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Working paper

The GAINS PMEH-Methodology - Version 2.0

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Abstract

This document describes the methodology developed for the GAINS PMEH project. This methodology provides a framework for translating detailed data on emission control technologies and measures, atmospheric transport, costs, socio-economic development and health indicators from the GAINS databases into such a format and level of aggregation that they can be displayed and turned into an interactive decision support tool at various spatial scales, in particular the megacity scale. As an example we discuss the prototype for Hanoi and its environs.

Key words: GAINS-City, sustainable development, decision support tools

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1 Introduction

Policy makers and city planners are often not aware of the complex implications of various regional, city or specific sectoral policies. These interactions are considered and analysed with a help of local air shed models to evaluate the impacts on air quality or with integrated assessment models, e.g., GAINS, where also regional air pollution, co-benefits on GHG emissions, and economic aspects are included. However, use of such models in discussion with policy makers is often difficult as they are rather complex, data hungry, and analysis of results requires often significant time and resources. A simpler tool to quickly evaluate impact of various interventions at a local and regional level is needed. Such a tool should also stimulate the involvement of several stakeholders a necessary step towards development of a successful air quality policy. GAINS-City captures the complexities associated with local and regional sources of air pollution, reflects interests of various stakeholders, and allows evaluating health and economic impacts of envisaged interventions. The latter is developed in collaboration with the local stakeholders representing governments and several industries and it includes a list of key measures applicable in a given region. The example applications include Delhi (collaboration with the local team in India) and most recently Hanoi and Jing-Jin-Ji region in China where local policy and scientific community is involved in the development of the final tool.

The main objective of the tool is to provide a simple interactive tool with which the interactions between air pollution and GHG mitigation, and in particular co-benefits can be explored. For this we have developed a web-interface (referred to here as the PMEH tool) that allows users to interactively study the environmental, health and cost implications of a set of policy interventions. The tool offers a predefined set of measures that the user can control by increasing or decreasing their implementation rate, while watching the implications on endpoints change. The interface of the PMEH tool for Hanoi is described in [2]. The focus of this paper is the documentation of the methodology used in performing the calculations of the tool and for deriving the input parameters.

The design of the tool developed in four steps: (1) generate a baseline scenario; (2) identify a set of relevant policy interventions and estimate their individual impact; (3) devise a methodology for representing the implementation of measures and efficiently calculating their individual, but also their joint effects on environmental endpoints; (4) devise an optimization routing that will identify a cost-effective portfolio for meeting a set of environmental objectives.

This document is organized as follows. In Section 2 we briefly review the underlying data that are used not only for generating the baseline scenario in Step (1), but also for deriving relevant characteristics of the policy levers in Step (2). Section 3 focuses on the environmental indicators the tool calculates at this stage, i.e. health and GHG indicators. In Section 5 we discuss how measures can be represented in the GAINS model and relevant information be extracted from the database for use in the PMEH methodology. In Section 7 we comment on the estimate of costs for the individual measures considered in the tool. In Section 8 we present the novel aspect of the methodology, namely to represent in a compact way the effects that different measures or policy interventions would have on pertinent indicators, including (geographically explicit) environmental implications and costs estimates.

2 The GAINS model database

The methodology used for the tool is based on and is largely consistent with the standard modeling methodology of the GAINS model that has been used in the past for multiple policy assessments in Europe and Asia. The current tool deviates from the standard GAINS methodology only insofar as the (i) the focus in this tool is on specific interventions that can interactively implemented by the user; (ii) the concentration and health calculation takes into account differential urban and rural population density and residential fuel use patterns; (iii) the spatial resolution in the present tool is higher than in the regional versions of the model.

The starting point of the current version of the tool is the country of Vietnam, which in the GAINS database is split into six regions: Southern Vietnam, and five regions in Northern Vietnam: Hanoi proper, Bac Ninh, Hung Yen, the wider Hanoi region, and the rest of Northern Vietnam. For the tool the five northern regions are taken into account.

For each of these regions, the GAINS databases provide projections, starting from economic and population growth, through projections of energy consumption and industrial production, livestock numbers and so forth. The GAINS model provides a default data set for all of these, based on national projections combined with downscaling algorithms.

A second component of the database are emission factors pertaining to different end-of-pipe technologies, covering a range of pollutants, including the Kyoto greenhouse gases, as well as particulate matter, as well as their precursor substances, such as SO_2, NO_x, NH_3 and VOCs. In addition to its physical characteristic, i.e. efficiency in changing emission factors, the technologies are further described in the database by their costs: by the investment costs per unit of activity, and the eventual total cost per unit of activity. The cost for the 'uncontrolled' situation, i.e. the absence of a specific emission control technology is characterized by zero costs.

The GAINS database also contains information on current and projected air pollution policies, in the form of what is called a 'control strategy', that is, a set of implementation rates of emission control technologies. The resulting mix or portfolio of technologies represents the policy in place. For example, in the absence of any policy, the default technology is an uncontrolled one, whose emission factor is unmitigated. On the other hand, if for a particular activity data there exists an emission standard, e.g. for flue gases from coal-fired power plants, this is represented either by a single technology or a mix of technologies that together achieve the emission standard.

3 Ambient annual $PM_{2.5}$ concentration calculation

The tool calculates a number of environmental endpoints, which are discussed in Section 4. Some of these are a function of the concentration field of $PM_{2.5}$, and here we describe how this is calculated in the tool. The concentration of ambient $PM_{2.5}$ in a particular grid cell of size 2 km x 2 km is modeled as a function with two components: (i) a background contribution, which is governed by the primary and secondary $PM_{2.5}$ that is transported into the grid cell through atmospheric processes that operate on larger spatial and temporal scales; and (ii) a local contribution (urban increment) that only depends on the local emissions of low level sources of primary $PM_{2.5}$.

3.1 Long-range transfer matrix

The long-range contribution of primary and secondary $PM_{2.5}$ is modelled using a source-receptor matrix derived from EMEP model runs on a $0.5° \times 0.5°$ grid. In particular, the $PM_{2.5}$ concentration in grid cell i can be written as:

$$C(\mathrm{PM2.5})_i = \sum_j \left[\pi_{ij} \cdot \mathrm{Em(PPM)}_j + \sigma_{ij} \cdot \mathrm{Em(SO_2)}_j + \nu_{ij} \cdot \mathrm{Em(NO}_x)_j + \alpha_{ij} \cdot \mathrm{Em(NH_3)}_j + \upsilon_{ij} \cdot \mathrm{Em(VOC)}_j + k_i\right] \tag{1}$$

where $\mathrm{Em(PPM)}_j$ represents the total primary PM2.5 and the sum runs over all emitting regions j. The constants $\pi, \sigma, \nu, \alpha, \upsilon$ are the source-receptor matrices for the corresponding pollutants contribution to the PM2.5 concentration and the constants k_i are grid cell specific.

