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Integrated Assessment Modeling to support decision makers in planning air quality and low carbon win-win policies. A socio-economic and health perspective.

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Sommario

I cambiamenti climatici e la qualità dell'aria sono fenomeni con diverse estensioni spaziali e risoluzioni temporali, nonostante ciò sono altamente connessi poiché gran parte dei fattori che li causano derivano dalle stesse attività, ovvero quelle antropiche. Le politiche economiche e ambientali che ambiscono a studiare uno dei due fenomeni devono tenere in considerazione gli impatti che si possono avere sull'altro, in una prospettiva definita come "win-win", dove entrambi vengono mitigati. I modelli di valutazione integrata (Integrated Assessment Models) possono essere dei validi strumenti per valutare sia le emissioni di gas serra, causa del cambiamento climatico, che la qualità dell'aria, e quindi descrivere gli impatti sulla salute umana, gli ecosistemi e sul sistema socio-economico.

Questo lavoro di tesi propone la formalizzazione e implementazione di due nuovi problemi decisionali:

1. un'ottimizzazione multiobiettivo dove le concentrazioni di $PM_{2.5}$ e il costo della politica vengono minimizzati. La variabile di decisione è il tasso di applicazione delle misure di abbattimento delle emissioni, che includono misure di efficienza energetica, misure tecniche (end of pipe) e misure di sostituzione dei combustibili. Il problema è risolto con il metodo dei vincoli.

2. Un problema decisionale per la definizione di politiche a basso impatto emissivo, il quale permette di definire un mix efficiente di produzione di energia

elettrica da sorgenti rinnovabili e fonti fossili, così da poter alimentare l'elettrificazione del parco veicoli leggeri. Vista la complessità del problema e il numero di obiettivi (due indici di qualità dell'aria, emissioni di gas serra e costi), il problema è risolto con un approccio enumerativo, discretizzando le variabili di decisione nell'insieme di ammissibilità e selezionando le soluzioni non dominate.

Il primo problema è stato applicato e risolto su un dominio francese, l'Île-de-France, con lo scopo di analizzare l'efficienza di misure tecniche ed energetiche nella riduzione dell'esposizione della popolazione alle concentrazioni di $PM_{2.5}$ e quindi nel diminuire gli impatti sulla salute umana dovuti all'inquinamento atmosferico. L'inclusione delle misure di efficienza energetica e delle misure di tipo comportamentale nel problema permette di raggiungere anche importanti riduzioni di gas serra. Questo studio è stato possibile grazie alla collaborazione con l'Istituto Nazionale Francese per la Riduzione del Rischio Ambientale e Industriale (INERIS), che ha fornito gli inventari emissivi francesi e le simulazioni del modello deterministico di qualità dell'aria necessarie ad identificare i modelli sorgente-recettore.

Il secondo problema è implementato e risolto su un dominio in Lombardia. Sono stati studiati e descritti diversi mix di produzione di energia elettrica per rispondere all'incremento di domanda causato da futuri scenari di mobilità a basso impatto emissivo (mobilità elettrica e utilizzo del biometano), per valutare come si possano massimizzare gli impatti sulla riduzione di gas serra, l'inquinamento atmosferico e i costi di implementazione.

Abstract

Even if climate change and air pollution have different spatial and temporal extents, they are highly interconnected because most of their drivers are the same, meaning human activities. Policies that target one aspect must consider the other, in a win-win perspective, aiming at mitigating both. Integrated assessment modeling is a valuable tool to comprehensive analyze both air quality and greenhouse gases emissions.

The present study aims at designing new decision problems formalized and solved using different methodologies implemented through the integrated assessment modeling system MAQ, proposing a tool able to perform a comprehensive assessment of air quality, energy demand, GHG emission and health, socio-economics and ecosystems impacts.

This study proposes the formalization and implementation of two decision problems:

1. an air quality multiobjective optimization where $PM_{2.5}$ and policy implementation cost are minimized. The decision variables are the application rates of the emission abatement measures and the problem is solved using the ε-constraint approach.

2. a low emission energy policy problem where an efficient mix of renewable and non-renewable electricity production is found to power the light vehicles

fleet electrification. Due to the complexity of the problem and the number of objectives (two air quality indexes, greenhouse gases emissions and the cost) the problem is solved applying an enumeration algorithm aimed at discretizing the decision variables in the feasible set and selecting non dominated solutions.

The first decision problem is applied to a case study on Île-de-France, analyzing the effectiveness of end of pipe and energy efficiency measures in reducing $PM_{2.5}$ exposure, therefore premature mortality caused by air pollution. The implementation of energy and behavioral measures allows also to reach important greenhouse gases reductions. This study was possible thanks to the collaboration with the French national institute for industrial environment and risks (INERIS), that supplied French emission inventories and the air quality chemical transport model simulations needed to train the source receptor models.

The second decision problem is applied to a case study on Lombardy. Different sources electricity mixes are studied to supply a low emission road transport policy and understand how to maximize impacts on GHG emission, policy costs and air pollution.

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Introduction

Among the environmental problems that our society has been facing in the last decades, air pollution reduction and climate change control are the most discussed. These two phenomena have different temporal and spatial scales, therefore in many political and scientific areas these environmental issues are dealt with by different policy departments and scientific communities, whereas, they are highly connected. In fact, climate change impacts on local air quality and, on the other way around, air pollution has consequences on climate [1, 2].

Greenhouse gases (GHGs) emissions and air pollution have the same drivers, meaning the human activities whose emissions alter the composition of atmosphere. For example, livestock activities emit ammonia (NH_3) and methane (CH_4): ammonia is a precursor of secondary particulate matter (PM) and methane is a high potential global warming greenhouse gas. Energy production and transport sectors emit both CO_2 and various pollutants (mainly nitrogen oxides, sulphure dioxides, volatile organic compounds and primary particulate matter), PM concentrations precursors.

Impacts on human health of these two phenomena are well known. Air pollution is the main environmental cause of premature mortality worldwide. In 2018, the 74% of the urban European population was exposed to $PM_{2.5}$ concentration exceeding the WHO guidelines values (EEA, 2020) and the premature deaths attributed to $PM_{2.5}$, NO_2 and O_3 exposure were respectively 379000, 54000 and

19400. Climate change has disruptive impacts on physical, biological and ecological systems, affecting human health with injuries and premature deaths related to extreme weather events, changes in the prevalence and geographical distribution of food and water related illnesses and other infectious diseases [3].

In the past 25 years several Air Quality and Climate Change Integrated Assessment Models (IAM) have been established to help decision makers in planning energy, environmental and air quality policies: IAMs can be classified in (1) policy-evaluation models, that take a small set of policies and the consequences of these policies are evaluated in a ”what-if” exercise. Consequences are assessed with a set of environmental, economic, health impact, social indicators. (2) Policy-optimization models, that identify key policy control variables optimizing policy goals (environmental, economic, health impact, social targets). IAMs can be a valuable instrument in the definition of air quality-climate change win-win policies.

This study focuses on the formalization and solution of decision problems, aiming at defining win-win policies, targeting both air pollutants and GHG emissions. Two multiobjective problems are formalized, decision variables are treated differently: in the first case they are continuous, in the second one they are discretized in the feasible set. The Multi-dimensional Air Quality (MAQ) system is a tool that allows to implement and solve domain specific non-linear decision problems. The problems formalized in the methodology are implemented and solved for two different case studies.

The first one is a multiobjective optimization over the Île-de-France region: objective of this study is analyzing efficient policies for the reduction of population exposure to $PM_{2.5}$. For this case study, emission databases, emission abatement measures databases and surrogate air quality models are implemented in the MAQ system, with the collaboration of collegues from the French national institute for industrial environment and risks (INERIS, France). A multiobjective problem, with non-linear objectives ($PM_{2.5}$ population weighted annual average concentrations and policy implementation costs) and non-linear constraints, is formalized and solved using the ε-constraint approach. The decision variables are the application rates of the emission abatement measures.

Particulate matter in Île-de-France and specifically in the Paris metropolitan area has diverse sources: about 60% of its budget is considered to be emitted locally, mainly from residential heating, vehicle exhaust, and non-exhaust traffic emissions [4, 5], while the remaining fraction is attributed to transport from other French and European regions [6, 7]. The Paris area experiences recurrent $PM_{2.5}$ pollution episodes, furthermore the European Commission recently decides to refer France to the European Court of Justice because of a ”systematic failure” to meet EU ambient air quality limits of particulate matter in the areas of Paris and Martinique [8].

The second study, based on the work published in IEEE Transactions on Automation Science and Engineering Special Issue ”Advances in automation and optimization for sustainable transportation and energy systems” [9], aims at defining the efficient electricity sources mix to power an electric light vehicle fleet. A decision problem, where $PM_{2.5}$ concentrations, NO_2 concentrations, GHG emissions and total cost are minimized, is formalized and solved [9]. Due to the number of objectives and the complexity of the problem, an enumeration approach is used to generate a finite set of feasible scenarios. The decision variables are discretized distributing the electricity production on different sources, according to domain specific constraints related to production feasibility and legislation. Non-dominated solutions in all the objective spaces are selected among the feasible scenarios. The study is implemented and solved for the Lombardy region, an area often under study because of high pollution levels (PM, NO_2 and O_3), due to high population and emission density and unfavorable meteorologic conditions [10, 11].

The case study focuses on road transport sector because, although the last decades are characterized by a gradual decrease of global CO_2 emissions in most sectors, road transport is still an exception: in 2016, European traffic GHGs emissions were 26.1% higher compared to 1990 levels [12]. Furthermore, the European road transport sector accounted in 2017 for the 39% of total NO_x emission, a precursor of both NO_2 and PM. Technological improvements in internal combustion engines (to reach the stricter European emission standard) and on vehicle weight [13] have been applied lately to reduce the traffic environmental impacts. Also, the implementation of behavioral measures, such as lowering speed limits or soft mobility policies [14], for the reduction of fuel consumption or kilometers driven, has been studied in literature. But the need for further improvements in air quality and to massively reduce transport CO_2 emission lead to study new solutions where electric vehicles (EV) can play a significant role. One drawback of a massive EV penetration is the consequent rise in the electric energy demand. Vehicle fleet electrification can have a large potential for GHGs and pollutants emissions reduction, but it is strongly related to the energy mix used to produce electricity. This case study works towards responding to this problem defining efficient electricity production mixes and defining a methodology useful to support the energy transition road map.

Both studies are aimed to highlight that the need to reduce the human activity (energy consumption, distance traveled, fuel use) is becoming a key element both in low carbon transition policies and air quality planning, where the only use of end of pipe technologies to abate emissions showed to be insufficient [15, 16]. In this context, the integrated assessment of energy and environmental systems, considering costs and impacts on human health and ecosystems, is becoming more relevant [17, 18].

The thesis work is structured as follows:

- **Chapter 1** presents the state of art of Integrated Assessment Modeling.
- **Chapter 2** formalizes the decision problems describing objective functions, decision variables and constraints. The first part focuses on the formalization of a multiobjective air quality optimization. The second part describes a low emission energy decision problem. The third part summarizes the methodology used to compute health impacts in terms of mortality, morbidity and external costs.
- **Chapter 3** describes all the models and databases that compose the Multi-dimensional Air Quality system (MAQ).
- **Chapter 4** presents the Île-de-France case study, it includes a description of

the case study set up, surrogate models identification Design of Experiment and the results of a multiobjective optimization tackling $PM_{2.5}$ population exposure.

- **Chapter 5** presents the Lombardy region case study on low emission road transport scenarios. It describes the case study set up in terms of energy production data and projection for Italy and Lombardy and results are reported describing air quality, GHG emission reductions, policy costs, energy savings and human health benefits.

- **Chapter 6** presents the conclusions of the current work and possible future developments.

CHAPTER 1

Integrated assessment of air quality and low carbon win-win policies

In this chapter the integrated assessment approach is introduced, describing the interaction between energy and air quality modeling. A brief description of widely used models and tools available in literature is proposed.

