Trade-offs between energy cost and health impact in a regional coupled energy–air quality model: the LEAQ model

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Abstract

This letter presents a methodology for an integrated energy–air quality model in a cost and impact trade-off framework, applicable at the regional scale. ETEM (the Energy Technology Environmental Model) minimizes the energy cost at a given level of sectoral emissions. An efficient, reduced-order Eulerian air quality model (TAPOM-Lite) simulates some consecutive days where the meteorological conditions are favorable to the occurrence of an ozone episode. A health impact function has been developed to perform the feedback from ozone concentrations to the energy cost. The decomposition optimization problem is solved using an Oracle-based technique. We report on an implementation for the Grand Duchy of Luxembourg, varying the parameters of the impact function.

Keywords: DALY: disability-adjusted life years, integrated assessment, energy, photochemistry, oracle-based, convex optimization

1. Introduction

Energy and the environment are two forefront research agendas facing the European urban arena and they are often competitive in nature. The global importance of both disciplines has invited the need for a coupled modeling approach that will simultaneously address both issues.

An integrated assessment approach, also referred to as 'meta-modeling' [1] has become an important technique in addressing interdisciplinary problems and provides solutions for searching for environmental friendly and energy efficient European cities.

Our current interests are to extend the modeling work of [2] and perform a cost and impact trade-off analysis between energy cost and ozone pollution impact on health. In both approaches, the meta-model couples two sub-models: (a) a dynamic partial equilibrium model which represents the energy sector and which minimizes the total energy cost, (b) an air quality model which calculates the resulting ozone production. In [2], the authors have performed a cost-effectiveness analysis where the ozone concentration is bounded at a fixed level. The approach was to provide an optimal emission trajectory to reach specific targets defined by the European Air Quality Directive [3]. In this trade-off analysis, the optimal emission trajectory is the result of an equilibrium between the energy cost and the willingness to pay for the health consequences of ozone pollution induced by the energy infrastructures.

Ozone is a commonly present pollutant in the urban and suburban environment; it is a constituent of photochemical smog, and is damaging to human health. Many studies have been carried out that relate ozone concentrations to the increase in chronic respiratory conditions, hospital admissions, and premature mortality [4–6].

Unlike a cost–benefit analysis, which accounts for all the expected cost and benefits expressed in monetary value, using indicators like net benefits, this approach focuses specifically on the impact of ozone pollution on human health. In recent decades, integrated assessment models for climate change were commonly used in cost–benefit mode, examples are DICE [7] and MERGE [8]. Our approach performs a trade-off between
energy cost and health impact, and not a complete cost–benefit analysis, using an energy and an air quality model at the regional scale.

Cost–benefit approaches have also been used in local air pollution problems, e.g. [9], proposing a mathematical programming approach that includes demographics, abatement costs, and air pollution parameterization. Here, an optimal control strategy is used to improve air quality and reduce health impact. Other recent local cost–benefit problems include traffic regulation [10, 11] as well as risk analysis for air borne hazardous waste and the cost associated with sensors [12].

The form of the impact is based on the approach of Manne [8]. An important difference here is that we model an objective based on an impact weighted cost as opposed to a damage function which impacts on the consumption per capita. Manne divides damages into two types, market and non-market damages. Market damages have direct economic consequences and can therefore be treated with more direct economic tools (e.g. taxes). Such damages include sectoral (e.g. loss to forests, fisheries, agriculture, energy, water, construction, travel, tourism), loss of property (e.g. capital loss, dry land loss), and some natural disasters (e.g. storms, floods, droughts, hurricanes). Non-market damages includes biodiversity (e.g. wetland loss, species loss), human well-being (e.g. human activity, morbidity/mortality, air pollution, migration) and other types of natural disaster (e.g. storms/floods, droughts) hurricanes. Some of the damages (e.g. natural disasters) can fall into both categories [13]. In this letter, we address only ozone impact in terms of morbidity/mortality; no direct market value can be allocated and therefore we consider non-market damages.