3.2 Local primary contribution: the urban increment

In addition to the long-range contribution, there is a local contribution to PM2.5, resulting from local low-level sources. In principle, there could be many interpretations of what is a local and what is a low-level source; consistent with previous work with the GAINS model, here we consider three classes of primary PM2.5 to be local and low-level: (i) emissions from transportation; (ii) emissions from the domestic sector (residential and commercial); (iii) trash burning. Before discussing them individually, let us first describe the general approach.

The local primary contribution in region j, from a sector-fuel(-technology) combination (s, f, t) in an urban/rural subregion z, being transported into a small grid cell g lying in a large grid cell i can be described as:

$$\mathrm{PPM}_{jsfzig} = \sum_t \mathrm{pop}^{jz} \cdot \mathrm{apc}^{jsfz} \cdot \mathrm{cs}_{jsft} \cdot \mathrm{EF}_{jsft} \cdot \left(\zeta_i^{jz} + \xi_i \cdot f_{ig}^{jsz} \cdot 900\right) \tag{2}$$

where:

$$\mathrm{pop}^{jz} = \mathrm{share}^{jz} \cdot \mathrm{pop}^j \tag{3}$$

is the urban/rural population in region j which is derived as a share of the total population in region j;

$$\mathrm{apc}^{jsfz} \tag{4}$$

is the activity per capita in urban/rural subregion z of region j;

$$\mathrm{cs}_{jsft} \tag{5}$$

is the control strategy in region j for the sector-activity-technology combination sft. The factor 900 is a weighting factor, resulting from scaling from the coarse to the fine resolution.

Equation (2) can be rewritten as:

$$\mathrm{PPM}_{jsfzig} = \mathrm{Em}^{jsf} \cdot \mathrm{share}^{jz} \cdot \left(\frac{\mathrm{apc}^{jsfz}}{\mathrm{apc}^{jsf}}\right) \cdot \left(\zeta_i^{jz} + \xi_i \cdot f_{ig}^{jsz} \cdot 900\right) \tag{6}$$

And for the concentration contribution in grid cell g in cell i in region j:

$$\mathrm{PPM}_{jig} = \sum_{s,f} \mathrm{Em}^{jsf} \sum_z \mathrm{share}^{jz} \cdot \left(\frac{\mathrm{apc}^{jsfz}}{\mathrm{apc}^{jsf}}\right) \cdot \left(\zeta_i^{jz} + \xi_i \cdot f_{ig}^{jsz} \cdot 900\right) \tag{7}$$

This formula applies to all low-level sources of $\mathrm{PM}_{2.5}$, in particular the transportation, domestic, and the trash burning sector. For transportation, the pattern f_{ig} is assumed to be the same for urban and rural areas, so that here $f_{ig}^{jsz} = f_{ig}^{j,\mathrm{TRA}}$, and Equation (7) simplifies to

$$\mathrm{PPM}_{jig,\mathrm{TRA}} = \mathrm{Em}^{j,\mathrm{TRA}} \cdot \left(\xi_i \cdot f_{ig}^{j,\mathrm{TRA}} \cdot 900\right) \tag{8}$$

The total local contribution in the small grid cell g (as part of the large grid cell i), lying (at least partly) in source region j, is thus given by

$$\mathrm{PPM}_{jig,\mathrm{total}} = \mathrm{PPM}_{jig,\mathrm{TRA}} + \mathrm{PPM}_{jig,\mathrm{DOM}} + \mathrm{PPM}_{jig,\mathrm{WASTE}} \tag{9}$$

The total $\mathrm{PM}_{2.5}$ concentration in the small grid cell is thus:

$$C(\mathrm{PM2.5_{tot}})_{jig} = C(\mathrm{PM2.5})_i + \mathrm{PPM}_{jig,\mathrm{total}} \tag{10}$$

4 Environmental endpoints

4.1 Calculating health impacts from ambient $\mathrm{PM}_{2.5}$

As discussed ambient PM2.5 concentrations in a 2km x 2km grid cell g (within a large grid cell i) lying in region j are calculated as the sum of a long-range contribution and a local contribution

$$\mathrm{PM2.5}_{jig} = \mathrm{PM2.5}_{i,\mathrm{LR}} + \mathrm{PPM}_{jig,\mathrm{total}} \tag{11}$$

where there long-range contribution is given by Eq. (1), and the local contributions are given in Eq. (9).

The full health impact calculation follows the Global Burden of Disease (2013) approach [4] and specifies premature mortality with respect to disease and age, using non-linear disease and age specific integrated exposure response functions (IERs) developed by [3] and further updated recently.

To avoid adding too much additional complexity, GAINS-4 employs a more simplified approach. Instead of age and disease specific risk functions, we assume an all-cause all-age (adult) dose response function which is linearly related to $PM_{2.5}$ exposure, similar to the approach taken in GAINS-Europe [7]:

$$RR = 1 + \beta\,[\mathrm{PM}] \tag{12}$$

where RR is relative risk and β is a constant. In GAINS-Europe, following the recommendations of assessments by WHO-Europe (REVIHAAP, HRAPIE), β is chosen as $\beta = 0.006/\mu gm^{-3}$. Recognizing the fact that typical PM exposure levels in Hanoi are higher than in Europe, and that the relative risk curves flatten at increasing PM exposure, we assume $\beta = 0.003/\mu gm^{-3}$ here, as was done in studies in the context of GAINS-Asia.

The population attributable fraction of deaths (PAF) can be calculated as

$$PAF^j = \frac{\sum_{i,g} \frac{pop^j_{ig}}{pop^j}(RR_{ig}-1)}{1+\sum_{i,g} \frac{pop^j_{ig}}{pop^j}(RR_{ig}-1)} \tag{13a}$$

$$= \frac{\sum_{i,g} \frac{pop^j_{ig}}{pop^j}\beta\,\mathrm{PM}_{ig}}{1+\sum_{i,g} \frac{pop^j_{ig}}{pop^j}\beta\,\mathrm{PM}_{ig}} \tag{13b}$$

If $\sum_{i,g} \frac{pop^j_{ig}}{pop^j}(RR_{ig}-1)$ is small enough, Eq. 13b can be approximated as

$$PAF^j \approx \sum_{i,g} \frac{pop^j_{ig}}{pop^j}\beta\,\mathrm{PM}_{ig} \tag{14a}$$

$$= \frac{\beta}{pop^j} \sum_{i,g} pop^j_{ig}\mathrm{PM}_{ig} \tag{14b}$$

Premature deaths $deaths\_AAP^j$ in region j are calculated as

$$deaths\_AAP^j = PAF \cdot deaths\_BL^j \tag{15a}$$

$$= \frac{\beta}{pop^j}\left(\sum_{i,g} pop^j_{ig}\mathrm{PM}_{ig}\right)\cdot deaths\_BL^j \tag{15b}$$

with $deaths\_BL^j$ the baseline deaths above the age of 30 in region j. In the absence of better information, we can derive an estimate for $deaths\_BL^j$ from national total projected deaths by downscaling with population numbers in each region,

$$deaths\_BL^j = pop^j \cdot \frac{deaths\_BL^V}{pop^V} \tag{16}$$

with $deaths\_BL^V$ and pop^V the projected deaths over 30 and total population for Vietnam in the year of analysis, as available from e.g. UN World Population Projections. Combined with Eq. 16, Eq. 15b becomes

$$deaths\_AAP^j = \beta\,\frac{deaths\_BL^V}{pop^V} \sum_{i,g} pop^j_{ig}\mathrm{PM}_{ig} \tag{17}$$

