Application of Genetic Algorithms for the Optimisation of Multi-Pollutant Multi-Effect Problems

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Abstract: In this paper, crucial aspects of the implications and the complexity of interconnected multi-pollutant multi-effect assessments of both air pollution control strategies and the closely related reduction of Greenhouse Gas (GHG) emissions will be discussed. The main aims of the work described here are to identify the core problems which occur when trying to apply current state-of-the-art methodology to conduct integrated assessments – in this context, cost-benefit assessment (CBA) as well as cost-effectiveness assessment (CEA) – using sophisticated computer models and propose solutions to the problems identified. The approaches described will display the integrated use of databases, efficient Genetic Algorithms (GA) and already existing software tools and models in a unified model framework. The first part of the paper discusses the need for new developments in one particular field of Integrated Assessment Models (IAMs), the use of (typically) country-specific single pollutant abatement cost curves, which have been applied in a large number of modelling approaches with the aim to find cost effective solutions for given air quality targets. However, research conducted to find such cost effective solutions for the non-linear problem of tropospheric ozone abatement (dealing with two primary pollutants and their rather complex relationship to form tropospheric ozone) identified basic problems of cost-curve based approaches even in this two-pollutant case. The approach discussed here solves the key problems identified, making extensive use of databases in order to provide fast and high quality model input for CEA and CBA. In addition to that, the application of Genetic Algorithms will be discussed as a means to address extremely complex, vast solution spaces which are typical for the tasks IAMs are set to solve nowadays. In the final part of the paper, diversity increasing operators and methods to increase the performance of the GA to find optima are described and first results of extensive model runs are discussed.

Keywords*: genetic algorithms; optimisation; environment; air quality; climate change*

1. SCOPE

As air quality limit values have become more stringent during the last 20 years, and with the need to reduce emissions of greenhouse gases beyond the scope of no-regret technologies to achieve the Kyoto commitments, the costs of emission control has constantly gained importance. In international negotiations for instance the protocols to the UNECE Convention on Long-Range Transboundary Air Pollution (CLRTAP), the analysis of cost-effective ways to reduce emissions played a major role since the 1970s. Binding emission control targets for Sulphur Dioxide (SO_2) and Nitrogen Oxides (NO_x) were agreed upon with the backing of model calculations of the related costs of control strategies (cf. Amann et. al 1996, 1999; Ap-Simon 1994a,b, and 1996; Bailey 1996 as well as Gough et al. 1995, 1998), and even the most recent protocol to the CLRTAP, the Gothenburg Protocol was designed on the basis of IAM calculations using the RAINS model developed by IIASA.

2. PROBLEM FORMULATION

Integrated Assessment Models (IAMs) applied in this context mostly use(d) single abatement cost curves as input to their optimisation tools, in order to identify the least-cost ways to achieve given reduction targets, and to assess the overall costs of strategies. Typically, the analysis focussed on a single pollutant (e.g. SO_2, NO_x) with a (usually) linear relationship between emissions and concentrations, respectively emissions and effects. The case of acid rain and acidification in general (Gough et. al. 1995) is one of the most prominent examples, where reductions of emissions of SO_2 and/or NO_x would usually lead to reduced deposition in the same order of magnitude. The assessment models had to take into account transport of pollutants through the air to some extent, in order to map the regional distribution of deposition changes, while chemical transformation of pollutants did not play a major role yet.

When air pollution by tropospheric ozone became the focus, the modelling task turned more difficult, as the relationship between the emissions of ozone precursor substances NO_x and Non-Methane Volatile Organic Compounds (NMVOCs), and to some extent Carbon Monoxide (CO) as well as the formation of ground level ozone is not linear. Thus, the assessment models needed to include more complex mechanisms to account for these non-linearities. At the same time, the results not only needed to address the question, which measures to take in order to achieve a cost-effective solution, but instead had to tell, which pollutant to be controlled, and where – thus making the optimisation task more complex as the location and distribution of emission sources matters (cf. Friedrich and Reis, 2000). But even apart from the modelling aspects, the case of two pollutants to be controlled introduced an issue that has not been properly solved up to date. While in a single pollutant case, the costs per unit of pollutant controlled by a specific measure are usually easy to pinpoint, given sufficient information about activity rates, the technology and the economics of the respective installations, the situation becomes more difficult as soon as two pollutants were to be controlled, and measures existed, which would reduce the emissions of both pollutants when installed, usually with differing efficiency, thus creating the need for allocating cost proportions to single pollutant cost curves. Even though there are some possible ways to split the costs into different proportions and allocate these to different single abatement cost curves, most of them are more or less arbitrary and reflect more the preference of the model developer than anything. Furthermore, this approach implies a source for inconsistencies, as model solutions may lead to results where the same measure is applied due to its position in one cost curve and excluded because of a later position in a different cost curve.