Non-market damages, including air pollution impact to health, are treated by Manne in terms of a willingness to pay index, effectively a tax that could be levied on an informed public according to their capacity to pay and their level of development. This approach, though appropriate in a global climate analysis treating greenhouse gas emissions and impact, is less applicable to a local pollution problem. Manne, for example, uses a computable general equilibrium model as a complete representation of the economy in the analysis, therefore a tax representing damage can be used that connects the total costs calculated in the model to an abatement strategy. As previously mentioned, in the trade-off approach, we use a partial equilibrium model, where costs are based only on the energy infrastructure costs and use impact (damage) as a way to alter energy costs, reflecting the willingness to pay; low cost and more polluting technologies are a trade-off to higher cost, but less polluting and therefore less impacting technologies. A weighted cost is developed and can be used as a decision support in the evolution of spatial and urban planning; practically, this is done via several scenarios in the trade-off strategy.

We use the concept of DALY, disability-adjusted life years, advocated by Anand and Murray et al [14, 15]. A specific application in terms of air pollution is given in [16]. In this letter, DALY quantifies the loss of life due to ozone pollution. The analysis provided in this letter would ‘weigh’ the cost and suggests a method in offsetting the loss of life via cleaner energy technologies. We implement the methodology in the context of the Luxembourg Energy–Air Quality (LEAQ) model (see figure 1). The Energy Technology Environmental Model (ETEM) computes the total cost of the energy system of the Grand Duchy of Luxembourg and uses a detailed database that integrates, among many other technical parameters, the technology emissions coefficients of the ozone precursors, NOx, and VOC. The study focuses on the impact of the resulting secondary pollutant, ozone. Other pollutants, such as particulate matter (PM) are not considered here even though they are also problematic in terms of impacts on human health.

The air quality model is TAPOM-Lite and an Oracle-Based Optimization Engine, OBOE, implements an algorithm to resolve the overall problem, as described in the following sections. Notation. In this letter, lowercase boldface will be used to denote vectors, while uppercase boldface will denote matrices. When the indices are indicated, the vector or the matrix is not boldfaced.

2. The energy model

The Energy Technology Environmental Model (ETEM) is used to assess urban sustainable development policies [17] and belongs to the techno-economic MARKAL-TIMES family [18]. These are a dynamic partial equilibrium class of models which minimize the total discounted energy cost composed of the investment costs in new capacities, the fixed costs of installed capacities, the variable costs of the activities and the salvage costs of the installed capacities. The discounted costs are summed over all periods (with a discount rate of 3%). The energy supply should satisfy the demands in energy services in transport, industry, residential and commercial. The flows in the energy system are ensured by an overall balance equation where the production of energy is equal to its consumption plus the related loss. The shadow prices of this equation supply the endogenous market prices of the energy forms. The import prices are exogenous and change over time according to [19]. ETEM contains an extensive description of conversion and demand technologies. The efficiency changes are modeled by the definition of subsequent generations. The specific details of the models are available in [2].

The ETEM is an optimization problem of the linear form,

$$
\min_{\mathbf{x}} \mathbf{c}^T \mathbf{x} | A \mathbf{x} = \mathbf{b}, \mathbf{x} \geq 0,
$$

where \( \mathbf{x} \in \mathbb{R}^n \) is the vector of decision variables (the investments in new technologies and the consumption and the
production of installed technologies), \( c \in \mathbb{R}^n \) is the cost vector, the matrix \( A \in \mathbb{R}^{m \times n} \) and the vector \( b \in \mathbb{R}^m \) are the problem’s data (description of the energy system and its technical coefficients). The constraint \( Ax = b \) describes the reference energy system of the region.