1.1 The DPSIR framework

The European Environmental agency (EEA) defined the DPSIR scheme (Drivers Pressures State Impact Response) to describe the interaction between environment and society [19], as shown in Figure 1.1. This scheme explains also the aim of Integrated Assessment Modeling (IAM), that combines knowledge from various disciplines (science, engineering, sociology, economics) to derive policy-relevant insights. Each component of the DPSIR scheme is implemented in the Integrated Assessment Modeling approach by a different model, methodology and database, including both physical and social sciences models, considering demographic, political, and economic variables [17].

IAMs aim at identify the *responses* that mitigate (or prevent) changes in the environment *state*, acting on the *pressures*, the *drivers* (meaning the human activities) or directly on the environment *state*. Changes in the environment state have *impacts* on human health, ecosystem and socioeconomic aspects.

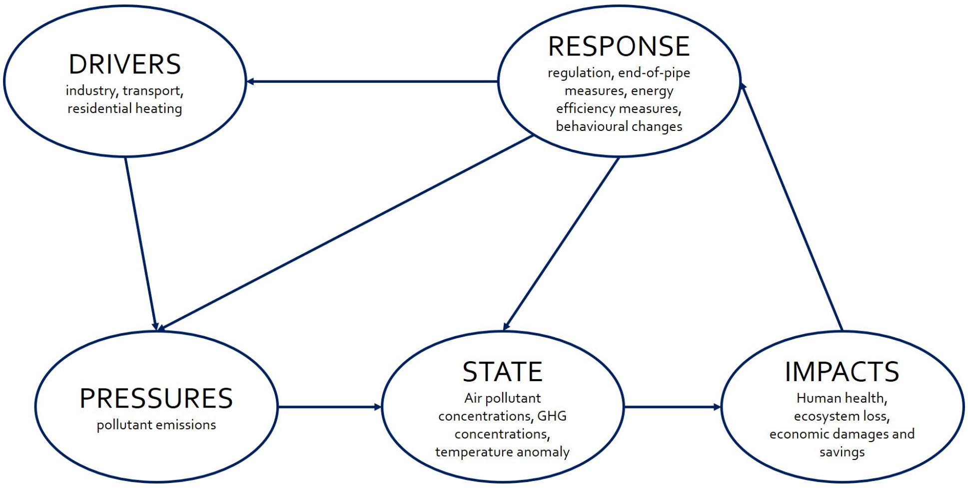

Figure 1.1: DPSIR framework adapted from EEA [19]

1.2 Integrated Assessment modeling: state-of-the-art

Integrated Assessment tools bring together data on:

- human activity levels (energy production, fuel consumption, land use);
- pollutant sources (air pollutants and greenhouse gases emission inventories);
- emission contribution to atmospheric concentrations and human exposure;
- information on potential emission reduction technologies, behavioral measures and energy efficiency interventions;
- measures implementation costs.

At the European scale, IAMs have been developed in order to provide a technical base for intergovernmental negotiations, such as the RAINS/GAINS model developed by the International Institute for Applied System Analysis (IIASA) [20]. GAINS (Greenhouse gas - Air pollution Interactions and Synergies) has been extensively used by the European Commission for the EU Thematic Strategy on Air Pollution to determine cost-efficient policies aimed at reducing emissions and analysing policies under the Convention on Long-range Transboundary Air Pollution (CLRTAP). GAINS can be coupled with energy simulation and energy optimization models. It has been used with MESSAGE (now in the last version MESSAGEix), a dynamic system optimization modeling framework [21]. MESSAGEix can be also linked to macroeconomic models, climate models and land use models. The system was used to develop one of the four Representative Concentration Pathways scenarios of 2014 IPCC [22].

At national scale the MESSAGEix and GAINS were applied in China to analyze energy consumption and emissions at the refining process level. The study introduce energy efficiency measures in the refining industry processes, studying energy, materials and water consumption and the air pollutant emissions [23].

GAINS model has been also used with PRIMES (Price-Induced Market Equilibrium System). PRIMES has been successfully applied to analyze the energy policies for Member States or at EU level [24, 25, 26]. It is composed of sub-models, as many as the number of investigated agents, and it determines the equilibrium energy price solving an equilibrium problem with equilibrium constraints (EPEC). EPEC is a mathematical approach that aims at modeling the energy market considering the behaviors of suppliers and consumers [27], providing forecasts on how the energy systems may evolve in future. PRIMES model has been coupled with GAINS model to integrate the air quality problem in the analysis, including non-CO2 gases and particulate emissions, and assessing the impacts in terms of air pollutant concentrations and air quality policy implementation costs [20].

GAINS model has been also adapted at country scale, for example in Italy [16], Netherlands [28], Belgium [29], Finland [30] and UK [31].

In Italy GAINS was also used with the TIMES model to define the Italian air pollution control plan (PNCIA, [32]). The final energy consumption was estimated for the energy and climate integrated national plan (PNIEC, Piano Nazionale Integrato Energia e Clima, [33]) using TIMES, then air pollutants emission reductions expected were computed. Air quality impacts were assessed through the Chemical Transport Model FARM (Flexible Air quality Regional Model [34]). TIAM is one of the most known energy system models (TIMES Integrated Assessment Model), developed by the Energy Technology Systems Analysis Program of the International Energy Agency [35]. It represents the possible evolution of the energy system at national/global scale over decades. The output scenarios are the result of the minimization of the discounted total system cost [36].

Integrated Assessment modeling tools have been developed also at regional scale. RIAT+, Regional Integrated Assessment Tool, has been developed in the framework of EU OPERA (LIFE09 ENV/IT/092) and tested on different European regions (Lombardy, Porto area, Brussels) [37, 38, 39]. AT+ methodology was further developed to include also energy efficiency and behavioral measures. This new system is the Multi-dimensional Air Quality system (MAQ), and have been tested over the Lombardy region [15].

1.3 Air Quality Integrated Assessment Modeling approaches

Air quality IAMs can have two main approaches: scenario analysis and optimization [17]. In scenario analysis an IAM computes the impacts of a set of emission reduction measures chosen a-priori by experts or defined using source apportionment techniques, aiming to identify the emission sources that contribute to air pollution and, therefore, find intervention priorities. The link between emissions and pollutants concentration can be described by deterministic models, such as Chemical Transport Models, or by computationally faster surrogate models.

In the optimization approach, the IAM defines a set of efficient measures through cost-effectiveness or multiobjective optimization. In the multiobjective optimization approach two or more conflicting indexes are minimized, for example an air quality index and the policy implementation cost. The cost-effectiveness optimization is a particular case of the multiobjective problem, were the cost is fixed, and the problem becomes a single objective minimization. In the optimization approaches the relationship between emissions and concentrations cannot be performed by CTMs because the approach requires an high number of iterations, therefore CTMs are computationally not adequate. Surrogate models are used instead, they are data-driven models aimed at mimicking the links between emissions and concentrations in a faster way.

1.4 Recent research and approaches

Scientific literature on environmental and energy systems analysis is focusing on the road transport sector at different spatial scales, traffic fleet management and technological improvement can have an important impact on air pollution, GHG emissions and the socio-economic sphere.

Recently, a tool targeting the road traffic sector in urban areas has been developed by the Joint Research Center. SHERPA City implements vehicle fleet data, traffic sector measures and atmospheric dispersion kernels to convert traffic emissions into contributions to the annual average NO_2 concentration, in a scenario approach [40]. The impacts of the implementation of low emission zones in urban areas are investigated also in [41], where authors proposed an approach using a CTM and a local meteorology module. In this case only NO_x emission and NO_2 concentrations are under study. Future low emission road transport scenarios are studied in [42], investigating climate, energy and air quality impacts of electric vehicles deployment scenarios and analyzing the the future prospects in Europe integrating environmental and economic aspects.

In [43] authors investigate the impacts on concentrations and emissions of EU countries' electric car deployment plans using the PRIMES model, already cited in section 1.2, with the sub-module TREMOVE that is an energy economic model for the transport sector. The modeling approach includes also DIONE, for the assessment of transport and energy policy options, and SHERPA for the air quality impact assessment.

These studies are mainly based on scenarios, meaning that the evaluation of the impacts is computed, using both CTM and surrogate models, after an a-priori definition of the policy and cost-efficiency is not included.

The multiobjective approach has been recently used in environmental system analysis, mainly focusing on climate change and environmental impacts interaction in the water resources management, building stock renovation, and agricultural systems. The problem of designing the control policy of a multipurpose water system was solved using a machine learning approach, including many objectives in the problem [44]. In [45] authors integrate multiobjective optimization and feedback control in the DICE model (Dynamic Integrated Climate-Economy model) to design self-adaptive climate policies trading off welfare maximization with Paris Agreement achievement. In [46] and [47] the authors address the problem of building stock renovation at regional scale. They determined the trade-offs between energy savings and their implementation cost solving a linear programming problem using a constraint method and selecting, through a cost-benefit analysis, the best type and spatial diffusion of the energy saving measures. The analysis considers GHG emissions, air pollutant emissions and costs.

Multiobjective decision problems have been also implemented to deal with the design of sustainable agroecosystems: [48] presents a problem where the economic income and agrobiodiversity are maximized while the intra-annual income variability is minimized. The problem is solved adopting the classical constraint method. In [49] agricultural water and land resources are optimized, solving an optimization problem that involves three objectives, corresponding to economic, environmental (GHG emissions) and social impacts.

In this thesis two decision problems are presented. The first one is a multi-objective optimization problem targeting air pollution and costs and considering all emission sources in the domain. The problem is solved through a constraint method. The second one focuses on how the electricity mix can impact on air quality, GHG emissions and costs. This problem aims at minimizing four indexes.

CHAPTER 2

Methodology

In this chapter, two different multiobjective decision problems are formalized and explained. The first one is an air quality planning problem (Section 2.1). The cost function is defined by an Air Quality Index, that represents the air pollution level in a domain and a policy cost index, that includes costs needed to abate emissions. The decision variables of this problem are the application rates of the emission abatement measures. Non-linear relationships link the decision variables to the emission reductions and the precursors emissions to the AQI. Therefore the problem can be formalized as a non-linear bi-objective decision problem. In this first case GHG emission are not included in the objective function, but they are computed ex-post.

The second decision problem presented in Section 2.2 aims at finding the electricity mix that satisfies the energy demand of a policy, minimizing a cost function composed by four indexes: two Air Quality Indexes (targeting $PM_{2.5}$ and NO_2 concentrations), greenhouse gases emissions and a total policy cost. The decision variable of the problem is the distribution of electricity production among renewable and non renewable sources. In this case all the indexes, except the AQIs, are linear and GHGs are included in the objective function.

A generic multiobjective decision problem aims at finding a set of values for the decision variables $\mathbf{x}$ that minimize a cost function $f(\mathbf{x})$. The set of decision variables is subject to equality and inequality constraints that must be satisfied, respectively $\gamma(\mathbf{x})$ and $\xi(\mathbf{x})$. The problem can be formalized as in Eq. 2.1.

$$\begin{aligned}
&\min_{\mathbf{x}\in X} f(\mathbf{x}) \\
&\text{subject to} \\
&\xi(\mathbf{x}) < 0 \\
&\gamma(\mathbf{x}) = 0
\end{aligned} \tag{2.1}$$

2.1 Multiobjective air quality decision problem

The multiobjective air quality decision problem aims at minimizing an air quality index and the policy implementation cost, satisfying a set of constraints related to the emission abatement measures [15]. The objective function $f(\mathbf{x})$ can be formalized as in Eq. 2.2.

$$f(\mathbf{x}) = [AQI(e(\mathbf{x})),\ TC(\mathbf{x})] \tag{2.2}$$

where:

- $AQI(e(\mathbf{x}))$ is the Air Quality Index that represents the level of air pollution in a domain;
- $TC(\mathbf{x})$ is the Total Cost of the emission abatement policy;
- $\mathbf{x} = [\theta, \phi, \psi]$ are the decision variables of the problem, meaning the application rates of emission abatement measures. $\mathbf{x} \in \mathbf{X}$, where $\mathbf{X} = [\Theta, \Phi, \Psi]$ is the set of applicable $\mathbf{x}$ values.