In this paper, these particular problems shall be discussed, with a focus on the current development towards multi-pollutant multi-effect assessment models, where a robust and transparent methodology to solve this problem could prove to be vital. In the second part, a new methodology to model the application of technical and non-technical emission control measures and the respective costs of abatement is introduced and discussed in detail. Finally, an outlook will be given with respect to the application of this new methodology in the European research project MERLIN (see http://www.merlin-project.info).

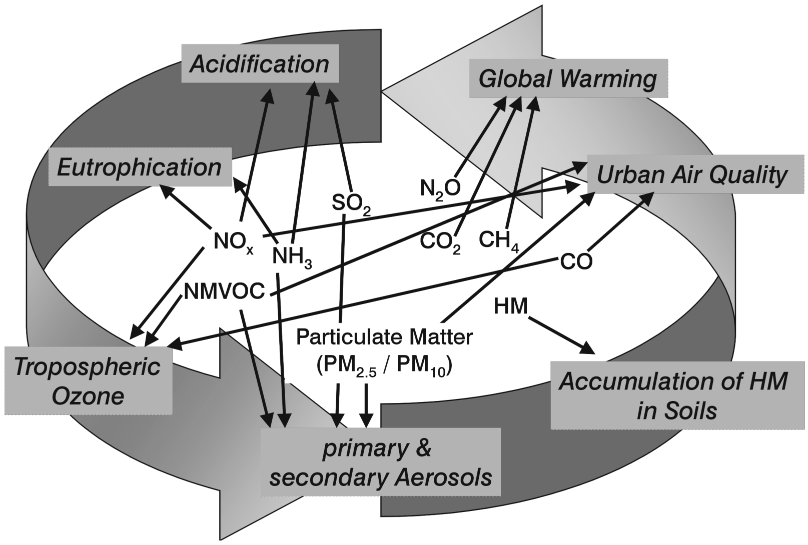


Figure 1. Illustrating the Multi-Pollutant Multi-Effect Environment for IAMs

3. IAMS IN A MULTI-POLLUTANT MULTI-EFFECT ENVIRONMENT

To the same extent that the knowledge about air pollution and its impacts increased, the development of more and more complex models to analyse various aspects of air pollution in an integrated way took place. *Figure 1* illustrates the level of complexity which is characteristic for current assessment tasks. And as it was indicated above, model concepts that have been suitable to address comparatively simple modelling and optimisation tasks are far less fit to cope with this level of complexity.

3.1 Limitations in the Use of Single Pollutant Abatement Cost Curves

As it was indicated in the problem formulation, single abatement cost curves for one specific pollutant and a source sector or country are widely used in IAMs. They usually serve the purpose to provide a function of costs and related emission (abatement) levels in a computable way, for instance as input to optimisation algorithms. However, the limitations of such single abatement cost curves are obvious, in particular in the view of the correlations between different pollutants and effects as indicated in *Figure 1*. Furthermore, generating abatement cost curves as input to optimisation leads to an artificial constraint of the models that are applied to find optimal solutions for a given task. As abatement options have to be ranked e.g. according to their unit costs (€/t), vital issues, such as a different abatement efficiency of a specific option depending on at what stage it is taken, cannot be accounted for (abatement measures applied to the same source sector often mutually influence their abatement efficiency, for instance, a measure that is applied first reducing x% of emissions from a specific source reduces the absolute efficiency – in terms of *tonnes of pollutant abated* – of a second measure applied to the same sector, and vice versa).

Hence, a new approach has to be taken that is able to reproduce the complex interconnections between pollutants and effects, but at the same time has to be transparent and simple enough to keep uncertainties to a minimum. Here the extremely fast increase in both computer speed and data storage and handling capacities provides the basis for innovative solutions. Basically, the same data as would be needed to generate abatement costs curves is collected, with more level of detail even to improve the reproduction of sector-specific characteristics. This comprises the following main data types:

- data on stock and activities (e.g. number of vehicles and annual mileage)
- data on measures (e.g. applicability, efficiency, implementation degree, costs)
- ‘meta-data’ (information on relationships between measures)

Instead of trying to process and split this data into single abatement cost curves, the optimisation model is given full access to the databases, thus being able to select, apply and evaluate abatement options with a considerable degree of freedom. And as an additional benefit, this approach permits the inclusion of structural changes due to the implementation of abatement options, for instance increasing an activity of one sector in order to reduce that of another.