In addition to the existing constraint, the model calculates the sectoral pollutant emissions \( e = e_{j,k,\sigma} \) (expressed in tons per year) for each pollutant \( j \in J \) := \{NO\textsubscript{x}, VOC\}, each time period \( k = 1, \ldots, K \) and each emitter sector \( \sigma \in \xi \). The sectors of interest are agricultural, industrial, residential, commercial, and transport. The sectoral emission vector \( e = e_{j,k,\sigma} \) is calculated using a linear relation between the fuel consumption of the sector technology and stoichiometric coefficients \( p \). The objective of the ETEM is described by the following formulation,

\[
\gamma(e) = \min_{x} \{ c'x | Ax = b, \; p'x = e \leq e_0, \; x \geq 0 \}, \tag{2}
\]

where decision variables \( e_0 = \tilde{e}_{j,k,\sigma} \) represent the vector of yearly maximum sectoral emissions. By construction, we ensure that equation (2) has an optimal solution and that the constraint \( e \leq e_0 \) on sectoral emissions is an equality at optimality (e.g. when an optimal solution \( x^* \) is found, we have \( e = e_0 \)).

Aggregated emissions \( \tilde{e} \) are distributed according to a cadaster map and a 24 h emission scheduling. The distribution uses a sector fraction \( f_j(s) \) of the total emissions and a Kronecker delta cadaster map,

\[
\delta_{\sigma,\sigma'} = \begin{cases} 
1, & \text{if } \sigma = \sigma' \\
0, & \text{if } \sigma \neq \sigma'.
\end{cases}
\]

An hourly sectoral-scheduling function, \( h_{\sigma}(t), \; t \in [0, T], \; T := 24 \text{ h} \) is used in the distributed emissions,

\[
e'_{j,k}(t, s; \tilde{e}_{j,k,\sigma}) = \lambda h_{\sigma}(t) f_j(s) \delta_{\sigma,\sigma'} \tilde{e}_{j,k,\sigma},
\]

and a conversion constant \( \lambda \) transforms the total emission in tonnes per year to g s\(^{-1}\) m\(^{-2}\).

### 3. The air quality model

The air quality model is a upgraded version used in a previous experiment [2]. The model (TAPOM-Lite [22]) is a three-dimensional Eulerian model with a simulation volume containing a discretized mesh and follows typical air quality schemes found in the atmospheric transport–diffusion model CIT, developed at the California Institute of Technology and the Carnegie Mellon Institutes [20], and in the TAPOM model developed at the Federal Institute of Technology at Lausanne (EPFL) and implemented at the Joint Research Centre of Ispra (JRC-Ispra) [21]. A reduced order scheme is used to efficiently calculate ambient levels of air quality [22] and is calibrated against the TAPOM model. Spatial values of pollutants are calculated for a given 24 h time period \( T \) over space \( s \in S \) for period \( k \). Emission \( e'_{k}(t, s; \tilde{e}_{j,k,\sigma}) \) in g s\(^{-1}\) m\(^{-2}\) are converted to concentrations in parts per billion (ppb) \( p_k(t, \cdot, \cdot) \), and averaged over the day,

\[
p_k(s; \tilde{e}_{j,k,\sigma}) = \frac{1}{T} \int_T p_k^*(t, s; \tilde{e}_{j,k,\sigma}) \, dt. \tag{4}
\]

The upgraded version of TAPOM-Lite includes improved emissions scheduling and meteorological routines.

In previous work [2] a cost-effectiveness problem involved solving the energy cost problem with regulation average over threshold (AOT) limits. The AOT is a measure of the ozone concentration exceedences over a certain threshold measured during the day, e.g. AOT40 with a threshold at 40 ppb [3]. In the present trade-off problem, impact is dependent on average ozone concentration and is not limited by a threshold.

Spatial and period dependent air quality levels, \( p'_k(s; \tilde{e}) \), are used for local air quality indices. The simulation region is divided into two regions \( S_c \), \( c = 1, 2 \). Each region is defined according to the population density \( \delta(s) \) based on 2010 (see table 1)

\[
S_c = \begin{cases} 
\{ s \in S | \delta(s) \leq \delta_0, \; c = 1 \\
\{ s \in S | \delta(s) > \delta_0, \; c = 2 \}
\end{cases}
\]

A threshold density \( \delta_0 \) representing the average population density for the capital Luxembourg, [23] and deliminates the urban and rural regions, see figure 3.