2.1.1 Decision variables and constraints

The emission abatement measures can be classified in:

1. end of pipe measures: they reduce the emission of a pollutant p right before it is released in atmosphere, according to its removal efficiency re^p, without

reducing the energy consumption. $\theta_t \in \Theta_k$ is the application rate of the t-th end of pipe measure belonging to the set Θ_k of all technologies that can be applied to the activity k.

2. energy efficiency measures: they abate the emissions reducing the activity levels (i.e. electricity consumption, kilometers driven, numbers of animals in livestock). They include both energy efficiency technologies, for example the use of low energy domestic appliances or energy efficiency intervention in buildings, and behavioral measures, such as active mobility measures, that reduce the cars fuel consumption lowering the amount of kilometers driven. $\psi_f \in \Psi_k$ is the application rate of the f-th energy efficiency measure belonging to the set Ψ_k of all energy measures that can be applied to activity k.

3. fuel switch measures: they substitute a fuel with another one that is more efficient (less emitting), such as substitute diesel with natural gas or lpg. Fuel switch measures can be defined in couple, the active measure increase one fuel/source use and the passive measure decrease the substituted fuel consumption. $\phi_s \in \Phi_k$ is the application rate of the s-th fuel switch measure belonging to the set Φ_k of all fuel switch measures that can be applied to activity k.

The measures application rates (θ, ψ, ϕ) are constrained, according to the functions ξ and γ in Eq. 2.1.

- The application rates can vary between an upper and a lower bound: for active fuel switch measures $\phi_{s,MIN} = 0$, for passive fuel switch measures $\phi_{s,MIN} = -\infty$ and $\phi_{s,MAX} = 0$.

$$\begin{aligned} &\theta_t^{MIN} \leq \theta_t \leq \theta_t^{MAX} \\ &\psi_f^{MIN} \leq \psi_f \leq \psi_f^{MAX} \\ &\phi_s^{MIN} \leq \phi_s \leq \phi_s^{MAX} \end{aligned} \tag{2.3}$$

- The sum of the end of pipe measures application rates acting on each sector activity must be less or equal to 1, because measures that reduce a precursor p in an activity k are mutually exclusive. Mutual exclusion constraint is applied also to energy and fuel switch measures: the sum of those measures reducing energy (activity level) of an activity can be maximum equal to 1.

$$\sum_{t \in \Theta_k : re_t^p > 0} \theta_t \leq 1$$
$$\sum_{f \in \Psi_k} \psi_f + \sum_{s \in \Phi_k} \phi_s \leq 1 \tag{2.4}$$

- Mass conservation associated with the application of the end of pipe measures for each activity and each precursor. This constraint means also that it is not possible to abate less emission than the basecase (θ^{MIN}).

$$\sum_{t \in \Theta_k} re_t^p \cdot \theta_t \geq \sum_{t \in \Theta_k} re_t^p \cdot \theta_t^{MIN} \tag{2.5}$$

- The amount of energy (represented by the activity level *al*) reduced substituting a fuel (passive measure) with a more efficient one (active measure) must be equal to the increase of energy produced by the new fuel.

$$al_{k1} \cdot \phi_{k1_{ACT}} + al_{k2} \cdot \phi_{k2_{PAS}} = 0 \tag{2.6}$$

2.1.2 Objectives

Air Quality Index

The AQI is an aggregated index that describes the level of air pollution in a domain, it can be defined by various indicators, such as the average annual concentrations of $PM_{2.5}$ or NO_2, the population weighted mean or the number of cells in the domain over a threshold value (e.g. air quality European limit values).

The variation of the AQI due to the application of emission abatement measures is defined in Eq. 2.7.

$$\frac{\partial AQI}{\partial \boldsymbol{x}} = \frac{\partial AQI}{\partial e} \cdot \frac{\partial e}{\partial \boldsymbol{x}} \tag{2.7}$$

The first term ($\frac{\partial AQI}{\partial e}$) defines the non linear relationship between the precursors emissions and air pollutant concentrations. This relation can be described by Chemical Transport Models (CTMs) or by surrogate models. In the optimization approach, only surrogate models can be used to estimate concentrations, because CTMs are not computationally efficient enough to deal with the number of simulations required [50, 51].

The second factor ($\frac{\partial e}{\partial x}$) describes the relation between the emissions variation and the application rates of abatement measures. The emission of a pollutant p in a cell c of the domain is defined as in Eq.2.8.

$$e(\theta, \phi, \psi)_p^c = \sum_k [al_k^c \cdot ef_k^p \cdot (1 - (\sum_{s \in \Phi_k} \phi_s + \sum_{f \in \Psi_k} ce_f \cdot \psi_f)) \cdot (1 - \sum_{t \in \Theta_k} re_t^p \cdot \theta_t))] \tag{2.8}$$

where:

- k is the human activity producing the emissions;
- al_k^c is the activity level in the cell c of the domain. The activity level represents the intensity of an activity in the domain, for example the electricity consumption, the number of kilometers driven by a class of road transport vehicles, the amount of animals in livestock;
- ef_k^p is the emission factor of the precursor p for the activity k;
- ϕ_s is the application rate of the fuel switch measure s, belonging to the set Φ_k of all fuel switch measures that can be applied to activity k;
- ψ_f is the application rate of the energy efficiency measure f, belonging to the set Ψ_k of all energy measures that can be applied to activity k;
- ce_f is the fuel consumption reduction efficiency of the energy measure f;
- θ_t is the application rate of the end of pipe measure t, belonging to the set Θ_k of all end of pipe measures that can be applied to activity k;
- re_t^p is the removal efficiency of the end of pipe measure t for the pollutant p.

Total cost

The total cost of the policy is computed as the sum of the measures implementation cost in each cell.

$$TC(\mathbf{x}) = \sum_c \sum_k C_k^c(\mathbf{x}) \tag{2.9}$$

The measures implementation cost $C_k^c(\mathbf{x})$ is computed as in Eq. 2.10.

$$\begin{aligned} C_k^c(\theta,\phi,\psi) = & \sum_{t\in\Theta_k} [uc_t \cdot al_k^c \cdot (1-(\sum_{s\in\Phi_k} \phi_s + \sum_{f\in\Psi_k} ce_f \cdot \psi_f))] \\ & + \sum_{f\in\Psi_k} [uc_f \cdot (al_k^c \cdot (1-\sum_{s\in\Phi_k} \phi_s)) \cdot \psi_f] \\ & + \sum_{s\in\Phi_k} [uc_s \cdot (al_k^c \cdot (-\sum_{s\in\Phi_k} \phi_s))] \end{aligned} \tag{2.10}$$

where uc_t, uc_f and uc_s are the unit costs expressed in M€/alu (Activity Level Unit) of respectively end of pipe, energy efficiency and fuel switch measures.

2.1.3 Problem solving

A multiobjective decision problem with conflicting objectives can be solved by means of different algorithms. In this case the ε-constraint approach is used. The cost index becomes a constraint and the problem is solved for different cost values bounds.

Infinite number of Pareto optimal solutions exists, creating the Pareto front in the objectives space. A solution is non-dominated (or Pareto optimal, or Pareto efficient) if none of the objectives can be improved without degrading the others [52].

2.1.4 Ex-post analysis: greenhouse gases emissions

Greenhouse gases emissions are not part of the objective function but they are computed ex-post, as a result of the efficient air quality scenarios. GHG considered are CO_2, CH_4, N_2O and F_{gases}. Emissions of GHG are computed as in Eq. 2.11. Furthermore the GHG emissions are aggregated in a CO_2 equivalent indicator, considering each gas Global Warming Potential (GWP).

$$e(\theta,\phi,\psi)_g^c = \sum_k [al_k^c \cdot ef_k^g \cdot (1-(\sum_{s\in\Phi_k} \phi_s + \sum_{f\in\Psi_k} ce_f \cdot \psi_f)) \cdot (1-\sum_{t\in\Theta_k} re_t^g \cdot \theta_t))] \quad (2.11)$$

$$GHG(\theta,\phi,\psi)_g = \sum_g e_g \cdot GWP_g \quad (2.12)$$

2.2 Low emission energy policy decision problem

In this section a decision problem aiming at supporting energy scenario assessment is formalized. The objective function in Eq. 2.1 is defined by four indexes.

$$f(\mathbf{x}) = [AQI_{PM_{2.5}},\ AQI_{NO_2},\ TC,\ GHG] \quad (2.13)$$

where:

- $AQI_{PM_{2.5}}$ is the Air Quality Index for $PM_{2.5}$, $PM_{2.5}$ yearly average spatial mean concentration.
- AQI_{NO_2} is Air Quality Index for NO_2, NO_2 yearly average spatial mean concentration.
- GHG represents the greenhouse gases emissions, in CO_2 equivalent, emitted in a year in the domain.
- TC is the total cost, that includes the energy policy costs, the implementation of new renewable energy plants, imported electricity cost and the end of pipe measures applied to reduce the air pollutant emissions.
- $\mathbf{x} = [nr, r]$ is the decision variable that includes the electricity production from renewable (hydroelectric, photovoltaic, biomass, biofuels, biogas/biomethane, waste) and non-renewable sources (natural gas, liquid fossil fuels and coal).

2.2.1 Decision variables and constraints

The decision variables r and nr are related to the electricity demand D: the total production of electricity and the imported electricity must satisfy the demand, as formalized in Eq. 2.14.

$$\sum_{j=1}^{n_r} r_j + \sum_{i=1}^{n_n} nr_i + u = D \tag{2.14}$$

where:

- r_j is the renewable electricity production from the source j;
- n_r is the total number of renewable sources;
- nr_i is the non-renewable fuel electricity production from source i;
- n_n is the total number of non-renewable sources;
- u is the electricity imported from all areas outside the domain;
- D is the electricity demand in the domain, computed as in 2.15 and 2.16.

$$D = D_0 + \Delta D \tag{2.15}$$

$$\Delta D = u + \sum_{k}^{n_t} \Delta x_k \tag{2.16}$$

D_0 is the base-case electricity demand and ΔD is the demand increase caused by the energy policy, in this case the electrification of the light vehicle fleet. $n_k = n_r + n_n$ is the total number of sources (renewable and non-renewable) in the domain. Δx_k is computed for each road transport vehicle class w and fuel y, as in Eq. 2.17.

$$\Delta x_k = \frac{\varepsilon_k \cdot \Delta al_k}{\eta_e \cdot \eta_{pd,k}} \tag{2.17}$$

where η_e and $\eta_{pd,k}$ are respectively the electric vehicle engine efficiency and the power production and distribution efficiency, ε_k is the share of the total increase in energy demand that can be produced by the activity k. The variation of activity level in road transport sector activities Δal_k can be computed as:

$$\Delta al_k = \sum_{w \in W} \sum_{y \in Y} al_{w,y} \cdot \eta_y \tag{2.18}$$

where:

- $al_{w,y}$ is the activity level of the vehicle class w and fuel y;

- η_y is the efficiency of the fuel y internal combustion engine;
- W is the set of considered road transport vehicle types;
- Y is the set of vehicle fuels.

The amount of renewable energy produced in a scenario is constrained, as defined by the decision problem constraints functions $\gamma(\mathbf{x})$ and $\xi(\mathbf{x})$ (Eq. 2.1).