4.2 Calculating health impacts from indoor $PM_{2.5}$

The calculation of premature deaths from household air pollution (HAP, also labeled indoor air pollution) follows a slightly different approach because (a) Eq. 12 does not hold at the high concentration levels experienced in indoor pollution, and (b) the approximation as used in Eq. 14a cannot be taken because relative risk is no longer close to 1.

A wide range of indoor PM2.5 exposure levels for solid fuel users with traditional cookstoves has been measured in different household surveys; the Global Burden of Disease 2010 study used average levels of 337 μgm^{-3} for women and 250 μgm^{-3} for men. Since we do not distinguish the population into men and women, we use 300 μgm^{-3} as a typical exposure (also the IERs are so flat in this concentration range that they are rather invariant to the exact level of exposure). Improved cookstoves with fan can reduce both emissions to ambient air as well as indoor air quality; we assume that indoor concentrations drop to 70 μgm^{-3} in households equipped with fan stoves. Replacement of traditional stoves is one of the policy measures in GAINS-4 and is the only measure which modifies indoor exposure and the resulting premature deaths.

In the baseline, no fan stoves are used. We can therefore calculate a total number of HAP related premature deaths in CLE $deaths\_HAP\_BL^j$ using the equivalent of Eq. 13a but specific to disease d and age a,

$$PAF^{jda} = \frac{\sum_f \frac{pop_f^j}{pop^j}(RR_f^{da} - 1)}{1 + \sum_f \frac{pop_f^j}{pop^j}(RR_f^{da} - 1)} \tag{18}$$

where the exposure groups pop_f^j are now distinguished only by household fuel (either solid or non-solid). All age groups have the same fuel use shares. Equivalent to Eq. 17, we can write

$$deaths\_HAP\_BL^j = \sum_{d,a} PAF^{jda} \cdot deaths\_BL^{jda} \tag{19}$$

The resulting $deaths\_HAP\_BL^j$ can be tabulated. An increase of the baseline population can be expected to lead to a proportional increase of premature deaths from HAP.

Performing the equivalent calculation with 100% fan stoves, corresponding to 70 μgm^{-3} exposure, we find that the number of premature deaths drops to 60% of its baseline value.

Therefore, for a share of application λ of the cookstove replacement measure ($\lambda \in [0, 1]$) the number of premature deaths from HAP is given by

$$deaths\_HAP^j(\lambda) = deaths\_HAP\_BL^j \cdot \frac{pop^j}{pop\_BL^j}(1 - 0.4\ \lambda)\ . \tag{20}$$

4.3 Greenhouse gas emissions

The GAINS model covers all Kyoto greenhouse gases. In the current version of the tool we have also included all Kyoto gases. We have used the global warming potentials (GWPs) of the IPCC Third Assessment Report in order to convert them into CO_2-equivalent masses and to aggregate them. Emissions of individual gases are either calculated with an IPCC Tier 1 methodology, or for sectors for which better information is available higher tier methodologies[5, 6, 8]

5 Representation of selected measures in the GAINS model

The action of each of the measures can be described by an alternative scenario in the GAINS model. In this section we describe, for a selected set of measures, how they are implemented using the GAINS database input data. In Section 10 we described how, starting from a particular setting of the sliders in the tool (i.e. the implementation rates for each measure) a new scenario is generated in the GAINS model that represents the implementation of the measures. Here we describe the measures in more detail by sector.

5.1 Power plants

For power plants we distinguish end-of-pipe control measures from fuel switches that change the underlying activity data in the model and affect the structure of the energy supply system. In both cases we consider here only measures for coal-fired power plants.

5.1.1 End-of-pipe measures

In this version the tool offers two separate emission reduction measures, those that target NOx emissions and those that target SO_2 and particulate emissions. In the former case, the measure represents the implementation of the best NOx emission control technology available, namely selective catalytic reduction. In the latter case, the measure represents the implementation of the best available SO2 (advanced flue gas desulfurization) and the best particle reduction technology (high efficiency dedusters).

5.1.2 Coal-to-gas

Replacing coal- with gas-fired power plants offers multiple benefits, including higher conversion efficiency, more operational flexibility, low investment costs, and - not least - lower emission of air pollutants and greenhouse gases.

GAINS represents different types of coal- and gas-fired power plants, with different characteristics. To keep things simple, we assume that for this measure, as coal use is reduced and gas consumption increases, coal is being reduced in all types of coal-fired power plants proportionally, and the additional gas is used only in newly-built modern gas-fired power plants. In practice this could mean any mix of gas turbines and combined cycle plants, depending on foreseen operation. We assume that on average the coal plants in the baseline have an electricity conversion efficiency of 38%, and the newly built gas plants have an efficiency of 45%. At this stage we do not assume that an of the plants is used for district heating or cooling.

5.2 Industry

Basically, here we distinguish measures targeting process emissions in several distinct industry subsectors, and end-of-pipe measures for combustion/boilers in industries. For process emission measures we distinguish the following industries: cement, iron and steel, chemicals, and all other industries grouped together. The measures for these subsectors target SO2, NOx and particles, and represent the best available technologies, such as high efficiency dedusters and stage 3 process emission controls for SO2 and NOx.

For boilers we distinguish NOx from SO2 and PM emission controls, analogously to the situation in the power plant sector. In contrast to the process reduction measures here we do not distinguish different industries but assume that the measure is implemented across all subsectors.

5.3 Households

In this version of the tool we consider as emission control options for the residential sector: (i) to introduce briquettes to cook stoves that use dirtier coal (ii) to replace traditional cook stoves burning biomass with modern stoves (iii) a ban on residential trash burning. For the latter we not only assume full implementation but also full compliance.

5.4 Transport

In this sector we consider the following options for emission reductions:

- Diesel particle filter. Here we assume that by introducing a particle filter on diesel vehicles reduces the emissions of primary PM2.5 to the equivalent of an Euro-6 standard. This can only be achieved if the sulfur content of diesel simultaneously is reduced to around 500 ppm.

- Euro-6 standards for gasoline cars. Here we assume that an Euro 6 standard is applied to all gasoline vehicles, in particular cars.

