	1.71	1.71	1.71	1.71	1.71	1.71	1.71	1.71	1.71

Table 1B: A schedule of moments of new investments corresponding to values shown in Tab. 1A (t_s, t_e – years of start and end of new investment).

Source	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
Techn.	2	1	1	1	6	1	1	1	1	1	1	1	1	7	2	1	1	1	1	1
t_s	1	-	-	-	0	-	-	-	-	-	-	-	-	0	0	-	-	-	-	-
t_e	2	-	-	-	1	-	-	-	-	-	-	-	-	1	1	-	-	-	-	-

Table 2A: Values of imposed constraints (J_{MAX}*10^6), the obtained costs (c_t) and environmental objective function ($J(d)$*10^6) in the consecutive time stages.

t	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
J_{MAX}	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
c_t	0.0	9.36	124	124	124	124	124	124	124	124	124	124	124	124	124	124	124	124	124	124
$J_t(d)$	3.24	3.24	0,49	0,49	0,49	0,49	0,49	0,49	0,49	0,49	0,49	0,49	0,49	0,49	0,49	0,49	0,49	0,49	0,49	0,49

Table 2B: A schedule of moments of new investments corresponding to values shown in Tab. 2A (t_s, t_e – years of start and end of new investment).

Source	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
Techn.	7	1	2	7	8	1	1	1	1	1	1	6	7	8	2	1	1	6	1	1
t_s	0	-	0	0	0	-	-	-	-	-	-	0	0	0	0	-	-	0	-	-
t_e	1	-	1	1	1	-	-	-	-	-	-	1	1	1	1	-	-	1	-	-

Table 3A: Values of imposed constraints ($J_{MAX}*10^6$), the obtained costs (c_t) and environmental objective function ($J(d)*10^6$) in the consecutive time stages.

t	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
J_{MAX}	0.25	0.25	0.25	23	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	25	0.25	0.25	0.25	0.25	0.25	0.25	0.25
c_t	0.0	16.8	223	223	223	223	223	223	223	223	223	223	223	223	233	223	223	223	223	223
$J(d)$	3.24	3.24	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25

Table 3B: A schedule of moments of new investments corresponding to values shown in Tab. 3A

(t_s, t_e –years of start and end of new investment)

Source	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
Techn.	7	5	8	8	8	1	1	1	1	1	1	8	8	8	8	1	1	8	1	1
t_s	0	0	0	0	0	-	-	-	-	-	-	0	0	0	0	-	-	0	-	-
t_e	1	1	1	1	1	-	-	-	-	-	-	1	1	1	1	-	-	2	-	-

Computer simulation results obtained for the problem with cost constraints (P2)

Table 4A: Values of imposed constraints (C_{MAX}), the obtained costs (c_t) and environmental objective function ($J(d) * 10^6$) in the consecutive time stages.

t	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
C_{MAX}	5	5.5	4.5	13	7	8	6	5.5	7	5.5	6	5.8	6.1	5.9	6.3	7.5	7	5.8	7.5	10.5
c_t	0.0	0.3	4.4	5.8	5.8	5.8	5.8	5.8	5.8	5.8	5.8	5.8	5.8	5.8	5.8	5.8	5.8	5.8	6.7	10.5
$J(d)$	3.24	3.24	2.9	2.55	2.55	2.55	2.55	2.55	2.55	2.55	2.55	2.55	2.55	2.55	2.55	2.55	2.55	2.55	2.50	2.28

Table 4B: A schedule of moments of new investments corresponding to values shown in Tab. 4A (ts, te – years of start and end of new investment).

Source	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**
Techn.	1	1	1	1	4	1	1	1	1	6	1	6	4	7	1	3	1	2	1	1
t_s	-	-	-	-	2	-	-	-	-	19	-	19	18	1	-	19	-	16	-	-
t_e	-	-	-	-	2	-	-	-	-	20	-	20	18	1	-	20	-	17	-	-

Table 5A: Values of imposed constraints (C_{MAX}), the obtained costs (c_t) and environmental objective function ($J(d) * 10^6$) in the consecutive time stages.

t	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**
C_{MAX}	15	12	14	13	18	16	15	17	15	14	13	14	15	13	14.5	17	14	17.5	17	21.5
c_t	0.0	0.9	12.9	12.9	12.9	12.9	12.9	12.9	12.9	12.9	12.9	12.9	12.9	12.9	12.9	12.9	13.2	16.8	16.9	19.1
$J_t(d)$	3.24	3.24	2.03	2.03	2.03	2.03	2.03	2.03	2.03	2.03	2.03	2.03	2.03	2.03	2.03	2.03	2.03	1.92	1.92	1.84

Table 5B: A schedule of moments of new investments corresponding to values shown in Tab. 5A (t_s, t_e – years of start and end of new investment).