First, renewable energy production should be at least what imposed through legislation for a specific year (Eq. 2.19) and, secondly, the maximum and the minimum energy production possible for each renewable and non-renewable source is subject to domain specific limitations, such as the availability of the source and plants in the domain and fuel specific legislation limits (Eq. 2.20 and 2.21).

$$\sum_{j=1}^{n_r} r_j \geq \alpha \cdot (D - u) \tag{2.19}$$

$$lb_j^r \leq r_j \leq ub_j^r \tag{2.20}$$

$$lb_i^{nr} \leq r_j \leq ub_i^{nr} \tag{2.21}$$

where:

- α is the renewable electricity production share imposed;
- lb_j^r and ub_j^r are respectively the production upper and lower bounds for each renewable source j;
- lb_i^{nr} and ub_i^{nr} are respectively the production upper and lower bounds for each non-renewable source i.

2.2.2 Objectives

Air Quality Indexes

The assessment of the air quality impacts depends on the emission variation due to the application of emission abatement policies. They can include energy efficiency abatement measures, fuel switch measures and end of pipe measures, as described in Section 2.1.

The emission variation of pollutants p from each electricity source k, due to the application of the energy policy, is defined as in 2.8. In Eq. 2.22 emissions definition is formalized making explicit the decision variable of this problem, the electricity production (meaning the activity level of sector-activities related to electric energy production).

$$e(\mathbf{x})_p^c = \sum_k [(x_k^0 + \Delta x_k) \cdot ef_k^p \cdot (1 - \sum_{t \in \Theta_k} re_t^p \cdot \theta_t)] \tag{2.22}$$

where:

- $p \in P = \{NO_x, NH_3, PPM_{10}, PPM_{2.5}, SO_2\}$
- x_k^0 is the basecase electricity production from the source k;
- Δx_k is the variation in electricity production from the source k due to the energy policy;
- ef_k^p is the emission factor of the pollutant p for the source k;
- re_t^p is the removal efficiency of the end of pipe measure t for the pollutant p applied to the power plants;
- θ_t is the application rate of t-th end of pipe measure;
- Θ_k is the set of end of pipe measures that abate emissions caused by the activity k.

The link between emissions and the m-th Air Quality Index (AQI) can be formalized as:

$$AQI_m = h(e(\mathbf{x})) \text{ with } m = 1, \ldots, m_{tot} \tag{2.23}$$

where m_{tot} is the total number of AQI computed, in this problem two AQIs are considered: $AQI_{PM_{2.5}}$ and AQI_{NO_2}. Different types of surrogate model can be used, in this work Artificial Neural Network (ANN) based statistical models are implemented to compute $h(e(\mathbf{x}, \theta))$.

Greenhouse gases emissions

Greenhouse gases emissions GHG_g^c in a cell c depend on power production from each activity k as:

$$GHG_g^c = \sum_k (x_k^0 + \Delta x_k) \cdot ef_k^g \tag{2.24}$$

where:

- $g \in G = \{CO_2, CH_4, N_2O, F_{gas}\}$
- ef_k^g is the emission factor of the fuel k for the greenhouse gas g.

Total cost

The total energy policy cost is described considering the following unitary costs:

1. energy policy costs: electric vehicle, hydroelectric plants revamping, photovoltaic plants (uc_k);
2. imported electricity cost (uc_u);
3. cost of the end of pipe measures (uc_t).

The total cost of the policy scenario is computed as in Eq. 2.9, but considering also the cost of the imported electricity, it can be written as in Eq. 2.25:

$$TC(\mathbf{x}) = \sum_k (x_k \cdot uc_k + al_k \cdot \sum_{t \in \Theta_k} uc_t \cdot \theta_t) \tag{2.25}$$

where al_k is the Activity Level of each emitting activity in the domain (excluding the electricity production activities, that are the decision variables defined by x_k).

2.2.3 Problem solving

The decision problem aims at selecting the non-dominated energy solutions among N feasible scenarios, built distributing the electricity production among the different sources, according to the constraints defined in section 2.2.1. The number N of scenarios is chosen a-priori, evaluating how much the feasible set created can describe the possible variations of the decision variables.

Due to the number of objectives and the complexity of the problem, an enumeration approach is used [53]. In the enumeration approach a finite set of scenarios is listed, discretizing the decision variables (electricity production from each source) in the feasible set, applying the following steps for each scenario from 1 to N:

1. the discretization of the decision variables is computed assigning to r_j (renewable sources electricity production) and nr_i (fossil fuels electricity production) randomly values varying ε_k in Eq. 2.17;

2. constraints (Eq. 2.19 - 2.21) related to electricity sources production feasibility and legislation are checked;

3. if constraints are verified, the scenario is computed and listed in the feasible set, otherwise point (1) and (2) are repeated;

When N feasible scenarios are computed, non-dominated scenarios are extracted for each objective space, meaning $AQI_{PM_{2.5}}$ - TC, AQI_{NO_2} - TC and GHG - TC. The solutions are the scenarios that comprehensive minimize two Air Quality Indexes and greenhouse gases emissions, meaning that are extracted in all objective spaces.

2.2.4 Ex-post analysis: road transport meta-emission factors

Given the increase in electricity demand, the pollutants and GHG emissions for each source k, and the total kilometers td driven by vehicles in the domain, a meta-emission factor mEF^p for each pollutant can be computed as in Eq. 2.26.

$$mEF^p = \frac{1}{td} \cdot \sum_k \Delta D_k \cdot e_k^p \tag{2.26}$$

where $\frac{1}{td} \cdot \sum_k \Delta D_k$ represents the average energy consumption per kilometer.

2.3 Health impacts

In this section the methodology used to estimate air pollution impacts on human health in terms of morbidity and mortality is reported. Impacts are computed considering exposure to $PM_{2.5}$ and NO_2, following the methodology proposed by the

World Health Organization in the HRAPIE project (Health Risks of Air pollution In Europe) [54]. Concentration-response functions and relative risks values are referred to WHO [54], then partially modified and updated by the studies of CE Delft on health costs of air pollution in European cities [55, 56]. In the past years NO_2 impacts on health have been mainly attributed to $PM_{2.5}$ and Ozone, that are formed by nitrogen oxides, not to NO_2 itself, therefore NO_2 adverse impacts have been neglected to avoid double counting. Recently, different studies have shown a relation between long-term and short-term NO_2 exposure with negative health effects, even if the scientific discussion about considering NO_2 directly accountable for negative health effects is still open [57, 58].

In this study the health impacts are computed also for NO_2 considering the relative risk adjusted by [56], that takes into account the risk of double counting. For all-cause mortality, expressed in years of life lost (YLL), WHO relative risks are used (Table 2.1), accordingly to Eq. 2.27.

$$YLL_a = af_a \cdot pop \cdot agf \cdot inc \cdot ayl \tag{2.27}$$

af_a is the attributable fraction, it depends on coefficient β_a and concentration associated to the air quality index $a \in A = \{PM_{2.5}, NO_2, O_3\}$. It expresses incidents of premature mortality cases in the population attributable to the pollutant a risk factor. It is computed as:

$$af_a = \frac{e^{\beta_a \cdot AQI_a - 1}}{e^{\beta_a \cdot AQI_a}} \tag{2.28}$$

pop is the entire population and agf is the age group fraction considered for the selected impact. inc is the natural mortality rate of the population and it is domain specific, while ayl is the average years of life lost from somebody dying from air pollution and it is set for Europe at 10.3 years by the European Environmental Agency [59], values adopted in this work are reported in Table 2.1. $PM_{2.5}$ relative risk is given by the WHO, while NO_2 relative risk is taken from [56], that compute a specific relative risk correcting double counting with all-cause mortality of $PM_{2.5}$. Morbidity impacts are modeled using the concentration-response functions

crf, each health impacts hi_z is computed according to Eq. 2.29.

$$hi_{z,a} = crf_{z,a} \cdot pop \cdot agf_{z,a} \cdot rgf_{z,a} \tag{2.29}$$

where $crf_{z,a}$ is given for each health impact z and pollutant a, rgf is the risk group fraction. Values are reported in Table 2.2 and are based on [60] and [56].

External costs are evaluated considering the monetary value of each impact, reported in Table 2.3, adjusted taking into account the domain specific income. WTP (Willing To Pay) values reported in Table 2.3 are average EU28 values, the differences in income are corrected, according to the methodology reported in [56], multiplying the WTP by a coefficient given by the ratio between the average domain income in_D and the average EU28 income in_{EU} and applying an income elasicity given by δ, equal to 0.8.

$$WTP_D = WTP_{EU} \cdot \left(\frac{in_D}{in_{EU}}\right)^{\delta} \tag{2.30}$$

Table 2.1: Relative risks for mortality due to chronic exposure to $PM_{2.5}$ and NO_2 [56, 60]

Pollutant	Age group	RR per 10 μg/m^3	β per μg/m^3
$PM_{2.5}$	+30	1.062	0.0062
NO_2	All	1.0076	0.00076

Table 2.2: Impact values for morbidity endpoints [56, 60]

Core morbidity Endpoints	Risk group	RGF	Age group	CRF [1/μg/m3]
	$PM_{2.5}$			
Net Restricted activity days	all	1	all	9.59E-03
Work loss days	all	1	20-65$^{(*)}$	2.07E-02
Minor restricted activity days	all	1	18-64	5.77E-02
	PM_{10}			
Increase in mortality risk (infants)	infants	0.0019	0-5	4.00E-03
New cases of chronic bronchitis	all	1	18+	4.51E-05
Respiratory hospital admissions	all	1	all	7.03E-06
Cardiac hospital admissions	all	1	all	4.34E-06
Medication use/bronchodilator use	children	0.045	5-14	4.76E-03
	NO_2			
Prevalence of bronchitis in asthmatic children	children	0.045	5-14	5.25E-03
Respiratory hospital admissions	all	1	total	1.11E-05

$^{(*)}$Working people

Table 2.3: Monetary valuation of health effects of $PM_{2.5}$ and NO_2 for average incomes in EU28 [55, 56]

Core endpoints	Pollutant	Unit	Monetary Value [€]
Increase in mortality risks (YLL)	NO_2,$PM_{2.5}$	YLL	70000
Net Restricted activity days	$PM_{2.5}$	Days	157
Work loss days	$PM_{2.5}$	Days	94
Minor restricted activity days	$PM_{2.5}$	Days	52
Increase in mortality risk (infants)	PM_{10}	Cases	3600000
New cases of chronic bronchitis	PM_{10}	Cases	240000
Hospital admissions	NO_2,PM_{10}	Cases	2850
Medication use/bronchodilator use	NO_2,PM_{10}	Cases	2

CHAPTER 3

Integrated assessment modeling tool

The methodology described in Chapter 2 is implemented in the Multi-dimensional Air Quality system (Figure 3.1) using the software Matlab®. MAQ system [15] integrates 4 modules: (1) a set of databases collecting the information related to the impacts, in terms of cost and emission reductions, for a set of measures; (2) an AQI module, including models able to relate the emissions reductions to the air quality levels; (3) a module that includes optimization and enumeration algorithms, allowing the solution of the decision problem and (4) an impact module, that defines the impact of the decisions in terms of air quality, human health indicators, benefits and costs. The modularity of the structure allows to implement and solve specific decision problems designed and formalized defining spatial domain, objectives, decision variables and constraints.

In this chapter, a brief description of the sources of uncertainties in each MAQ module is also reported. IAMs are composed by different models and databases, and often they include a set of models whose output can be the input of other models, therefore the estimation of uncertainties can be a complex task because it must consider the uncertainties of each model as well as the uncertainty of overall system [61].