- Fuel efficient cars. We assume that the fuel economy of gasoline cars could be improved by up to 30 percent. Whether this is achieved by bringing more hybrid cars on the road, or smaller cars, is left open for discussion.
- Expanding bus routes. We assume that the number of buses could be doubled, replacing motorcycles at a ratio of 1 to 10.5. The new buses by default are assumed to run on diesel, but this measure can be combined with a switch to alternative fuels.
- Fuel switch in buses. Here we assume that buses could be made to run on an alternative fuel like LPG instead of diesel.
- Expansion of electric public transport. Here we assume that public transportation could be expanded to bring 5 percent of the gasoline cars off the road. This could be achieved by building or expanding an underground or tram system, or by operating trolleybuses. The extra electricity consumption is assumed to be generated by zero emission electricity, expanding the renewable electricity capacity.
- Electric motorbikes. It is assumed that gasoline motorbikes could be replaced by electric motorbikes, and that the extra electricity consumption is assumed to be generated by zero emission electricity, expanding the renewable electricity capacity. This measure interacts with the expansion of bus routes: once motorbikes are electrified, expanding bus routes does not further reduce emissions in this configuration.
- Improved inspection and maintenance. From the outset we assume that the presence of super-emitters increase the fleet emissions of diesel vehicles and motorcycles to levels that are 50 percent higher than they could be in the absence of super-emitters. Thus, an efficient inspection and maintenance program is assumed to reduce emissions from these sources by up to 33 percent.

5.5 Off Road Machinery

Here we distinguish two classes of machinery, agricultural (tractors) and construction machinery. For these two classes we assume that they can be equipped with emission control equipment that reduces emissions to Euro-6 standards, accompanied by the introduction of low-sulfur fuel.

5.6 Agriculture

Three sets of measures are considered here:

- Manure management. We assume that an ambitious control strategy for animal manure management could be introduced.
- Urea application.
- Ban of agricultural waste burning.

5.7 Other measures

Other measures may have a significant impact on emissions, but are currently not parametrized in the tool. These include road paving to reduce dust being (re)suspended, and spraying construction site for the same purpose. Other measures or sub-measures could be discussed and parametrized with the help of local experts.

5.8 Overall emission reduction potentials

One question of interest is whether the measures represent a significant reduction in emissions and impact. Figure 1 and Figure 2 show the maximum emission reductions that can be achieved by the above measures in each measure and region. These graphs were generated by implementing all measures for a given sector together (to take into account overlap between them), then calculating the resulting emission reduction at the regional scale, and finally aggregating them. This only works because, at this stage, there is no interaction between measures across sectors. Sector accounting becomes more challenging and somewhat arbitrary once the cross-sectoral effects of certain measures are taken into account (e.g. demand side management affecting electricity consumption in demand side sectors such as household, industry or transport, and, by implication, also production in the power sector).

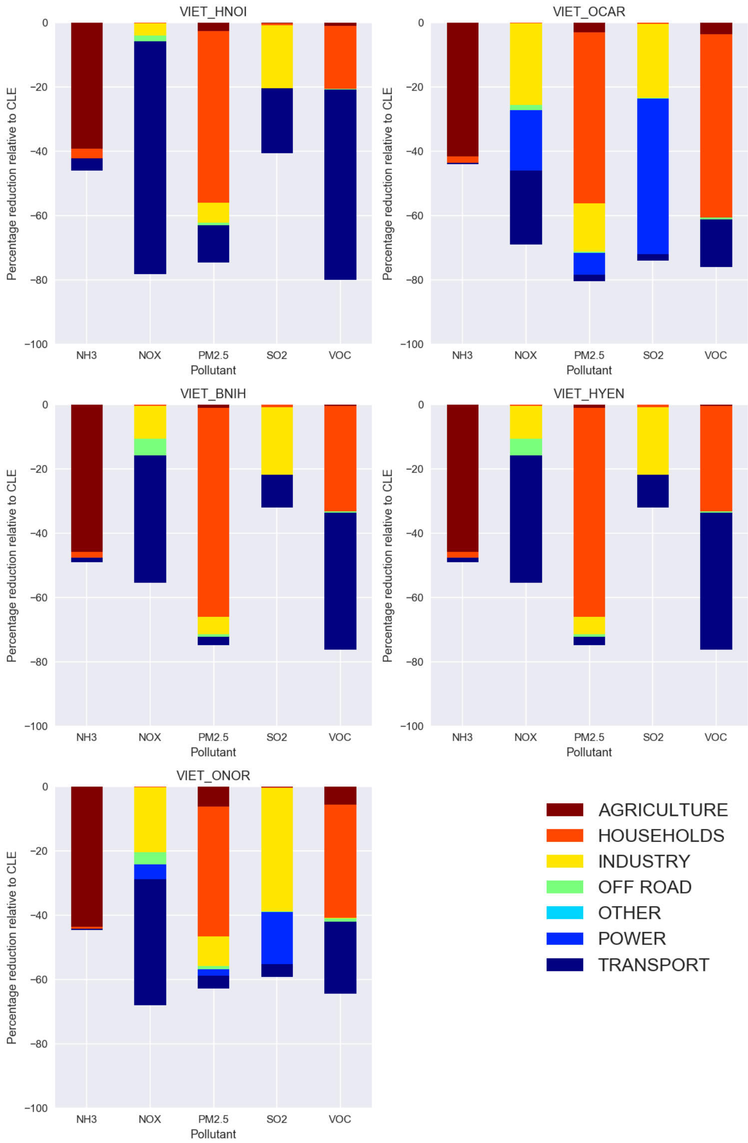

Figure 1: Maximum emission reductions resulting from measures in each sector and region

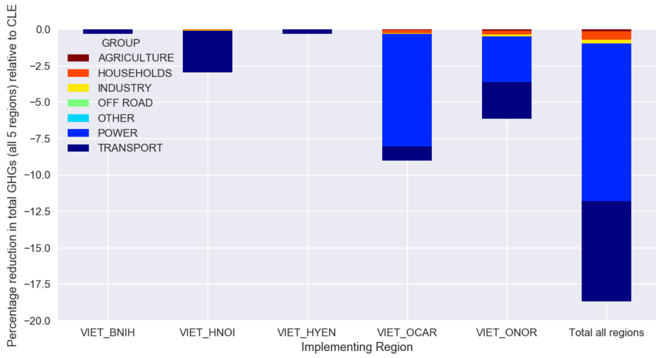

Figure 2: Maximum GHG emission reductions for the whole of Northern Vietnam as a result of implementing measures in each sector.

6 Drivers of emissions

The implementation of measures affect the emission reductions of various pollutants relative to a baseline. The baseline scenario is based on specific assumptions about energy consumption, and socio-economic activities in other sectors, as well as on the current legislation on emissions control.

However, these socio-economic activities depend in turn on fundamental drivers, such population size, income levels and other factors that shape consumption and production patterns. These are discussed in more detail below.