This ‘measure-matrix-approach’ creates a number of additional modelling opportunities, e.g. by making it possible to assess single measures, individual sectors or whole countries/regions with simple presets, as no pre-processing of data is needed. Moreover, it does reflect the real-world characteristics of abatement options to a far greater extent than before, as in most cases, costs of abatement options are expressed relative to its application on stock or by activities. In addition to that, abatement options usually address not only one single pollutant, but a portfolio of different pollutants, either reducing or increasing emissions. This is of particular importance for the assessment of multi-effect problems, as such analyses usually have to achieve conflicting targets. Finally, this approach is not limited to mere technical abatement options, as it can include structural measures (e.g. changes in the sectoral structure of electricity generation etc.) and non-technical abatement options in the same way.

3.2 Intelligent Algorithms to Solve Complex Problems

A second critical issue for the assessment of complex multi-pollutant multi-effect problems is that of optimisation. While IAMs to date usually apply either linear optimisation algorithms (Amann et al., 1999), or simple iterative approaches (Friedrich and Reis, 2000), finding optimal solutions in a solution space as complex and vast as it is characteristic for multi-effect problems needs faster approaches. Here, evolutionary (as well known as ‘genetic’) algorithms (EA) can be the ideal tool, even though they have not been widely applied in the field of air pollution

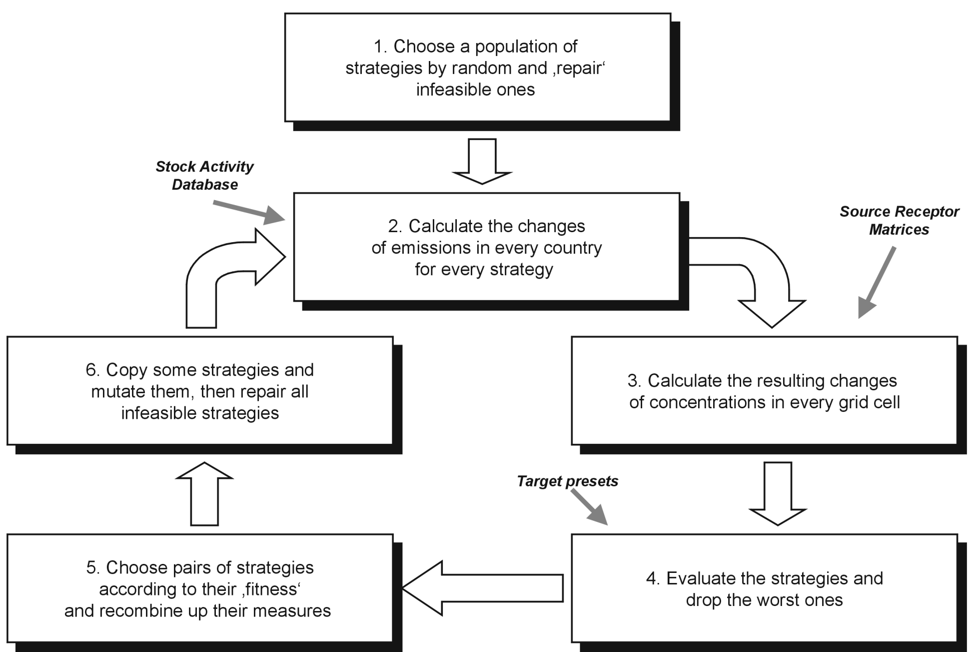


Figure 2. Implementation of an evolutionary algorithm in IAM

modelling yet (cf. Loughlin et al., 2000). As their name suggests, EAs optimise in a way similar to that of nature, using concepts such as recombination, mutation and fitness for survival to induce a process of evolution towards an optimal solution. An exemplary implementation is described here.

The optimisation algorithm as it is applied in the MERLIN project forms the core of an IAM to conduct cost-effectiveness (CEA) and cost-benefit analysis (CBA) of combined strategies to reduce air pollutant and greenhouse gas emissions simultaneously. This IAM is termed Optimisation Model for Environmental Integrated Assessment (OMEGA-2, the first OMEGA model was developed for the optimisation of Ozone abatement strategies, see Friedrich and Reis, 2000). The implementation of an evolutionary algorithm to identify optimal bundles of abatement measures is illustrated in *Figure 2*.

The decision to apply EA emerged, as it became clear that the problem to be solved was characterised by a vast solution space, as hundreds of different abatement options could be combined. For this particular situation, other approaches that were investigated, for instance global or local random choice, gradient based algorithms or divide and conquer strategies could not offer satisfactory performance. On the other hand, a 'black-box' situation had to be avoided, as for this particular task, the pathway to an optimal solution can provide as vital information as the solution itself.