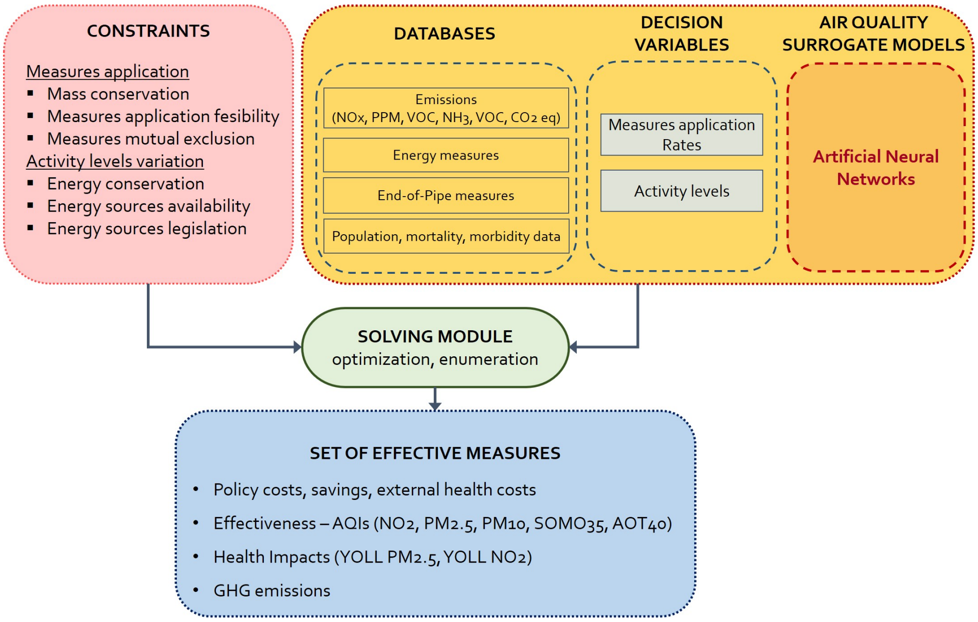

Figure 3.1: MAQ system structure

3.1 Emissions database

The emission database consists in a file for each cell of the domain. The domain is classified in Policy Application Domain, PAD, and external domain. For the PAD cells the database contains a file for each cell reporting the virtual emissions detailed for GAINS macrosector-sector-activity-technology that are present in the region. Virtual emissions are the pollutant levels that would be emitted by each sector-activity if no measures were applied. The external cells emission files report only the total emission for each precursor projected to the Current Legislation Scenario according to GAINS database projections and domain specific data. Those emissions are derived from a spatialized emission inventory (detailed by macrosector-sector-activity and fuel). Therefore this inventory is mapped into the GAINS classification in order to derive also, for each cell, the activity level values for the basecase. The emission macrosector considered are the ones defined by CORINAIR approach, the 11 macrosector categories in which emission activities are clustered by this approach are shown in Table 3.1. The emissions database preprocessing phase needs to take into account inconsistencies between GAINS and CORINAIR classification, furthermore the GAINS activity levels values are avail-

Table 3.1: CORINAIR [62] macrosector classification

Macrosector	Category description
1	Combustion in energy and transformation industries
2	Non-industrial combustion plants
3	Combustion in manufacturing industry
4	Production processes
5	Extraction and distribution of fossil fuels / geothermal energy
6	Solvent and other product use
7	Road transport
8	Other mobile sources and machinery
9	Waste treatment and disposal
10	Agriculture
11	Biogenic

able for the entire country (Italy, France) and they need to be down-scaled on the regional domain analysed.

Uncertainties are related to the emission inventories as well as to the different emission classification methodology used in GAINS and CORINAIR. The main sources of uncertainties in this phase are related to:

- the mapping procedure of national or regional emission inventories in the GAINS classification, needed to use the GAINS end of pipe measures databases.

- Activity levels rescaling from the national domain, given by GAINS for reference years, to the regional domain, described by the emission inventory.

- The projection of the emission inventory to the base case year used in the IAM tool (in this work 2018 for Lombardy region, 2020 for Île-de-France. The projection in the MAQ system is related to the activity levels estimated in GAINS for the inventory and the projection years and to the variation in the application rates of the end of pipe measures in these years.

Uncertainties can be reduce when national domain is considered in the MAQ system, thus the down-scaling of activity levels is not necessary and if the temporal distance between inventory and projection years is minimized.

3.2 Measures database

Two main databases are needed to describe the set of emission abatament measures and the emissions in a domain. Emission abatement measures application rates, meaning the penetration of the use of such technologies in the domain, are defined in two databases, one for the end of pipe measures, that limit pollutants emissions right before they are released in atmosphere with no variation in the activity level (fuel consumption), and the second one for the energy measures. The latter includes energy efficiency technologies (i.e. electricity production with photovoltaic panels, heat cost allocation in buildings,low energy domestic appliances...), behavioural measures (i.e. commuting by bike, public transit or walking instead of using the private car) and fuel switch measures, that substitute a fuel with another one that is more efficient in reducing air pollution (i.e. increase in methane or LPG cars instead of new diesel cars). All the energy measures can lower the activity level, therefore the related emissions.

The end of pipe measures database includes information about their removal efficiency for each pollutant, the unit cost and the activity level of the sector activity the measures can be applied to. These data are derived from the GAINS model database where they are reported and collected by country [20].

The energy measures database was firstly implemented in the VALUTA project [63, 38] for Lombardy region and then updated with behavioral measures [14]. It includes technologies for the combustion in energy and transformation industries (macrosector 1), non-industrial combustion plants (macrosector 2), combustion in manufacturing industry (macrosector 3) and road transport and other mobile sources (macrosectors 7 and 8). In macrosector 7 behavioral (active mobility) and fuel switch measures are also included. The unit costs of these measures, expressed in M€/alu (Activity Level Unit, mainly Petajoule), were computed in the VALUTA project and are derived from different sources reporting values on the local market [64, 65]. For new plants, a replacement period of 20 years with a discount rate of 5% and a yearly maintenance cost of 10% of the investment have been assumed [38]. Each measure database is domain specific and depends on emissions and activities in the domain as well as regional and local regulations.

The uncertainties related to the measures databases are linked in general to the uncertainties of the *responses* in the DPSIR framework (1.1) and they must take into account the knowledge of costs and externalities associated with the application rates of each measure, the emission inventories, the air pollution in the domain under study and societal consensus on control strategies [61].

3.3 AQI module: source-receptor models

Surrogate models are data-driven models aimed at mimicking the links between emissions and concentrations in a faster way, allowing multiobjective or cost-effectiveness approaches. They need to be identified using a set of CTM scenarios. In literature there is a wide variety of air quality surrogate models, based on different hypotheses, spatial scales and temporal horizons.

- In GAINS, functional linear relationships have been developed for changes in annual mean $PM_{2.5}$ concentrations, deposition of sulphur and nitrogen compounds as well as in long-term levels of ground-level ozone. The parameters of these relationships are country specific and they have been derived from a sample of several hundred runs of the full EMEP Eulerian model with systematically perturbed emissions of the individual sources [20]. EMEP (European Monitoring and Evaluation Programme model) is the chemical transport model developed by the cooperative program for monitoring and evaluation of the long-range transmission of air pollutants in Europe, under the CLRTAP. It has been extensively used to describe the atmospheric dispersion of air pollution in Europe and to assess impact of the Thematic Strategy for Air pollution.

- SHERPA surrogate models assume a linear relationship between concentration and emission changes. In SHERPA the variation in concentrations due to emission reduction is computed with a model for each cell and SR relationship are defined using a set of CHIMERE model runs [66]. These models can be used also in RIAT+, a regional integrated assessment tool able to perform both scenario and optimization approach [67].

- CAMS Air Control Tool is a web-based fast response scenario forecasting. In this toolbox forecast surrogate models are implemented. They are 2nd order, 4-dimension polynomial regression models, identified at each grid point, for each forecast day and for each species in an automated daily machine learning, based on 12 CHIMERE scenarios runs [68]. CHIMERE is an offline and, in the v2020r1, online chemical transport model. It is widely used in research institutes and in operational centers for forecast [69, 70, 71].

The AQI module is directly impacted by the uncertainties in the emission database, that is the main input, moreover surrogate air quality models can be a source of uncertainties related to other aspects:

- the Design of Experiment of the CTM simulations needed to train the models, it is essential in the definition of a range of emission and target variations that the model can ”learn”.
- The Chemical Transport Model used to compute the identification set, in terms of model formulation and variability due to the stochastic nature of atmospheric processes [61]. Generally, they are evaluated through measurements, and also uncertainties related to the measurements themselves, generally well known, should be considered.
- Assumptions made for the formalization of the SR model, such as the treatment of non-linearity behaviors or the assumption of linearity between emission and concentrations.
- Spatial resolution and flexibility of the model: for example the implementation of a country to grid approach (i.e. GAINS SR models), or a model for each cell (i.e. SHERPA SR models), or a regional model (ANN implemented in this work and in [15]).

In MAQ system different type of surrogate models can be implemented to describe the variation in the air quality index due to the variation in emissions. In the studies presented, neural networks (ANNs) surrogate models are used.

Artificial Neural Networks, that aim at capturing the non-linear relationship between emissions and concentrations, have been trained for Lombardy region using a set of 14 TCAM simulations. TCAM (Transport Chemical Aerosol Model) is an Eulerian CTM that implements different chemical schemes for gaseous chemistry and it implements a fixed-moving approach to represent particles in aerosol phase. It has been applied to a domain in northern Italy, centered on the Milan metropolitan area [72, 73]. ANN have been implemented in RIAT+ (Regional Integrated Assessment Tool) and in the MAQ system [15]. The same approach has been used in the study reported in Chapter 4, for the Île-de-France region, using CHIMERE simulations for the training.

ANNs are data-driven models with an architecture that emulates a biological neural network especially in terms of learning characteristics, parallel processing and self-adaptation. They are widely used for non-linear systems modelling and identification, due to their flexible structure that allows to capture complex nonlinear behaviors [74].

A neural network is composed by nodes and the links between them. Each node contains a computational element called neuron, upstream and downstream of a node represents the neuron input and output. The node performs the weighted sum of the inputs and transmits the result to an activation function. The activation function can be linear or non-linear, non-linear activation functions are widespread because they allow to describe more complex systems. Different types of neural networks can be defined changing the topological features of the network (number of neurons and layers), the weights of the inputs and the type of transfer functions.

The networks are trained (identified) to ensure that a specific input lead the output to mimic a specific target, varying the weights of the connections between the basic structures of the network [75]. The learning algorithm iteratively compares the outputs with the target values and progressively refine the network parameters until a certain figure of merit assumes a value lower than a specified tolerance [76]. Weights refining can be computed using different techniques, the ANN im-

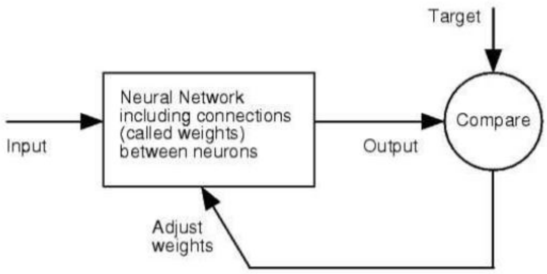

Figure 3.2: Training of neural network models [75]

plemented for this study are trained using a back propagation algorithm [77]. This algorithm modifies the connection weights after each test, according to the error between output and target 3.2.

In MAQ system two types of SR models are implemented:

- emission-concentration models (EMI-CONC), that link the total emissions for each pollutant in a cell c, considering also the adjacent cells, and the AQI in the cell c.

- Δemission-Δconcentration models (DELTA) that link the variation of emission to the variation in concentrations with respect to a selected base case.

3.4 Solving module: optimization and enumeration algorithms

According to the decision problem defined, two solving algorithms are implemented in the MAQ system.

The multiobjective optimization algorithm implements the ε-constraint method and it is used when the decision variables are treated as continuous, as in 2.1. This method, described in section 2.1.3, is implemented in the MAQ system using the Matlab®software Optimization Toolbox, that allows to find the minimum of constrained non-linear multi-variable function [78].

An enumeration approach is used when the objective function is composed by more than two indexes, as in 2.2, and the complexity of the problem requires a discretization of the decision variable to generate a feasible set of finite scenarios.