The integrated level per region is then

\[
p_{k,c}(\tilde{e}_{j,k,\sigma}) = \frac{1}{|S_c|} \int_{S_c} p'_k(s; \tilde{e}_{j,k,\sigma}) \, ds,
\]

\( k \in K \), \( c = 1, 2 \). The summarized function (2 components per period)

\[
p(\tilde{e}) = \begin{pmatrix} p_{1,c}(\tilde{e}_{j,k,\sigma}) \\ p_{2,c}(\tilde{e}_{j,k,\sigma}) \end{pmatrix}.
\]

We also define a decision variable \( \tilde{p} = \tilde{p}_{k,c} \) along \( p(\tilde{e}) \) within the optimization algorithm (see section 5).

### 4. Impact function

We model the current population \( \rho_{inc,k} \) and expected increase of inhabitants \( \rho_{inc,k} \) for each region \( c \) and period \( k \) using reasonable values based on population census and anticipated growth [23].

\[
\rho_{k,c} = \rho_c + \begin{pmatrix} \Delta \rho_k \alpha \\ \Delta \rho_k (1 - \alpha) \end{pmatrix} \begin{cases} 
1, & \sigma = 1 \\
2, & \sigma = 2
\end{cases}
\]

A scenario dependent parameter \( \alpha \) places population increase either in urban or rural areas. Ozone concentration, resulting in poor air quality will reduce the life of individuals. The impact \( v \) is the number of person-years lost in the population due to ozone [16] and is the product of the DALY [14, 15] and number of people affected

\[
\beta = \prod_{i=1}^8 \beta_i,
\]
of emissions.

The scaled cost and the impact functions are defined in terms of the decision variable \( \hat{x} \). The maximum feasible value for \( v \) and represents rural and urban space. The sketch of the range for \( v(\hat{x}, x) \) is shown in figure 2. The origin of the graph, low NO\(_x\) and VOC emissions represent high ETEM costs and low impact. High NO\(_x\) and VOC emission represent low ETEM costs, but high impact. A trade-off is found in the interior of the parameter space.

The problem is non-differentiable and requires such typical methods that fall into the category of cutting plane techniques. For an overview of the vast literature on the subject, see e.g. Goffin and Vial [26]. We use the OBOE to solve equation (11). The details of the cutting plane methodology are given in [2] and details of the algorithm used in the optimization iterative process are given in [27].

### Table 1. Model definitions.

| Description | Values and units |
|-------------|------------------|
| \( p \)    | Average ozone concentration ppb |
| \( e \)    | Pollutants emissions tonnes yr\(^{-1}\) |
| \( j \)    | Pollutants NO\(_x\), VOC |
| \( k \)    | Coupled periods 1, \ldots, \( K \) |
| \( \gamma \) | Total discounted energy cost M€\(_{2005}\) |
| \( c \)    | Cost vector M€\(_{2005}\) |
| \( x \)    | Vector of decision variables PJ |
| \( A \)    | Energy description matrix — |
| \( b \)    | Technical coefficients — |
| \( \sigma \) | Emitter sectors |
| \( f_n \)  | Emission sectoral fraction [0, 1] |
| \( h_e \)  | Emission time schedule [0, 1] |
| \( \delta_{x,\nu} \) | Emission spatial indicator (0, 1) |
| \( \lambda \) | Emission conversion factor tonnes yr\(^{-1}\) g\(^{-1}\) s m\(^2\) |

### Impact function

\[
\mathcal{I}(\hat{x}, x) = \sum_{k \in K} \sum_{s \in S} \beta_k \cdot \hat{p}_{k,s} \cdot \rho_{k,s} , \quad (8)
\]

\[
v(\hat{x}) = v(\hat{x}, x) . \quad (9)
\]