In principle, the problem to be solved can be formulated as follows: from all possible abatement options ('measures'), the set of measures has to be identified, which fulfils all criteria (in this case air quality limit values and GHG emission limits) simultaneously at least costs.

Steps 1 and *2* form the initialisation to start the optimisation and enter the loop, where – in our case – abatement options are selected to reduce a variety of emissions to air. In step 3 the resulting changes of concentrations of pollutants are calculated, using so-called source-receptor matrices (SR-M). To reduce computational effort in this step, the resolution of the matrices will first be reduced and then gradually increase every generation run, until the finest grid resolution of 50x50 km will be achieved.

Thus using the total costs of the abatement measures and the preset thresholds that are still exceeded, the strategies can be evaluated in step 5. This approach allows different weights for limit values that are not achieved, introducing a so-called "fitness value" which will then be used to discard the worst performing strategies.

Pairs of strategies (parent-generation) are selected according to their degree of fitness, which will pass their measures on to two newly formed strategies (child-generation). In a first step, an n-point crossover mutation approach will be implemented in the algorithm, as it is illustrated in *Figure 3* (in this case, a two-point cross-over,) where the parent measures are cut in a number of pieces, which are then recombined to form the offspring.

The position of the measures within the strategies will play an important role as well. If, for instance, two strategies with sufficient fitness are selected in step 5, it would be harmful, to place measures of the first strategy which, for instance, focus mainly on reduction of one particular pollutant in one country at the beginning and those of the second strategy at the end. In this case their offspring (the next generation) would probably consist of one strategy, that has no such measures at all and one that has twice as much as needed, thus resulting in unbalanced individual strategies in the next generation.

To overcome this, groups of measures are formed that have more or less similar effects, where some measures may be members of several groups. This will be done automatically, so new measures can easily be added to the measure database. The strategies will consist of several sections, and every section can only include measures of one single group. So the mixing up of measures in step 5 will either be done by copying the whole measure group of one parent strategy or by n-point-crossover. Aside from solving the problem mentioned above, the measure groups also allow small variations of the strategies, as follows.

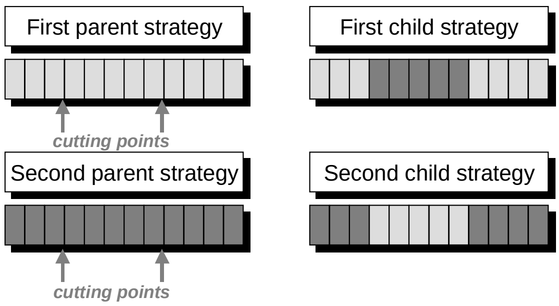


Figure 3. Illustration of a 2-point-crossover mutation

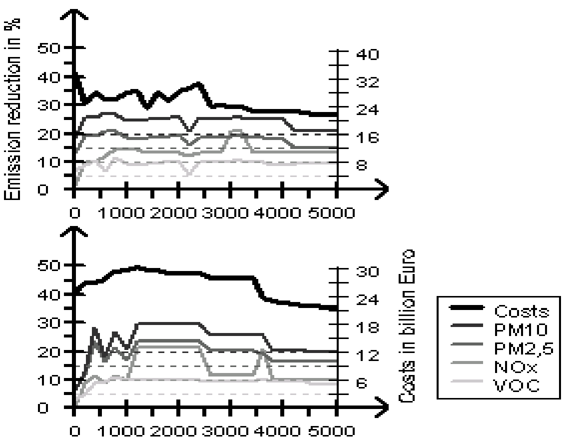
Most evolutionary algorithms simulate mutation of the individuals. In step 6, some strategies are chosen by random, and one or more of its measures will be replaced by other ones, that roughly, but not exactly, have the same effect. Because this is the case for measures of the same group, each one which fits into the same position of the strategy (and thus is a member of the same section) can be chosen. To make sure, that the fitness cannot decrease from generation to generation, the chosen strategy shall be duplicated, and only the copy will be allowed to mutate. This combination of a global search method (the crossover of strategies, done in step 5) and a local one (mutation as done in step 6) is often considered to be the key to the power of EAs in optimisation problems.

The following improvements of the EA-approach are in the process of being implemented and tested:

- Inclusion of special strategies as subsets of the starting population, to direct the search to regions of the solution space, which indicate potential for local/global optima.
- Preference for pairs consisting of solutions of the same neighbourhood to support local search.
- Enhancement of the fitness of young solutions, i.e. leaving the mutation operator enough time to improve them locally, so they are not prematurely suppressed by older ones.
- Use of diversity increasing operators, preventing the search to ignore promising regions too early in favour of few strategies with high fitness.
- Simulation of SINEs (short interspersed elements) to provide points to the crossover operator where cutting is done with increased probability.