The approach, described in section 2.2.3, is implemented using Matlab®and the solutions are non-dominated scenarios in all objective spaces.

3.5 Impact module

The impact module contains data and functions needed to compute health impacts, external costs, energy and health savings. The implementation of this module in MAQ needs a set of domain specific data:

- population data in terms of inhabitants (gridded over the domain according to the spatial resolution used);
- population age distribution;
- mortality rates for age groups;
- asthmatic children rate;
- average income of the domain;
- fuel costs;

All these data are processed from domain specific information and national average values, available in Eurostat database [79]. The health impact assessment can be a source of uncertainties resulting from the exposure assessment and the epidemiological analyses that link exposure to the health outcomes. The main sources of uncertainties are:

- the estimation of each health outcome, in terms of incidence rates: health outcomes may not be specifically linked to air pollution due to additive or synergistic effects with other factors, it is difficult to directly identify deaths caused by a mixture of cumulative toxicity (exposure to more than one pollutant, smoking etc).
- Exposure assessment, uncertainties can result from biases in the exposure model or inaccurate inputs.
- Relative Risks estimated by the epidemiological models.

- Temporal scale of effects in long-term exposure studies [61].

CHAPTER 4

Efficient policies to reduce $PM_{2.5}$ exposure in Île-de-France

In this Chapter the case study over Île-de-France is presented. The multiobjective optimization problem, defined in Chapter 2, where an air quality index and the policy implementation costs are minimized in order to define the efficient air pollution abatement policies, has been implemented using the MAQ system [15].

4.1 Materials

The regional domain has a spatial resolution of 0.0625° x 0.03125° and it has a total extent of about 254 km (77 cells) in longitude and 564 km (55 cells) in latitude (Figure 4.1). The implementation of the system needed different databases and models, as described in Chapter 3: (1) end of pipe and energy measures databases, (2) emission database, (3) demographic data and (4) source receptor models.

4.1.1 Measures databases

Two databases are implemented, one for the end of pipe measures and the second one for the energy measures. The end of pipe technologies are derived from the GAINS model database for France. Measures costs, removal efficiencies and

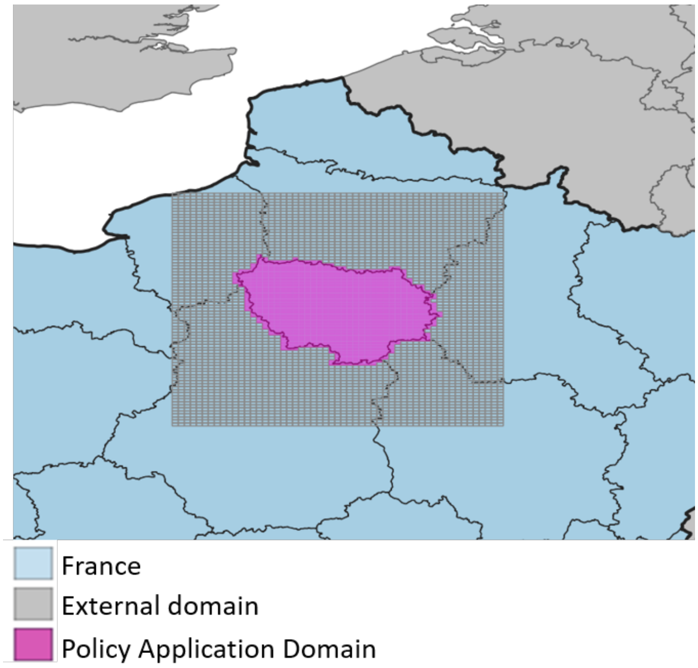

Figure 4.1: Île-de-France MAQ domain

activity levels are downloaded for the REF_pre2014_CLEv.Dec2018 scenario for the years from 2005 to 2030 and for REF_MTFR scenario for 2030 [80]. These two scenarios, implemented by IIASA, are referred to PRIMES activities projection (2016) taking into account, for the first one, the legislation already in place in 2014 while, for the second one, the full implementation of the technical emission control measures (MTFR: Maximum Technical Feasible Reduction).

The energy measures are derived from the VALUTA project database implemented for Lombardy region [63, 38, 14]. It was adapted to Île-de-France region:

- considering only measures applicable to existing (and emitting) sector activities in the Île-de-France domain;
- excluding measures implemented in Lombardy because of specific regional regulations (for example the ”stars” classification of stoves, the introduction of the mobility manager role in the companies [63]);
- selecting energy efficiency measures suitable for the policy application domain, for example excluding the installation/revamping of hydroelectric plants, that are not present in the region.

4.1.2 Emission and activity levels database

The emission database consists in a file for each cell of the domain (4235 cells). The domain is classified in Policy Application Domain (PAD, the optimization domain, the pink cells in Figure 4.1), that covers the Île-de-France region, and external domain. External cells emissions are projected to the Current Legislation Scenario (2020) according to France GAINS emissions.

MAQ emissions are processed from a spatialized CORINAIR France emission inventory (detailed by macrosector-sector-activity and fuel) for 2007, supplied by the French National Institute for Industrial Environment and Risks (INERIS).

4.1.3 Population data

Economic indicators, health data and geodata for the Île-de-France have been downloaded from Eurostat and GISCO databases.

1. Inhabitants: 1 km^2 gridded population data for 2011 are available from GISCO, the geographic information system of the European Commission, developed by Joint Research Center and DG Regional Policy - REGIO-GIS [81].

2. Population, age groups distribution, mortality data for age groups and morbidity data (i.e. asthmatic rate for age group) are given by Eurostat for year 2018 for the entire France [79].

3. Mean equivalized net income, needed to compute the external costs is also given by Eurostat for France [79].

4.2 Source-Receptor models: Design of Experiment, identification and validation

Source-Receptor ANN models were trained using a set of 14 CHIMERE scenarios, one model for each target (PM_{10}, $PM_{2.5}$ and NO_x concentrations) has been implemented in the MAQ system, all the models tested were identified using the 80% of the dataset and validated on the remaining 20%.

The main objective of the Design of Experiment (DoE) is to generate a limited number of instances that evenly cover the extent of possible emission variations. In the optimization approach emissions could vary between a minimum value, defined by the Maximum Feasible Reduction scenario (MFR) and a maximum value, described by the basecase scenario. For the computation of $PM_{2.5}$ concentrations SR models are trained using 14 CTM scenarios defined to describe a wide range of input variations (particulate matter precursors are: NO_x, NH_3, VOC, primary PM and SO_2), between two extremes (LOW and HIGH). In Eq. 4.1 is reported the emission of precursor p in the scenario s that depends on the reduction $R(s,p)$.

$$e_{s,p} = R(s,p) \cdot (HIGH_p - LOW_p) + LOW_p \tag{4.1}$$

4.2.1 Lower bound and upper bound scenarios

Lower bound and upper bound scenarios (HIGH and LOW projections) do not correspond to ”real” emission scenarios but they are useful to estimate, for each cell, the maximum and minimum emissions expected in the solution of the multiobjective problem. They are implemented starting from four artificial scenarios (S1, S2, S3 and S4) built considering the France emission inventory for 2015 and the GAINS model database for 2020 and 2030 in terms of activity levels (al) and emission abatement technologies application rates (θ):

$$S1_{p,ms} = EMI_{INV_{p,ms}} \tag{4.2}$$

$$S2_{p,ms} = EMI_{INV_{p,ms}} \cdot (1 - \frac{EMI\_BY\_BC_{p,ms} - EMI\_FY\_MFR_{p,ms}}{EMI\_BY\_BC_{p,ms}}) \tag{4.3}$$

$$S3_{p,ms} = EMI_{INV_{p,ms}} \cdot (1 - \frac{EMI\_BY\_BC_{p,ms} - EMI\_BY\_MFR_{p,ms}}{EMI\_BY\_BC_{p,ms}}) \tag{4.4}$$

$$S4_{p,ms} = EMI_{INV_{p,ms}} \cdot (1 - \frac{EMI\_BY\_BC_{p,ms} - EMI\_LY_{p,ms}}{EMI\_BY\_BC_{p,ms}}) \tag{4.5}$$

where:

- EMI $_{INV}$ is the 2015 emission inventory;
- EMI_BY_BC is the emission projection obtained using the application rates

and the activity levels estimated from GAINS year 2020;

- EMI_FY_MFR are emissions projected to 2030, applying the MFR application rates and the activity levels for 2030;

- EMI_BY_MFR are emissions projected to 2030 applying the MFR application rates for 2030 and the 2020 activity levels;

- EMI_LY is the projection of emissions using 2020 application rates but final activity levels for 2030.

For each cell of the domain and each pollutant p, minimum and maximum emission values are identified between the four scenarios. These new minimum and maximum emission values are respectively reduced and increased by the 20% and define the two extreme scenarios LOW and HIGH.

$$LOW_{c,p} = 0.8 \cdot \sum_{ms} min(S1_{ms,c,p}, S2_{ms,c,p}, S3_{ms,c,p}, S4_{ms,c,p}) \tag{4.6}$$

$$HIGH_{c,p} = 1.2 \cdot \sum_{ms} max(S1_{ms,c,p}, S2_{ms,c,p}, S3_{ms,c,p}, S4_{ms,c,p}) \tag{4.7}$$

12 scenarios between LOW and HIGH have been implemented applying the Sobol sequences based algorithm. Through this procedure, a set of values, corresponding to the reductions of precursors emission for each scenario $R(s,P)$, has been selected. These values are shown in Table 4.1

Table 4.1: R(s,P) values for the $PM_{2.5}$ ANN training scenarios simulated with CHIMERE

Scenario	NO_x	VOC	NH_3	SO_2	PPM
1 (HIGH)	1	1	1	1	1
2 (LOW)	0	0	0	0	0
3	0	1	1	1	1
4	1	0	1	1	1
5	1	1	0	1	1
6	1	1	1	0	1
7	1	1	1	1	0
8	0.25	0.25	0.25	0.75	0.25
9	0.25	0.75	0.25	0.75	0.25
10	0.25	0.75	0.75	0.75	0.25
11	0.50	0.50	0.50	0.50	0.50
12	0.75	0.25	0.75	0.75	0.25
13	0.75	0.75	0.25	0.75	0.25
14	0.25	0.25	0.75	0.25	0.75

Table 4.2: R(s,P) values for the NO_2 and O_3 ANN training scenarios simulated with CHIMERE

Scenario	NOx	VOC
1 (HIGH)	1	1
2 (LOW)	0	0
3	0	1
4	1	0
5	0.25	0.25
6	0.25	0.75
7	0.50	0.50
8	0.75	0.25
9	0.75	0.75

For the computation of NO_2 and Ozone concentrations 9 CTM scenarios are selected (in this case the precursors are NO_x and VOC), as shown in table 4.2.

4.2.2 Chemical Transport Model simulations

Scenarios defined in the Desing of Experiment, and reported in Tables 4.1 and 4.2, were simulated by colleagues of the the French National Institute for Industrial Environment and Risks (INERIS), using the Chemical Transport Model CHIMERE.

The CTM runs were carried out on the whole France, starting from emissions spatialized over Europe according to the EMEP (European Monitoring and Evaluation Program) grid (0.1° x 0.1°), for the 14 scenarios and for the following pollutants: NH_3, NMVOC, SO_x, NO_x, $PPM_{2.5}$ and Coarse particles (between 2.5 and 10 μm). Emission reduction scenarios were applied on the whole Europe. Then, final CHIMERE emission input files were down-scaled over the France domain on a 0.0625° x 0.03125° grid, according to the land use. Pollutant emissions are also speciated over 55 model-species and temporal profiles are applied (per month and per day-of-the-week).

For the identification of the surrogate models, the Île-de-France domain, defined in Figure 4.1 were extracted from the emissions and target scenarios, obtaining a set of 14 scenarios with a spatial resolution of 0.0625° x 0.03125°, 77 x 55 cells.