7 Costs

Applying technological measures to improve air quality or to mitigate greenhouse gas emissions is associated with costs, and the GAINS database includes information on these costs, so that the costs for different measures and combinations of these can be calculated and compared.

However, while total cost is not necessarily a good measure that can easily be compared across measures, the annualized cost of a measure (i.e. total net present value over the lifetime) is. For calculating this we take into account investment costs, as well as fixed and variable operating costs, including changed fuel costs resulting from a fuel switch. In this calculation use a 4% social planner discount rate. For details on how costs are annualized and total costs are calculated, see the GAINS model documentation e.g. [1]. Also, the total upfront investment requirement is a useful indicator by itself, which is why we provide it separately in the tool.

In the following it is useful to consider costs for end-of-pipe measures separately from those that affect underlying activity levels (such as fuel switches, efficiency improvements, or modal shifts in the transportation sector), before combining them later into an overall cost assessment.

7.1 End-of-pipe control measures

End-of-pipe control measures are measures that do not change the underlying activity levels. These measures include emission control technologies for power plants, industrial facilities and vehicles, such as three-way catalysts. In the GAINS model it also includes certain changes of practices, such as land-filling/composting or recycling versus the burning of residential or agricultural waste (which does not directly affect the amount of waste generated) or better inspection and maintenance programs (which does not affect the kilometers driven by a car, or the amount of gas transported by a pipeline.

Some of these end-of-pipe control measures have both an investment cost component and an operating and maintenance cost component, while others require only negligible or even no investment. For each end-of-pipe measure the GAINS model database contains cost information both for investment and on other costs. Some of the maintenance may involve the use of energy, which is why some cost components also depend on the assumptions of future energy prices. Naturally, cost for technology may differ across regions, though in the absence of evidence to the contrary it is assumed that across sub-regions within a country, for any technology the costs the same.

7.2 Measures affecting activity data

In addition to end-of-pipe technologies some emission reduction measures actually address the underlying activity data. For example, restructuring the power plant sector by phasing out coal-fired plants while expanding gas plants or renewables can be though of as a fuel switch that reduces one activity (coal combustion) while increasing another (gas combustion or power production from wind). Similarly, Other examples include end use efficiency improvements, which typically leave the amount of useful energy or energy service unchanged, but reduces the amount of final energy used for providing the service, which in turn reduces the amount of primary energy needed to generate the secondary and final fuels. Finally, another class of measures affecting activity data are modal shifts (from privately owned vehicles to public transport), which are more difficult to model in terms of costs because: it is difficult to estimate the costs for providing infrastructure; it is difficult to predict the effectiveness of the measure in reducing the use of privately owned vehicles; it is difficult to distinguish marginal from average effects, and hence to extrapolate from small-scale and localized evidence to broader expected effects.

7.3 Other comments

As indicated, for some options the above cost concept may fall short of covering the full cost to society. For example, while at this stage we have included for our cost estimate for a modal shift from privately owned vehicles to public transport only the difference in cost for the vehicles, we have not included yet the additional cost for paying the driver and maintaining the infrastructure not directly connected to the vehicles themselves, for example building and keeping up bus stops etc. However, it also needs to be established, on the other hand, whether a modal shift may also leave to a reduction in maintenance costs for the existing road network. Importantly, the GAINS cost methodology does not include time costs, a concept that some transport researchers use to rationalize modal choices. For example, total travel time including walking to the next bus stop may be longer than travel time for privately owned vehicles. While marginal differences in time costs for different transport modes can be observed and measured, scale and aggregation effects are more difficult to model. For example, while BRT with right of way may reduce the travel time compared to private vehicles in congested lanes, clearly there is a limit to the expansion of BRT. Conversely, while an extra bus may also be stuck in traffic and offers no time benefit, if all private vehicles were replaced with buses, traffic congestion will be less of an issue and passengers in general end up with lower time costs.

Even without this complication, it is difficult to estimate the cost of expanding public transport. For one, the cost will depend on the exact details of how this expansion is implemented, whether new bus stops, new roads or a new subway system will need to be built. Secondly, the investment needs in such cases often come in lumps and do not scale continuously. For example, a new subway line requires an investment that is independent of how many people will actually use the system (within its capacity).

At this stage we have kept our assumptions simple, but keep the option to add more detailed information to the tool at a later stage, when more detailed local information becomes available.

8 Methodology for efficient calculations

While the GAINS model allows for a detailed representation of activity data and emission control technologies in its database, the overhead for representing a compact list of policy measures is considerable, both in terms of data structure as well as data volume.

Hence, for PMEH we have developed an alternative framework in which only essential features are represented in the most compact way so as to still represent the a variety of measures and their interactions, as well as a well-defined set of environmental and economic endpoint for a succinct policy analysis.

To summarize much of what has been said above, here are some challenges in formulating the PMEH system:

- Policy interventions target different parts of the system:

- some measures only affect emission factors of a source, without changing the underlying activity ('end-of-pipe' measures);
- some measures reduce the underlying activity data of one or possibly more than one source. For example, a switch from coal to gas reduces the emissions from coal-fired power plants, but increases the emissions of gas-fired power plants. Similarly, a modal shift in the transport sector affects at least two sources;
- some measures may have a granular or discrete structure, e.g. they can only be implemented completely or not at all, while other measures could be applied continuously. For example,

- Policy measures ultimately affect environmental endpoint, but also intermediary outcomes, such as emissions. They are also associated with costs.
- In addition to policy measures, users may be interested in evaluating the effect that different assumptions about socio-economic drivers could have on endpoints and costs. For example, while our baseline scenario provides a projection of population and income growth over time, alternative assumptions about these drivers may have a distinct effect on future emissions, on the reduction potential of a measure, and the cost of implementation;
- Some measures in one sector may change the activities in another sector (energy savings in households reduce final energy consumption in household, but this may also affect the fuel input into power plants).
- Some measures implemented in one source region may affect the emissions and costs in another source region. For example, there are no significant power plants located in two of the source regions in and around Hanoi. Thus, any measure affecting electricity consumption (energy savings, expansion of the electric vehicle fleet, etc.). Thus, it will be necessary to distinguish the implementing region from the emitting/source region.
- The effects of different measures may interact or even interfere with each other. For example, while flue gas desulfurization is an effective measure to reduce SO_2 emissions from coal-fired power plants, its absolute effect by itself is reduced by the replacement of coal with gas: coal that is not combusted does not produce SO_2 emissions;
- A measure may not affect the emissions of all relevant pollutants in the same way. For example, while a reduction in coal combustion affects all relevant pollutants proportionally, a catalytic converter reduces the emissions of some pollutants, like NO_x and PM2.5, but also increases the emissions of NH_3 and N_2O, while CO_2 is unaffected.
- The list of measures to be included in the tool should not be considered static may need to be revised with the help of local expert. The PMEH system, it's menu structure and input data should thus be dynamically derived on the fly.
- In particular, the system needs to be flexible enough to be able to accommodate other endpoints (e.g. water quality or quantity indices) and corresponding measures that are currently not included in the GAINS model.
- The mathematical formulation should be:
  - simple and harmonized so that different measures are treated in the same way, and different end points are treated in the same functional form;
  - efficient, i.e. employ a minimal set of parameters, given the aggregation level of the end point functions;
- The mathematical formulation should lend itself to be used in an optimization algorithm that can be used for the cost-effectiveness analysis.