The constants \( \beta_k \)'s are defined in table 1. The mean number of people affected \( \hat{p}_{k,s}(x) \) converts the DALY into an impact \( v(P, \alpha) \). The regions \( S \) are shown in figure 3(c) and represents rural and urban space. The sketch of the range of variability for \( p(\hat{e}) \) as well as the impact \( v \) are given in figures 2(a) and (b). A maximum impact \( v_{\text{max}} \) represents the maximum feasible value for \( v \). The impact function \( \mathcal{I} \) is defined in terms of the decision variable \( \hat{x} \), and is subsequently used in the objective function. The term \( h \), 0 < \( h \) < 5 is an impact weighting term from the definition by Nordhaus [24]. The asymmetric quadratic form in the impact function is developed by Manne [8] and several scenarios are explored in [25]. The scaled cost and the impact functions are designed such that a feasible solution can be found in the range of emissions.

\[
\mathcal{I}(\hat{x}) = \left( 1 + \frac{v(\hat{x})}{v_{\text{max}}} \right)^{h} . \quad (10)
\]

5. Coupling model

The two scaled functions are combined in a problem objective where \( \hat{e} \) and \( \hat{p} \) are the decision variable vectors:

\[
\min_{\hat{e}, \hat{p}} \{ \gamma(\hat{e}) \cdot \mathcal{I}(\hat{p}) : \hat{p}(\hat{e}) = \hat{p} \leq 0 \} . \quad (11)
\]

A sketch of the costs, ozone levels, impact and objective function \( \gamma(\hat{e}) \cdot \mathcal{I}(\hat{p}) \), is shown in figure 2. The origin of the graph, low NO\(_x\) and VOC emissions represent high ETEM costs and low impact. High NO\(_x\) and VOC emission represent low ETEM costs, but high impact. A trade-off is found in the interior of the parameter space.

6. Optimization method

The problem is non-differentiable and requires such typical methods that fall into the category of cutting plane techniques. For an overview of the vast literature on the subject, see e.g. Goffin and Vial [26]. We use the OBOE to solve equation (11). The details of the cutting plane methodology are given in [2] and details of the algorithm used in the optimization iterative process are given in [27].
Figure 2. A sketch of (a) the energy costs, (b) average ozone level verse tonnes per year of NO\textsubscript{x} and VOC, (c) impact \(\nu\), and (d) objective \(F\) versus emission levels in tonnes per year. The latter two curves use \(\alpha = 0.5, h = 5\).

Assuming that the objective function is convex, an approximation to this function at a query point with the subgradient information, together called the oracle, is given to OBOE. A hyperplane approximation to the objective function at the query point is defined and is referred to as a cut. Both feasible and non-feasible cuts can be defined, depending on the query point and the shape of the objective and feasible region. The subgradient can be calculated analytically and have the following forms: the feasibility subgradient has the following form:

\[
\left( \frac{\partial p(\bar{\epsilon})}{\partial \bar{\epsilon}} - I \right)
\]

where \(I\) stands for the identity matrix of size \(2K\). The matrix \(\frac{\partial p(\bar{\epsilon})}{\partial \bar{\epsilon}}\) is computed using the finite differences by calling subsequently the air quality model with a small perturbation on emissions. The optimality subgradient is

\[
\left( \frac{\partial \gamma(\bar{\epsilon})}{\partial \bar{\epsilon}} \cdot I(\hat{p}) \right) \gamma(\bar{\epsilon}) \cdot dI(\hat{p})
\]

where \(\hat{p}\) is the optimal solution.

7. Implementation version

An implementation version of the model has been developed and tested according to a set of critical meteorological conditions. Poor air quality is determined by an exceedence, when pollutant concentrations are above the threshold of \(180 \mu g m^{-3}\) [3]. An episode represents a day or a sequence of days where the information threshold was exceeded at least once. A yearly counting of episodes is based on the European Directive related to ozone on ambient air. For Luxembourg, the critical ozone episodes from 2004–2008 are obtained from three rural and three urban air quality stations, figure 3(a). A total of 156 h of non-conformities were registered in all the stations of Luxembourg during this period.