Part of the dataset generated using CHIMERE model has been used to perform a sensitivity analysis and understand how the air quality indexes are sensitive to each precursor. The results are shown in Figure 4.2 and 4.3. In these plots the x-axis represents the basecase annual average concentration and the y-axis is the

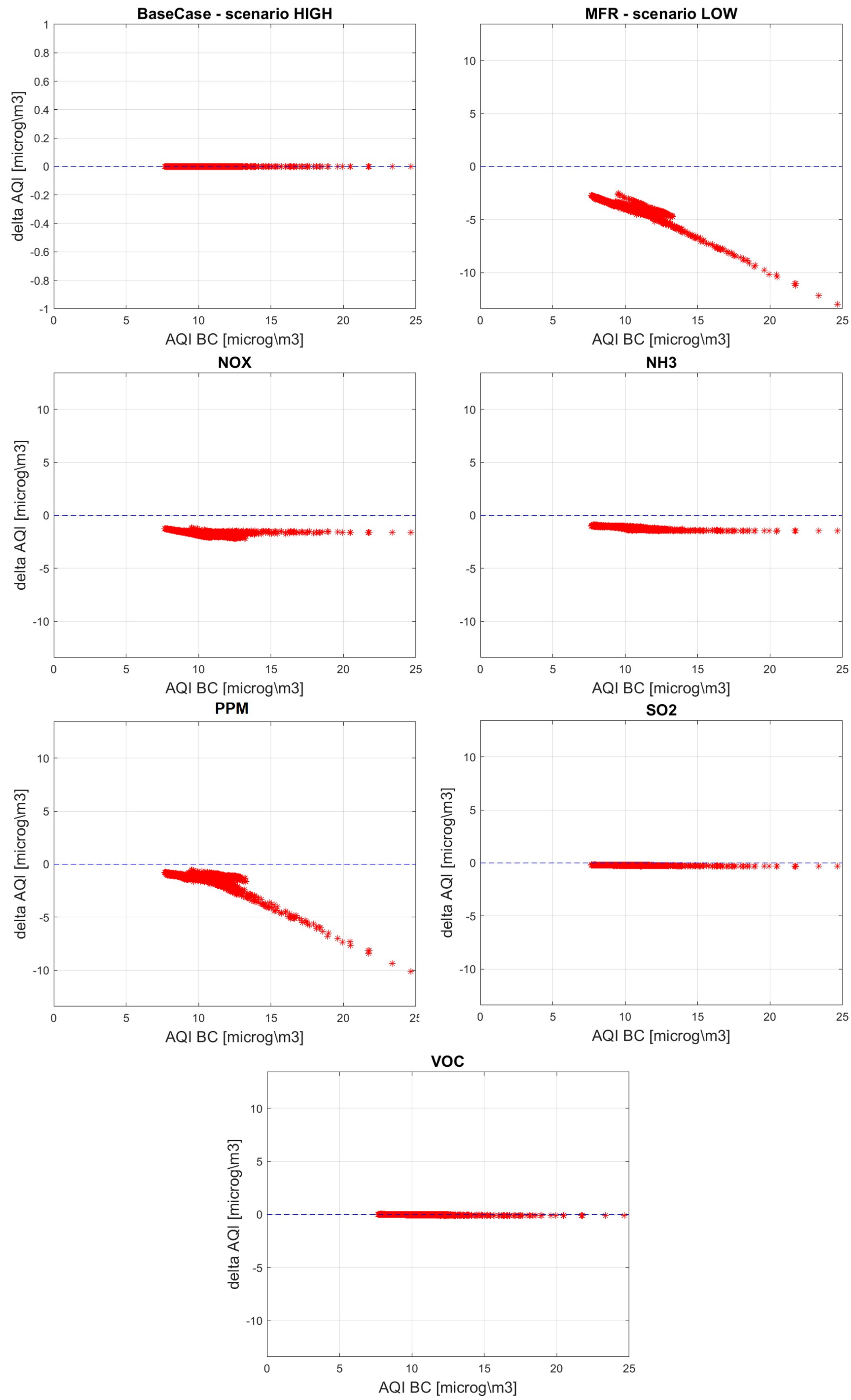

Figure 4.2: $PM_{2.5}$ ANN training dataset sensitivity analysis

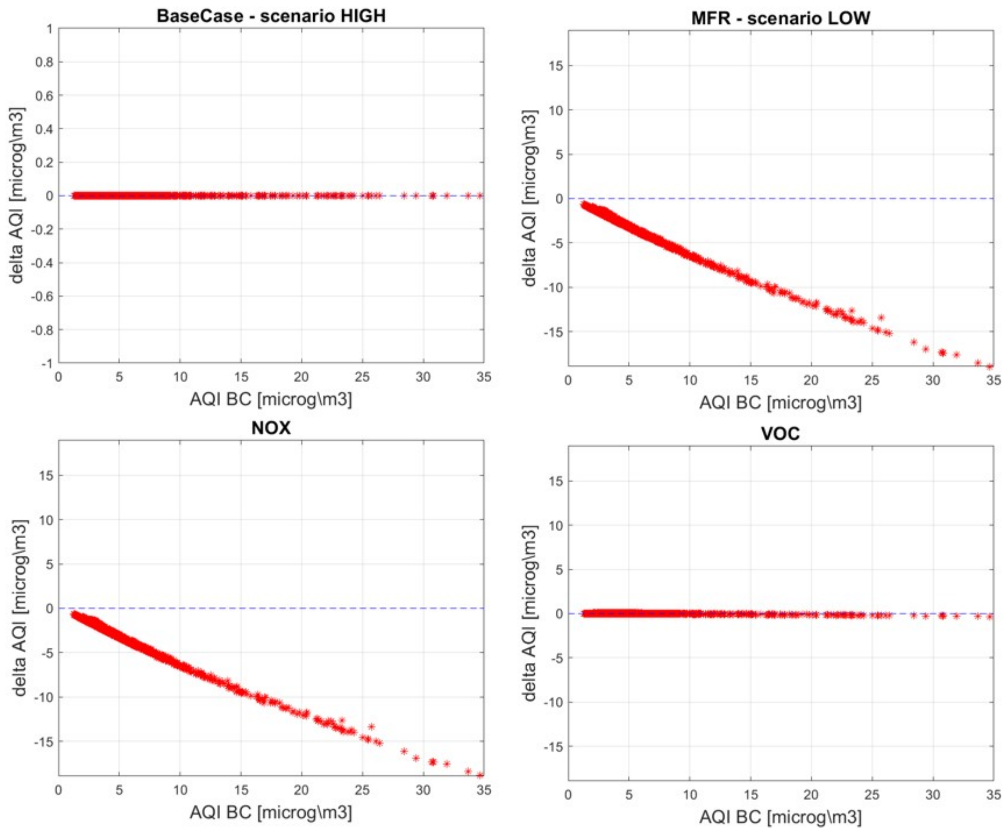

Figure 4.3: NO_2 ANN training dataset sensitivity analysis

variation in annual average concentrations duo to the maximum reduction of each precursor. Figure 4.2 shows that $PM_{2.5}$ concentrations reduction are mainly due to the abatement of primary particulate matter, but also sensitive to NO_x and NH_3. NO_2 concentrations (Figure 4.3) are insensitive to VOC emissions and results show they depend only on NO_x.

4.2.3 Artificial Neural Networks identification and validation

The set of scenarios reported in Table 4.1 were used to train artificial neural networks aimed at simulating $PM_{2.5}$ and NO_2 yearly average concentrations. Different tests were made to identify the best features of the net, in terms of shape of the input (and emissions radius of influence) and type of net (if emission-concentration or Δemission-Δconcentration). Three shapes of the input were tested, as shown in 4.4:

(a) four triangular slices;

(b) four rings;

(c) four rings and four slices (12 trapezoidal shapes + 4 triangular shapes)

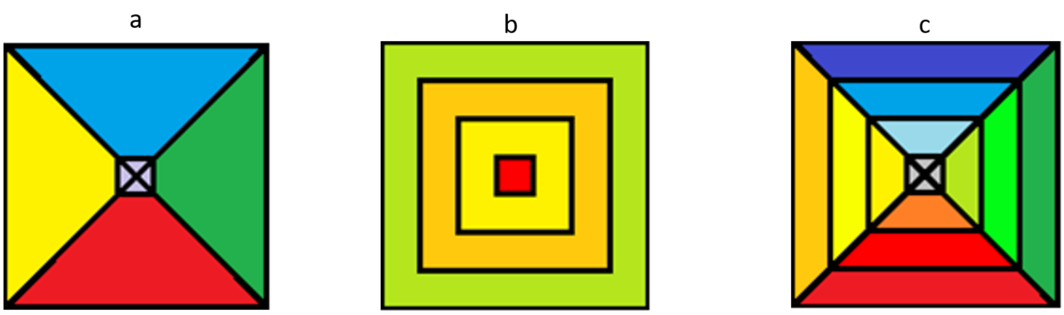

Figure 4.4: ANN input shapes: (a)four triangular slices, (b) four rings, (c) four rings and four slices (12 trapezoidal shapes + 4 triangular shapes)

All the tests carried on the dataset and the resulting statistics are reported in Appendix A. For the multiobjective optimization exercise, presented in Section 4.3 EMI-CONC ANN using slices input shape were implemented in the MAQ system for both $PM_{2.5}$ and NO_2. The features of the selected $PM_{2.5}$ and NO_2 nets are reported in Table 4.3. The number of neurons in the hidden layer and the number of layers were fixed, respectively 20 and 2, according to previous works published in literature [15]; tests on the activation and output functions are automatically made in the training phase and the chosen functions guarantee the best results achievable.

ANNs were trained using the 80% of the entire dataset, the validation phase was carried on the 20% of the total cells (distributed as one cell every five), the resulting statistics are reported in Table 4.4. The correlation between the ANN resulting concentrations and CHIMERE target values varies between 0.97 and 0.98 with a rmse of 0.44 µg/m^3 for $PM_{2.5}$ and 1.03 µg/m^3 for NO_2.

Validation scatterplots are reported in Figures 4.5 and 4.6.

Table 4.3: Selected $PM_{2.5}$ and NO_2 ANN features

Net name	Input shape	Net Class	Layers	Neurons	Activation function	Output function	Radius of influence (cells)
PM2.5_EC_a	Slice	EMI-CONC	2	20	logsig	tansig	6
NO2_EC_a	Slice	EMI-CONC	2	20	logsig	tansig	4

Table 4.4: Selected $PM_{2.5}$ and NO_2 ANN statistics

Net name	r	e max	rmse	expl var
PM2.5_EC_a	0.98	0.50	0.44	0.90
NO2_EC_a	0.97	1.85	1.03	0.92

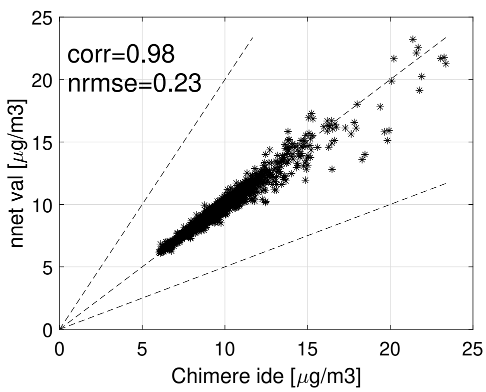

Figure 4.5: $PM_{2.5}$ ANN EMI-CONC input slice - validation scatterplot

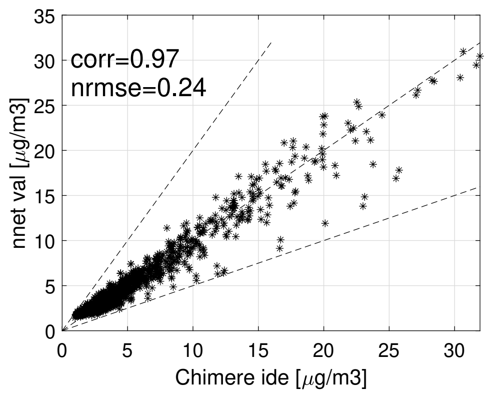

Figure 4.6: NO_2 ANN: EMI-CONC input slice - validation scatterplot

4.3 Multiobjective optimization results

MAQ system was used to perform a multiobjective optimization over Île-de-France. The objectives are the Air Quality Index, in this study the population weighted $PM_{2.5}$ yearly average concentration, and the policy implementation cost. In this section, results are discussed in terms of objectives, emissions (air pollutant and GHG) reduction, effectiveness in reducing AQIs, decision variables values, health impacts and energy savings.