As first result of OMEGA tested on some subsets of the final measure and stock/activity databases indicate, the diversity increasing operators seem to be most promising, since the whole population soon converges to some local optimum (see *Figure 4*), hence the mating operator did not have strong effects anymore.

Probably the most prominent of diversity



increasing operators are the "Messy Genetic Algorithms", proposed by Goldberg in 1989 and generalised by van Veldhuizen in 1999 to multi-objective problems. Unfortunately this approach is not suited well for interacting measures which in some cases might in-/exclude others or modify their effects. Hence, to force the algorithms to cover at least the major part of the search space, the target presets were altered by some vanishing trigonometric function, which takes the generation number as an argument. This can best be recognised by *Figure 5*, showing the optimisation progress restricted to the solvent use sector, where more or less only one single pollutant (non-methane volatile organic compounds, short: NMVOC) is of importance.

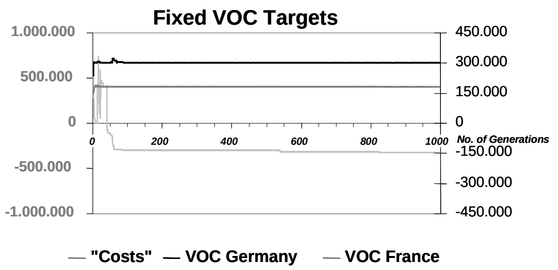


Figure 4. Premature convergence to local optimum

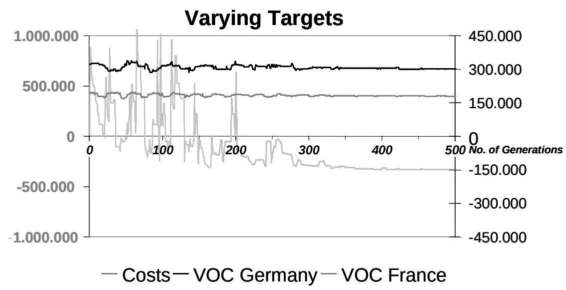


Figure 5. Changing VOC-Targets

Figure 6. : Twofold evaluation

Of course the algorithm computing time increases until it converges, but the optimum found in most runs was slightly better. Further improvement was achieved, when the best strategy of every generation was also evaluated by the fixed reduction targets and stored if it was the best one found so far, to be included in the population from time to time. Looking at this best abatement strategy of every generation the costs can only increase if it came closer to some reduction target (in any country), which was not met before.

For comparison *Figure 6* shows two typical optimisation runs, at the top with oscillating emission reduction targets and only a simple evaluation with regard to the distance to oscillating reduction targets, and below an optimisation run where every strategy is evaluated twofold (using the distance to the fixed reduction targets as well as to the oscillating targets). The upper figure indicates that when the optimisation approaches a threshold, which was not met so far, costs can increase in the early stage of the optimisation, but in contrast to the lower figure, shows a monotonic decrease of costs afterwards.

4. SUMMARY AND CONCLUSIONS

The previous sections have given an insight in both the most prominent problems for IAM in a multi-pollutant multi-effect environment, and innovative solutions to tackle them. To some extent, it is astonishing, that only little development in the field of IAMs for CEA and CBA could be witnessed during the last decade, while increasing computing power and growing knowledge about causes and effects of air emissions improved the situation for modelling to quite some extent.

However, as the problems to be addressed are marked by increasing levels of complexity, new approaches need to be taken. This is even more true, as the next development steps for IAMs are quite predictable. On the one hand, cross-media approaches need to be established, as research has already identified the importance of, for instance, deposition of air pollutants into surface water and soils. In a similar way, carbon sequestration in soils or oceans, or emissions of specific pollutants from soils to air are of importance. On the other hand, economic evaluation of environmental costs, both costs of abatement and external effects of environmental pollution, gains more and more importance for policy implementation. Thus, the full integration of models and tools for macroeconomic assessment of key indicators (e.g. GDP, employment effects, distributional effects, burden sharing etc.) has to be realised.

The benefits of this approach are obvious: No allocation of costs to single abatement cost curves is needed. Furthermore, measures are either applied, or not, reflecting a real-world choice of options. As the model selects measures from a database, maximum flexibility is achieved, new measures can easily be introduced, or others removed. Finally, the order in which measures are applied is taken into account. Hence, the problems described in Sect. 3.1. cannot occur.

5. ACKNOWLEDGEMENTS

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[1] http://www.merlin-project.info