The most serious episode, 19 July 2006, will be referred to as the test day (TD) and represents a day when exceedences were registered for all Luxembourg stations.

Simulations were done using a meteorological situation found on the TD from 06:00 to 21:00 (15 h) as measured at the stations located near but not directly at the location of the air quality stations [28, 29]. A characteristic SW, S, SE directional winds and temperatures varying from a low of \(22^\circ C\) to a high of \(35^\circ C\). Low wind speeds <2 m s\(^{-1}\) were also measured. In our approach, pollution across the border is treated as a fix quantity since scenarios are based on energy policy internal to Luxembourg only. The fixed averaged background and border concentrations for NO\textsubscript{x}, VOC and O\textsubscript{3} were taken from a European data source [28] and used in the simulation. The air quality model is validated via measurements, using an Index of Agreement as a means to test the validity of the air quality model and its simulation of the TD

\[
IoA = 1 - \frac{\sum_{i=1}^{N_m} (\phi_i - \bar{\theta})^2}{\sum_{i=1}^{N_m} (|\phi'_i| + |\theta'_i|)^2},
\]

where \(\phi_i\) and \(\theta_i\) denotes the predicted and observed values of \(i\), \(\phi'\) and \(\theta'\) are the means, \(\phi' = \phi_i - \bar{\theta}, \theta' = \theta_i - \bar{\theta}\) [30]. A value of \(IoA\) of 1 implies perfect agreement, 0 implies no agreement. Values are measured on a hourly basis from 06:00 to 21:00, \(N_m = 15\) and values for \(IoA\) are given in table 2.

The emissions depend on the energy sector demand and are distributed according to the cadastral map and road network, see figure 3(a). Table 3 gives the sectorial demand in the problem. The energy model is calibrated for the year 2005. The current period 2010–2015 and future periods 2015–2020
Figure 3. Luxembourg (greater region) maps (250 m resolution shown): (a) cadaster and simplified road map and air quality stations, (b) population density, and (c) urban/rural regions. Numbers 1, 2 and 3 in (c) represent the stations of St Nicolas, Luxembourg city and Esch-Alzette respectively.

Table 2. Sample stations—measurement and model for TD. Peak levels and duration over threshold (90 ppb) are given along with the index of agreement IoA.

| Station       | Measurement | Model          |
|---------------|-------------|----------------|
|               | Peak level (ppb) | Duration (h) | Peak level (ppb) | Duration (h) | IoA |
| Esch-Alzette  | 98          | 6             | 52              | —            | 0.76 |
| Luxembourg    | 92          | 2             | 100             | 5            | 0.82 |
| St Nicolas    | 98          | 3             | 100             | 7            | 0.57 |

and 2020–2025 are forecasted using reasonable infrastructure expansion assumptions based on population growth.

8. Results

Simulations were performed by varying two parameters: (1) a residency parameter $\alpha$, and (2) an impact factor $h$. We compare an equal habitations $\alpha = 0.5$ and urban/rural weighting $\alpha = 0.1, 0.9$ respectively. We also explore high, medium and low impact, by varying the weighting parameter $h = 0, 1, 3, 5$, see table 5. Technology changes are reflected in aggregate fuel consumption. Changes include substitution of fuels including an increase in hydropower and electric power and decrease in light fuel oil, coal and natural gas for the residential, commercial and industrial sectors. Likewise, an increase in diesel and electric fuel (e.g. diesel and electric cars) and a decrease in leaded and unleaded gasoline for cars is found in the transportation sector.

Air quality simulations were compared to measuring stations for a selected episode day. Some measurement

Table 3. Projected sectorial demands for periods in their appropriate units.

| Energy sector                  | 2010 | 2015 | 2020 |
|--------------------------------|------|------|------|
| Private cars (Mkm yr$^{-1}$)   | 4437 | 4561 | 4797 |
| All other transp. (Mkm yr$^{-1}$) | 780  | 782  | 784  |
| Industry (PJ yr$^{-1}$)        | 25   | 27.3 | 29.5 |
| Commercial/residential (PJ yr$^{-1}$) | 37   | 38.2 | 40.1 |
comparisons are shown including Esch-Alzette (south), for Luxembourg city (center), and St Nicolas (north).