With this in mind we define the PMEH system in the following way:
As as input we take two sets of values:

- the implementation rates for the policy measures
- the assumptions on socio-economic drivers.

Both can be selected by the user in the PMEH web interface by moving the associated sliders within prescribed limits. We represent these implementation rates and growth variables as variables $\lambda_{r,m}$, and they are indexed by the implementing region r ($r = 1,...,4$), and the measure m ($m = 1, ..., m_{\text{last}}$, where at this stage $m_{\text{last}} = 30$, though this could easily be expanded or restricted/aggregated; in fact the current measures in the tool are already grouped into clusters operating on different sectors). Since both measures and drivers are operated in the web interface through sliders, our most general formulation does not distinguish between a λ associate with a measure from a λ associate with a driver; only in the context of the optimization this distinction becomes relevant.

As output we consider a set of end-point functions, $F_f, f = 1, ..., n$, each of which depends on the set of variables $\{\lambda_{r,m}\}$, which we denote as λ for short: $F_f = F_f(\lambda)$.

In the following we show that the end-point functions can be written as:

$$F_f = \sum_{a=1}^{2} F_f^{(a)} = \sum_{a=1}^{2} \sum_{\tau \in T_f^{(a)}} C_{f,\tau}^{(a)} \cdot \prod_{(m,r)} \left(\frac{1 - \mu_{f,\tau,(m,r)}^{(a)} \cdot \lambda_{(m,r)}}{1 - \mu_{f,\tau,(m,r)}^{(a)} \cdot \lambda_{(m,r))}^{0}} \right)^{n_{f,\tau,m}^{(a)}} \tag{21}$$

where $T_f^{(a)}$ is the set of all distinct transformation units of the function $F_f^{(a)}$. The sum over (a) is only introduced to be able to conceive of a function as the sum of two functions that have the same functional form, for example the cost of measures construed as the cost for end-of-pipe measures plus the cost of activity (changes).

This is a multivariate polynomial of degree $\max_a \max_\tau \sum_{(m,r)} n_{\tau,m}^{(a)}$, and it is written in a form that clearly shows that there is a part related to the actual implementation rate of the measure m in region r $\lambda_{(m,r)}$, and constant coefficients, $C_{f,\tau}^{(a)}$ that can be calculate from the baseline scenario.

Thus, in practice the coefficients $C_{f,\tau}^{(a)}$ carry the following indices: f for the function they describe, τ for the transformation properties, and (a) to distinguish two possible terms (this is relevant when costs from end-of-pipe measures are added to the costs of changes to the energy system).

8.1 Efficient representation: single measures

The essence of Equation (21) can easily seen by the following argument. Instead of an impact end-point function let us focus first on the emissions of a particular pollutant p from a particular sector-activity combination (s, f) in a particular region j, and let us denote the baseline value (no measures implemented) as $E_0(j, s, f, p)$. As we implement the measure m in region r (assume $r = j$ for the time being) to it maximum extent, we find that the emissions change according to:

$$E(j, s, f, p, \lambda_{j,m} = 1) = (1 - \mu_{m,j,s,f,p}) \cdot E_0(j, s, f, p) \tag{22}$$

where the change parameter $\mu_{m,j,s,f,p}$ depends on the measure, the region, the sector-activity and the pollutant. The above describes the extreme case where the measure is fully implemented ($\lambda = 1$). Since we assume that we can interpolate the situation between this extreme case and the baseline, we can rewrite Eq. (22) for general $0 \leq lambda \leq 1$ as:

$$E(j, s, f, p, \lambda_{j,m}) = (1 - \mu_{m,j,s,f,p} \cdot \lambda_{j,m}) \cdot E_0(j, s, f, p) \tag{23}$$

Next we observe that the implementation of the measure m (i.e. setting $\lambda_{j,m}$ to a non-zero value) may have the same effect on the emissions of different pollutants and different sector-activity combinations. For example, if m is a measure that only affects SO_2 emissions from power plants, then (a) all other pollutants are unaffected:

$$E(j, s, f, p, \lambda_{j,m}) = E_0(j, s, f, p) \quad \text{for } p \neq \text{SO}_2 \tag{24}$$

and (b) emissions from all other sectors (for all pollutants) are unaffected:

$$E(j, s, f, p, \lambda_{j,m}) = E_0(j, s, f, p) \quad \text{for } s \notin \text{power plants} \tag{25}$$

Alternatively, we can keep the general formulation Eq. (23) but observe that:

$$\mu_{m,j,s,f,p} = 0, \quad \text{for} s \notin \text{ power plants OR } p \neq \text{SO}_2 \tag{26}$$

On the other hand, the SO_2 emissions from different sector-activity combinations in the power plants sector (coal vs gas, existing vs new plant) may change in different ways under the measure m. For example, gas plants may not be affected by SO_2 controls at all, while coal is. Similarly, old plants may be reduced relatively more by additional SO_2 controls than new plants because new plants may already be subject to existing regulation, or vice versa. Thus, suppose for the many different sector-activity combinations there are $n_{pp,m,so2}$ different ways in which SO_2 emissions from an sector-activity combination may change (e.g. 1%, 5 %, ... 23 %). Then there are only $n_{pp,m,so2} + 1$ different values (the +1 is there to account for the trivial value) for $\mu_{m,j,s,f,p}$ we need in Eq. (23). Thus it is more efficient to group (s, f, p) combinations into clusters that share the same value for $\mu_{m,j,s,f,p}$, i.e. are affected in the same way under the measure m:

$$E(j, u_{j,m}, \lambda_{j,m}) = (1 - \mu_{m,j,u_{j,m}} \cdot \lambda_{j,m}) \cdot E_0(j, u_{j,m}) \tag{27}$$

The set of all (s, f, p) that correspond to the same value of $\mu_{m,j,s,f,p}$ we call a *homogeneous unit*, $u_{j,m}$. For each measure the total set of (s, f, p) combinations can be partitioned into clusters of homogeneous units. How many different homogeneous units there are for a given measure depends on the measure and how the measure transforms the pollutant emissions from different sector-activity combinations.

8.2 Efficient representation: interaction between measures

The above describes the behaviour of the emissions of different (s, f, p) combinations under the application of one measure m. If measures where complementary in the sense that any homogeneous unit that corresponds to a non-zero μ for one measure would correspond to $\mu = 0$ for all other measures, this would suffice to describe the whole system of measures and their actions on the homogeneous units identified by writing out Eq. (27) one after the other. In this case a homogeneous unit for one measure would automatically also be a homogeneous unit for another measure.