Source	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**
Techn.	1	1	1	2	4	1	1	1	1	1	1	2	4	4	2	1	7	4	1	1
t_s	-	-	-	16	1	-	-	-	-	-	-	1	1	1	1	-	19	18	-	-
t_e	-	-	-	16	1	-	-	-	-	-	-	1	1	1	1	-	19	18	-	-

Table 6A: Values of imposed constraints (C_{MAX}), the obtained costs (c_t) and environmental objective function ($J(d) * 10^6$) in the consecutive time stages.

t	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
C_{MAX}	25	22	24	23	28	26	25	27	25	24	23	24	25	23	24.5	27	24	27.5	27	31.5
c_t	0.0	1.7	22.6	22.6	22.6	22.6	22.6	22.6	22.6	22.6	22.6	22.6	22.6	22.6	23.8	23.8	23.9	25.1	26.9	31.3
$J(d)$	3.24	3.24	1.80	1.80	1.80	1.80	1.80	1.80	1.80	1.80	1.80	1.80	1.80	1.80	1.73	1.73	1.73	1.69	1.66	1.54

Table 6B: A schedule of moments of new investments corresponding to values shown in Tab. 6A

(t_s, t_e –years of start and end of new investment)

Source	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
Techn.	1	1	1	3	6	2	1	1	1	1	1	2	2	8	2	1	1	2	2	2
t_s	-	-	-	18	1	17	-	-	-	-	-	1	1	1	13	-	-	1	16	16
t_e	-	-	-	18	1	17	-	-	-	-	-	1	1	1	13	-	-	1	16	16

Simulations were performed for 20-year period, and three different sets of constraints imposed on J_{MAX} for problem (P1) and on (C_{MAX}) for problem (P2), respectively. The respective results are presented in tables 1AB - 6AB. Tables with indexes A show (in consecutive years) constraints imposed on emission sources, expensed funds and obtained values of environmental damage function, related to the applied desulfurization technologies.

Tables with index B show a schedule of new technologies implementation (technology number 1 – a base one – means no investment and no emission reduction). Due to the cost constraints, some emission sources are not modernized, it is denoted by "–" in the tables. Table 4B contains values of (t_e) beyond the time horizon (t=20). It means that investment is not finished during the time horizon considered. Generally values at ends of considered time horizon are not very reliable, but it is common effect in this type of computations.

Results presented in tables 1AB-3AB (problem (P1) present rather expected fact, that the lower are limitations for environmental cost function, the higher are costs of pollution reduction. And similarly, it can be easily noticed in tables 4AB-6AB for problem (P2), the higher the cost constraints values, the lower level of pollution and more pollution sources are equipped with more effective (and more expensive in investment and exploitation) desulfurization installations. Solutions of both problems are rather similar and it can be noticed that even the same pollution sources remained without modernization.

5. Conclusions

The evolutionary methods presented in this article have been successfully tested on three sets of cost and environmental function constraints. Evolutionary computations for the problem formulated in the paper lasted about 5.5 hours on the computer equipped with Athlon 1,8 GHz processor with Linux operating system. The authors also performed series of test computations, where the heuristic computational algorithms have been applied and tested. Such an approach usually leads to a simple and fast computational process, but the accuracy of the obtained solutions is in general significantly worse than those discussed in the above sections. Moreover, the evolutionary algorithm formulation is more flexible, and relatively easily allows us to adopt the computational procedure to the specific problem formulation (as shown in the results presented above). On the other hand, the aspect of computing time (which is usually long in evolutionary method) is not a critical one in long-term scenario analysis.

Bibliography

Amman M., Cofała J., Heyes C., Klimont Z., Mechler R., Posh M., Schöpp W. (2004): The RAINS model. Documentation of the model approach prepared for the RAINS peer review 2004. IIASA Report, Laxenburg.

Carlson D.A., Haurie A., Vial J.-P., Zachary D.S. (2004): Large-scale convex optimization methods for air quality policy assessment, in: Automatica, 40, pp. 385-395.

Cichosz P. (2000): Systemy uczące się (in Polish), WNT, Warszawa.

Cofała J., Amman M., Gyarfas F., Schoepp W., Bourdi J.C., Hordijk L., Kroeze C., Li Junfeng, Lin Dai, Panwar T.S. Gupta S. (2004): Cost-effective control of SO_2 emissions in Asia, in: Journal of Environmental management, 72, pp. 149-161.

Haurie A., Kubler J., Clappier A., van den Berg H. (2004): A Metamodeling approach for integrated assessment of air quality polices, in: Environmental Modeling and Assessment, 1(9), pp. 1-12.

Holnicki P., Nahorski Z., Żochowski A. (2000): Modeling of Environmental Processes (in Polish). WSISiZ Publishers, Warszawa.

Holnicki P., Kałuszko A. (2004): Decision support for optimal emission reduction, in: Management of Environmental Quality, 15(3), pp. 250-257.

Holnicki P., Kałuszko A., Stańczak J. (2004): Application of „Soft Computing" methods for effective reduction of air pollution emission, in: IT support of socio-economic development and environment protection (in Polish), Badania Systemowe, 36, pp. 149-162.

Stańczak J. (1999): Rozwój koncepcji i algorytmów dla samodoskonalących się systemów ewolucyjnych, Ph.D. Dissertation (in Polish), Politechnika Warszawska.

Stańczak J. (2000): Algorytm ewolucyjny z populacją "inteligentnych" osobników, in: Proceedings of the IV Conference on Evolutionary Algorithms and Global Optimization (in Polish), Lądek Zdrój, pp. 207-218.

Stańczak J. (2003): Biologically inspired methods for control of evolutionary algorithms, Control and Cybernetics, 32(2), pp. 411-433.

Stańczak J., Holnicki P., Kałuszko A.(2005): Planning of SO_2 emission reduction using evolutionary algorithm, in: Proceedingd of the Eighth National conference on Evolutionary Computation and Global Optimization, Korbielów, Poland, pp. 207-214.

Trojanowski K., Michalewicz Z. (2001): Evolutionary Optimization in Non-stationary Environments, in: Journal of Computer Science & Technology, 1(2), pp. 93-124.