The energy model is calibrated on the year 2005 using the European Statistics Bureau [23] and the local statistics office of Luxembourg [31]. The emissions $\dot{e}$ (equation (11)) are aggregated over all sectors. Projects are done for the year 2010 and optimization and decision is done only for periods 2015 and 2020 ($k = 2, 3$). The integrated model is run in two fashions: (1) ETEM alone, and (2) the coupled model using varying $\alpha$ and $h$. With ETEM standalone, emissions increase for each period as air quality constraints are not activated and cleaner technologies will therefore not be selected. The coupled model gives lower ceilings, for both NO$_x$ and VOC, see table 4. ETEM standalone simulations show that levels of ozone are on average 13% higher in the rural area. This value is similar for all periods.

Total energy costs $\gamma$ represents a sum total of all energy used for all devices, including the source costs, device maintenance costs, and salvage costs, for all periods. Values are normalized to the ETEM standalone mode. The use of replacement technologies in the coupled model results in a cost increase of 4%, 12%, and 13% using $\alpha = 0.5, h = 1, 3, 5$ respectively. In all cases, abatement of emissions occur with respect to the ETEM standalone case. Cost also vary with the residency parameter $\alpha$; impact generally increases with rural weighting, consistent with higher ozone levels, figure 2. An increase in impact, even if marginal, results in a cost that is counterbalancing; thus a lower impact generally means higher cost and vice versa. The differences in years lost, $\nu$ between urban and rural weightings are small, less than a few per cent, yet the impact factor $\bar{I}$ accentuates this difference. Increasing $h$ and $\bar{I}$ increases costs differently than increasing $\alpha$ and $\bar{I}$. In the first case, the $\bar{I}$ curve rises rapidly in terms of NO$_x$ and VOC and the rise is faster with larger $h$. The model forces costs to increase as lower NO$_x$ and VOC values are sought to counteract increasing $\bar{I}$. In the second case, there is no equivalent counterbalance from a decrease NO$_x$ and VOC as the increase is not due to an exponential factor.

In terms of computation, the model requires 10–30 iterations (depending on the initial starting conditions). Typically a mix (about half) of the cuts are feasibility and these require $3 \times 2 = 12$ subgradients values representing the parameterization of three periods, the two regions and two primary pollutants. Therefore 12 independent air quality simulations must be done for each feasibility cut, giving a total of approximately $15 \times 12 = 156$ times, each requiring about 30 s (real time) to determine a 15 h simulation. The energy model requires approximately 20 s (real time). Tests were done on a PC (Pentium IV, 2.4 GHz, 6Gb RAM) machine.

### Table 4. Simulated aggregated (summed industrial, transportation, residential and commercial) sectorial emissions for an optimal solution run in four different scenarios $h = 0$ (ETEM standalone), and $h = 1, 3, 5$, but in all cases $\alpha = 0.5$.

| Periods | ETEM only | Coupled model |
|---------|-----------|---------------|
|         | $h = 1$   | $h = 3$   | $h = 5$   |
|         | $h = 1$   | $h = 3$   | $h = 5$   |
| NO$_x$ (kt yr$^{-1}$) | 15 617 | 15 618 | 13 962 | 14 389 | 13 372 | 13 797 | 12 714 | 13 104 |
| VOC (kt yr$^{-1}$) | 6 702 | 6 703 | 2 901 | 3 006 | 3 222 | 3 333 | 3 22 | 3 33 |

### Table 5. Total energy relative cost (compared to ETEM standalone), $\nu$ (impact), impact function, and relative objective, varying $\alpha$ and $h$.