However, in practice measures overlap in their action. For example, SO_2 emissions from a new large coal fired-power plant will be affected non-trivially by more than one measure we typically consider: additional SO_2 control, if fully implemented, reduces SO_2 emissions by, say, 80%, while a complete switch from coal to gas reduces SO_2 emissions by 100%. Thus, two measures affect the same (s, f, p) combination. One question one may ask whether it matters in which order these measures are applied? It turns out that for modeling purposes the order is not important. Equipping power plants with sulfur control and then replacing some of them with gas-fired power plants results in the same emissions as first replacing some of them with gas and then applying sulfur control measures to the remainder (for costs this argument needs to be modified, see below). Thus, the combined effect to two measures can be written as:

$$\begin{aligned} E(j, u_{j,m_1,m_2}, \lambda_{j,m_1}, \lambda_{j,m_1}) &= (1 - \mu_{m_1,j,u_{j,m_1}} \cdot \lambda_{j,m_1}) \cdot (1 - \mu_{m_1,j,u_{j,m_2}} \cdot \lambda_{j,m_2}) \cdot E_0(j, u_{j,m_1,m_2}) & (28) \\ &= (1 - \mu_{m_1,j,u_{j,m_1}} \cdot \lambda_{j,m_1}) \cdot E(j, u_{j,m_2}, \lambda_{j,m_2}) & (29) \\ &= (1 - \mu_{m_1,j,u_{j,m_2}} \cdot \lambda_{j,m_2}) \cdot E(j, u_{j,m_1}, \lambda_{j,m_1}) & (30) \end{aligned}$$

where the last two lines indicate that one can either apply measure m_1 to the emissions already affected by measure m_2, or *vice versa*.

Note that the set of homogeneous units for the combined transformation of measures m_1 and m_2 is the joint partition; i.e. the set of all intersections between sets of homogeneous units. Each of these intersections represented by u_{j,m_1,m_2} transforms with $\mu_{m,j,u_{j,m_1}}$ under m_1, and with $\mu_{m_1,j,u_{j,m_1}}$ under m_2.

Equation (28) suggests that in general we can write:

$$E(j, u_{j,\mathbf{m}}, \lambda_{\mathbf{j}}) = E_0(j, u_{j,\mathbf{m}}) \cdot \prod_m (1 - \mu_{u_{j,m}}) \tag{31}$$

which is already close to what we have written in Eq. (21), so we need to explain the remaining differences:

- Our discussion so far focused on emissions, but the same arguments apply to other functions, such as costs and investment requirements.

- It can also be applied to linear functions of these basic functions like emissions and costs. In particular, considering Eq. (1), it is obvious that also the PM2.5 concentration (and also the health impact functions) can be formulated in this way. Hence, in general the constant coefficients can be labeled as C instead of E_0, and they carry only an index for the homogeneous unit they represent under the joint transformation under all measures in all implementing regions.

- Functions that transform differently/have distinct clusters of homogeneous units can also be added (hence the sum in Eq. (21)). This is relevant for the functions for cost and investment requirements: each of these is the sum of the component for end-of-pipe technologies and the component for changes in the activity data.

- Our aim was to find a formulation that would not only cover combinations of measures, but also 'drivers' of change, such as population growth or income dynamics. [So strictly speaking the m in Eq. (21) represents measures *and* drivers. In order to be able to render this possible and offer the user the option to select these drivers *as an annual rate of change between a base year and a target year*, we had to introduce a scaling factor and an exponent:

  - The scaling factor λ_0 in Eq. (21) takes the value of the driver in the baseline, as derived from scenario data in the GAINS model (for measures, in contrast to drivers: $\lambda_0 = 0$). Thus, if a particular driver is set to its baseline value ($\lambda = \lambda_0$), the factor $\left(1 - \mu^{(a)}_{\tau,(m,r)} \cdot \lambda_{(m,r)}/1 - \mu^{(a)}_{\tau,(m,r)} \cdot \lambda^0_{(m,r))}\right)$ equals 1, hence the baseline function is recovered. For all drivers, we define $\mu = -1$. In this way, if a different value is chosen for the driver ($\lambda \neq \lambda_0$), this ratio represents the relative difference between using the baseline rate of change for the driver (as calculated from the GAINS database) and the rate specified by the user.
  - The exponent, n ensures that this relative difference between annual driver growth in the baseline versus the user choice is compounded between the base year and the target year. So if the base year is 2015, and the target year is 2030, $n = 15$. (for measures, in contrast to drivers: $n = 1$).

8.3 Efficient representation: function ratios

- Other useful functions to be displayed include, e.g. costs per years as a fraction of the annual GDP; or investments in relation to GDP.

- This can be achieved by defining an even more general functional form:

$$\mathcal{F}_{f,g} = \frac{F_f}{F_g} \tag{32}$$

  where F_f and F_g are of the form Eq. (21), for example to f = costs, g = GDP. This means that these ratio functions are explicitly written as:

$$\mathcal{F}_{f,g} = \frac{F_f}{F_g} = \frac{\sum_{a=1}^{2} \sum_{\tau \in T_f^{(a)}} C^{(a)}_{(f,1),\tau} \cdot \prod_{(m,r)} \left(\frac{1-\mu^{(a)}_{(f,1),\tau,(m,r)} \cdot \lambda_{(m,r)}}{1-\mu^{(a)}_{(f,1),\tau,(m,r)} \cdot \lambda^0_{(m,r))}} \right)^{n^{(a)}_{(f,1),\tau,m}}}{\sum_{a=1}^{2} \sum_{\tau \in T_g^{(a)}} C^{(a)}_{(g,2),\tau} \cdot \prod_{(m,r)} \left(\frac{1-\mu^{(a)}_{(g,2),\tau,(m,r)} \cdot \lambda_{(m,r)}}{1-\mu^{(a)}_{(g,2),\tau,(m,r)} \cdot \lambda^0_{(m,r))}} \right)^{n^{(a)}_{(g,2),\tau,m}}} \tag{33}$$

For easier reference, the function indices f and g here carry an additional index ($\rho = 1$ for numerator or $\rho = 2$ for denominator). For the trivial function $F_g = 1$, Eq. (8.3) collapses to Eq. (21).

The functional form Eq. (8.3) is the most general form considered for functions displayed in the PMEH interface. They are defined by two data sets:

- Coefficients $C^{(a)}_{\rho,\tau}$ that depend on the transformation behaviour τ, the term index a, and whether the partial function appears in the numerator ($\rho = 1$) or denominator ($\rho = 2$) of the overall function.

- values for μ, n, and λ^0, each of which depends on the term index a, the region (n does not depend on the region), the transformation behaviour τ and the measure m.

The entries for the function COST_per_GDP with index $\rho = 2$ (i.e. denominator) are obviously a copy of those of the function GDP (which naturally carry an index $\rho = 1$ (numerator)) and for which for $\rho = 2$ the function is trivial. Trivial functions are represented as having exactly coefficient $C_0^1 = 1$ and a trivial $n_{0,m}^1 = 0$ and/or $\mu_{0,m}^1$ for all m.

8.4 Efficient representation: further observations

- **Some measures require coefficients which, however, are zero in the baseline.** For instance, some measures generate new (s, f, p) combinations that are not present in the baseline. For example, how do the CO_2 emissions from gas-fired power plants change as a result of a switch from coal to gas if no gas-fired plants exist in the baseline? While this can be calculated straightforwardly in absolute terms, the formulation Eq. (23) in relative terms poses seemingly insurmountable problems (the increase from zero to any non-zero value) would require an infinite growth factor. Therefore it is necessary to seed the zero activity in the baseline and replace it with any small number that is large enough not to cause any numerical instability, but small enough not to visibly modify the baseline. For example, for a region that has no gas-fired power plants in the baseline, but for which the coal-to-gas option should be offered with a potential of 1 PJ of gas use, the choice of an initial value of 1e-4 seems justified: it does not affect the baseline emissions significantly, and would result in a value for μ of about 10,000, which is not so large as to push other numerical values beyond the computation range by multiplication.

- As an aside we also note that had we treated each (s, f, p) combination separately, rather than clusters of homogeneous units, there would have been many terms to calculate (roughly 4 x 300 x 5 just for the emissions, then multiplying this with large scale source-receptor matrices) while with the use of homogeneous units, even the final impact functions each contain not more than a couple of hundred coefficients. How many there are eventually, depends on the exact definition and combination of measures considered.

9 Cost-effectiveness analysis

The PMEH tool also offers the option to identify a portfolio of measures that meets two given environmental objectives at the lowest cost. This is achieved by running an optimization routine that selects the most cost-effective portfolio under constraints. These constraints are the maximum application rates for each measure, i.e. the upper and lower bounds for each slider.

Thus, we can formulate the optimization problem as:

$$\text{minimize Cost} = \sum_a \sum_{\tau \in T_{\text{cost}}^{(a)}} C_{\text{cost},\tau}^{(a)} \cdot \prod_{(m,r)} \left(\frac{1 - \mu_{\tau,(m,r)}^{(a)} \cdot \lambda_{(m,r)}}{1 - \mu_{\tau,(m,r)}^{(a)} \cdot \lambda_{(m,r))}^{0}} \right)^{n_{\tau,m}^{(a)}} \tag{34}$$

such that

$$0 \leq \lambda_{(m,r)}^{\min} \leq \lambda_{(m,r)} \leq \lambda_{(m,r)}^{\max} \tag{35}$$

To run the cost-effective analysis the user needs to make the following choices:

- A set of values for the drivers. The default values for the drivers are the baseline values.
- Two independent target values for the two indicators, i.e. for
  - greenhouse gas emissions;
  - the expected number of premature deaths from exposure to ambient PM2.5 concentrations.

Both target values must lie within the feasible range of the indicators. If a target value is specified that is too low, the optimization routine will not find a feasible solution and abort. [In general, the lowest value for both indicators can be estimated by setting all sliders to their highest values, i.e. by implementing all measures to their maximum extent.] If, on the other hand, a target value is specified that lies higher than the baseline value, the constraint is not binding and the optimization proceeds as if this constraint was not present.

In the current implementation we use a Java interface for the browser interface of the tool, and an API to GAMS. We have formulated the above optimization problem as a non-linear problem in GAMS and solve it with CONOPT on the server side.

10 Mapping back to the GAINS database structure

Once a set of slider settings $\{\lambda_{(m,r)}\}$ is arrived at to meet defined objectives, either by using the optimization or not, it is possible to map these values back into a GAINS model scenario implemented the GAINS database, which can be accessed online.

For this it is necessary to define the map (suppressing the regional index r)

$$\{\lambda_{(m)}\} \longmapsto (\text{AD, CS, EFs})_{\{\lambda_{(m)}\}} \tag{36}$$

where AD, CS and EFs represent activity data, control strategy and emission factors, respectively.

Different measures affect different GAINS scenario components differently. For example, end-of-pipe measures typically only affect the control strategy, while fuel switches or modal switches in the transportation sector change the activity data. The only example of a measure that affects the emission factors is the maintenance and inspection program in the transportation sector. As a result, most choices for $\{\lambda_{(m,r)}\}$ will not affect all components.

The mapping is implemented straightforwardly, and let's discuss this for the example of the control strategy CS. Both the control strategy for the baseline scenario, CS_{BL} and for the full implementation of measure m, $\text{CS}_{\text{FI},m}$, are known by construction (full implementation means $\lambda_m = 1$). Therefore, for any value of the implementation rate λ_m we can interpolate:

$$\text{CS}_{\lambda_m} = \text{CS}_{\text{BL}} + \lambda_m \cdot (\text{CS}_{\text{FI},m} - \text{CS}_{\text{BL}}) \tag{37}$$

Since we are assuming (and taking care that this is indeed the case) that the control strategies for different measures do not overlap on sector-fuel-pollutant combinations, the control strategy for the combined measures is then simply:

$$\text{CS}_{\{\lambda_{(m)}\}} = \text{CS}_{\text{BL}} + \sum_m \lambda_m \cdot (\text{CS}_{\text{FI},m} - \text{CS}_{\text{BL}}) \tag{38}$$

where the region index is understood each term under the sum is non-zero only for those sector-activity-technology combinations that are affected by measure m. The activity data and emission factors can be recovered from $\{\lambda_{(m,r)}\}$ in a similar fashion.

A Notation

j	source region
s	sector
f	activity
i	$0.5° \times 0.5°$ grid cell
m	measure
g	2 km x 2 km grid cell
r	implementing region
π_{ij}	source-receptor relation for primary PM2.5 between source region j and receptor cell i
σ_{ij}	source-receptor relation for SO_2 between source region j and receptor cell i
ν_{ij}	source-receptor relation for NO_x between source region j and receptor cell i
α_{ij}	source-receptor relation for NH_3 between source region j and receptor cell i
υ_{ij}	source-receptor relation for VOC between source region j and receptor cell i
$\lambda_{r,m}$	implementation rate of measure m in region r
$\mathrm{Em}(p)_j$	emission of pollutant p in region j
$\mathrm{C(PM2.5)}_i$	PM2.5 concentration resulting from long-range transport into grid cell i
PPM_{jim}	urban increment: contribution to primary PM2.5 in fine grid cell m from emissions in grid cell m
$\mathrm{C(PM2.5_{tot})}_{jim}$	Total $PM_{2.5}$ concentration, sum of long-range and local primary contribution
PAF^j	population attributable fraction of deaths in region j

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