| Urban weighted | Equal $s$ | Rural weighted | $h$ |
|----------------|-----------|----------------|-----|
| $\alpha = 0.1$ | $\alpha = 0.5$ | $\alpha = 0.9$ | |
| Rel. cost | 1.20 | 1.13 | 1.13 | 5 |
|           | 1.12 | 1.12 | 1.10 | 3 |
|           | 1.10 | 1.04 | 1.02 | 1 |
|           | 1    | 1    | 1    | 0 |
| $\nu$ | 0.294 | 0.292 | 0.294 | 5 |
|         | 0.296 | 0.298 | 0.304 | 3 |
|         | 0.339 | 0.336 | 0.338 | 1 |
| $\bar{I}$ | 2.53 | 2.36 | 2.10 | 5 |
|          | 1.57 | 1.57 | 1.60 | 3 |
|          | 1.21 | 1.21 | 1.21 | 1 |
|          | 1    | 1    | 1    | 0 |
| Rel. Obj | 2.53 | 2.37 | 2.38 | 5 |
|          | 1.74 | 1.76 | 1.77 | 3 |
|          | 1.33 | 1.26 | 1.24 | 1 |
|          | 1    | 1    | 1    | 0 |

### 9. Conclusions

The air quality model simulates the most severe air quality episode on 26 July 2006, representing the poorest air quality day in Luxembourg over the period 2004–2008. The energy model, uses calibration data from 2005. The two models are coupled and the generated data for the energy model are used to make projections for 2010, 2015 and 2020.

The integrated assessment approach presented here represents a second generation coupled energy/air model and is built around a first generation prototype [2]. In this version, we explore the air quality and the related health impact on urban and rural regions in Luxembourg. We simulate a poor air quality day and use this information (changing only emissions) for future periods in the coupled model. A complete list of pollutant coefficients and spatial information will be extended to have a better representation of the air pollution impacts at the regional scale. The energy infrastructure in future periods is then determined in relation to the air quality limitations.

A threshold population density, set at half the maximum, is used to define the two regions—rural and urban. The model calculates energy costs based on a calibrated year, 2005 and projections to 2010, 2015, and 2020.

A trade-off approach is used to determines a lowest cost energy infrastructure and a health impact due to poor air quality projections. The years lost from ozone inhalation on 70 000 potential new inhabitants is calculated along with total energy infrastructure cost that could be installed over the next 10
years. The model suggests keeping residential areas in the urban regions based on a very modest impact increase.

The energy sub-model is calibrated on data for 2005 and projects energy infrastructure through 2020 in 5 year steps. The air quality model then simulates one poor air quality day, necessarily overly constraining the integrated model and giving conservative estimates for costs and impact. This problem will be resolved using a more detailed seasonal emissions map and a mix of meteorological scenarios as input for the air quality model, now in progress [32]. Improvements to the spatial energy data base of the model will also allow for an improved and detailed air quality assessment.

This meta-model approach, presents a novel methodology that incorporates energy infrastructure, spatial habitation, and air quality impact in one convex optimization problem and can be useful in national policy planning. Non-technical measures can also be tested under the form of “what-if” scenarios, where the models are adjusted to represent the situation. For example, a ‘low emission zone’ scenario would be modeled by a change in the emission allocation map in the air quality model and by a decrease in the demand of urban private transport in the energy model. The overall model is flexible and can be used to analyze a detailed problem involving land use, energy infrastructure and health impact.

Finally, any meta-modeling approach faces uncertainties associated to the model results [33, 34]. These uncertainties might arise from input data, model parameters, model structure as well as change-of-scale due to the coupling of the different sub-models, typically developed for a different scale and purposes [35]. Therefore, it is important to assess and account for uncertainties associated to the model results and study the uncertainties propagated through a meta-model. A full uncertainty analysis is beyond of the scope of this letter as we focus here on the presentation of the integrated LEAQ assessment modeling approach. Nevertheless, the authors are aware of the problem and are conducting studies of the uncertainties of the emission allocation from the energy model [36], an initiative that will have direct links to the uncertainty analysis in integrated assessment modeling and decision making processes [37–39].

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