4.3.1 Objectives

The solutions of the multiobjective optimization problem are plotted in the objective space: on the x-axis is reported the cost over the base case, Current LEgislation scenario for 2020 (CLE2020). The y-axis represents the population weighted $PM_{2.5}$ yearly average concentrations (AQI). In Table 4.5 the population weighted concentrations of $PM_{2.5}$ and NO_2 of all the efficient policies computed are reported, from the basecase to the Maximum Feasible Reduction scenario at 40958 M€/yr. A focus on the area of maximum curvature of the Pareto front is shown in Figure 4.7. Detailed results are reported for the optimal policy at 500 M€/yr, that reaches a reduction of 25% in $PM_{2.5}$ exposure.

Table 4.5: Summary of the Pareto solutions in terms of yearly average population weighted $PM_{2.5}$ concentration, yearly average population weighted NO_2 concentration and the policy cost

Policy cost M€/yr	$PM_{2.5}$ µg/m^3	NO_2 µg/m^3
0 (CLE2020)	16.0	23.4
50	13.5	22.1
500	12.1	21.7
1000	11.5	21.0
40958	10.4	19.4

4.3.2 Air quality Indexes

Focusing on the 500 M€/yr optimal policy, the average spatial $PM_{2.5}$ concentrations can be improved from 9.9 to 8.7 µg/m^3 (by 12%), highly reducing the concentrations in the Paris metropolitan area. The population exposure decreases more and the reduction reaches 25%. Measures applied to reduce $PM_{2.5}$ exposure have a role also in reducing NO_2 average concentrations, from an average spatial mean of 7.0 to 6.1 µg/m^3 (that in terms of population weighted mean, it means a reduction of 7%). A comparison between the basecase and the optimal policy at 500 M€/yr

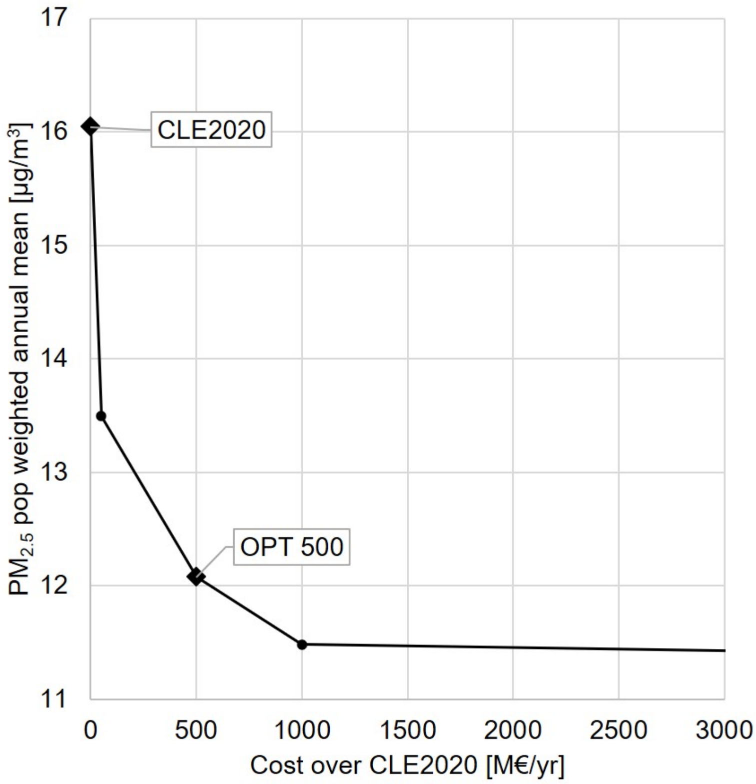

Figure 4.7: Pareto curve in the objective space (Cost vs.$PM_{2.5}$ population weighted mean concentrations), focus between 0 and 3000 M€/yr

of the spatial distribution of $PM_{2.5}$ and NO_2 is shown in the maps in Figure 4.8 and Figure 4.9.

4.3.3 Emission and costs

The optimal policy at 500 M€/yr shows a reduction in precursors emissions that vary between 0% (for NH_3) and 26.6% (primary $PM_{2.5}$), as shown in Table 4.6. Focusing on each macrosector, the results show a reduction of NO_x in macrosectors characterised by combustion activities from internal combustion engines (MS 7 and 8), energy production (MS 1 and 2) and, in minor extent, industry (MS 3). Primary particulate matter (PM_{10} and $PM_{2.5}$) is mainly abated in activities related to residential and commercial sectors and also in other mobility sources, such as construction machineries and railways (MS 8). A small reduction of VOC occurs, other than in MS 2, 7 and 8) in the solvent use sector (6.6%, that become 8.7% if biogenic emissions are not taken into account in the calculation). In Figure 4.11 costs over

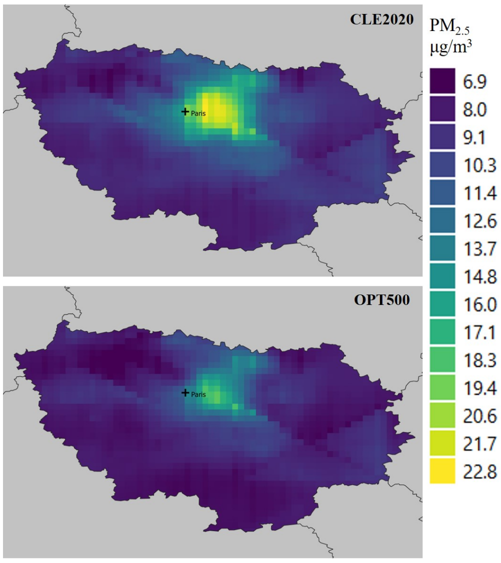

Figure 4.8: Spatial $PM_{2.5}$ concentration in µg/m^3 for the base case (CLE2020) and the optimal policy at 500 M€/yr

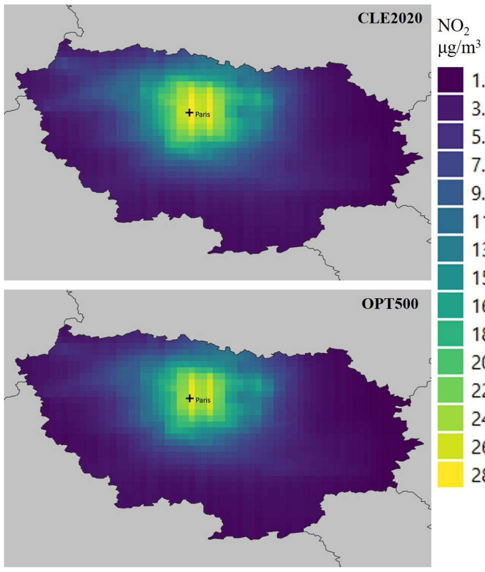

Figure 4.9: Spatial NO_2 concentration in µg/m^3 for the base case (CLE2020) and the optimal policy at 500 M€/yr

CLE2020, classified for type of measure, are reported. 96% of the investment is in energy efficiency measures, mainly allocated in the residential heating sector. This result depends on the cost of energy efficiency measures, that is higher compared to the end of pipe technologies, furthermore at CLE2020 end of pipe measures are already applied at some extent and there is not so much room for improvement. While, on the other hand, energy efficiency measures diffusion can be improved in all macrosectors.

4.3.4 Decision variables: measures selection and application

The emissions reductions depend on the application of end of pipe and energy measures, the decision variables of the problem. The database contains 906 measures, in Table 4.8 are reported the most relevant ones. The decision problem formalization includes both energy and end of pipe measures, therefore the results show the relevance of behavioral measures (included in the energy measures database) in reducing both residential heating and road transport activity levels. The results show that is more efficient targeting macrosectors 1 (combustion in energy and transformation industries) and 2 (non-industrial combustion plants) for the reduction of $PM_{2.5}$ concentrations (abating primary PM).

Table 4.6: Air pollutant emissions for the basecase CLE2020 and the optimal policy at 500 M€/yr

Emissions CLE2020 [t/yr]						
MS	NO_x	VOC	NH_3	PM_{10}	$PM_{2.5}$	SO_2
1	10034	276	17	257	129	10030
2	13099	4632	0	2896	2561	6021
3	6185	274	0	719	401	4096
4	1081	5222	121	5028	1788	3363
5	0	128	0	0	0	0
6	0	55819	0	0	0	0
7	55557	1434	2	2192	2142	91
8	5107	1691	0	339	309	235
9	57	270	717	444	381	42
10	0	0	4667	4638	953	0
11	0	22010	0	0	0	0
TOT	91120	91755	5523	16513	8663	23879
Emissions OPT500 [t/yr]						
MS	NO_x	VOC	NH_3	PM_{10}	$PM_{2.5}$	SO_2
1	8295	261	17	232	112	8848
2	10547	1798	0	1195	935	4620
3	5902	274	0	528	294	3920
4	1081	5222	121	5007	1776	3363
5	0	128	0	0	0	0
6	0	53105	0	0	0	0
7	45375	1248	2	1787	1742	75
8	4284	1354	0	172	163	235
9	57	270	717	444	381	42
10	0	0	4666	4638	953	0
11	0	22010	0	0	0	0
TOT	75541	85670	5523	14004	6355	21102
RED	-17.1%	-6.6%	0.0%	-15.2%	-26.6%	-14.8%

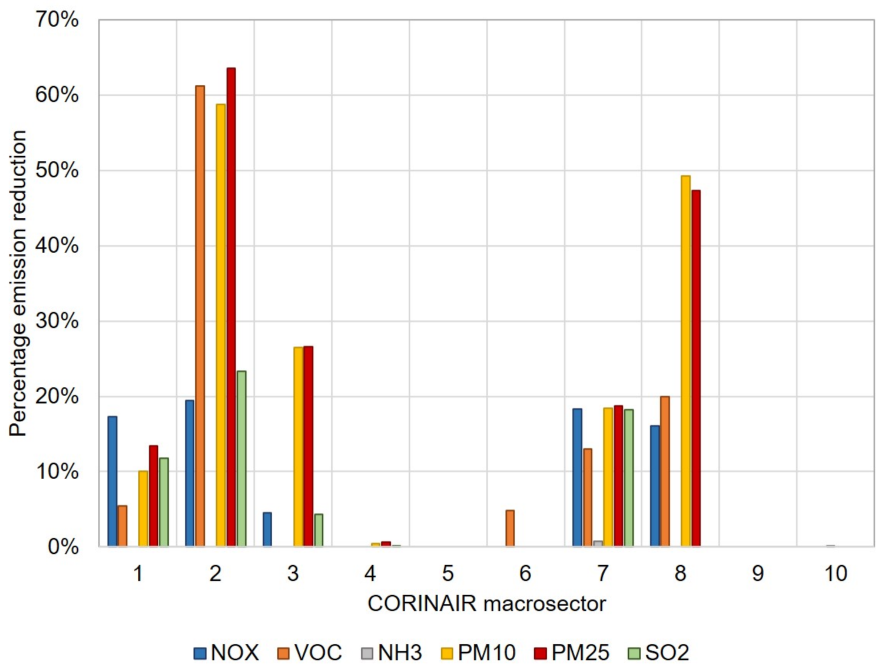

Figure 4.10: Percentage emission reduction over CLE2020 of the policy at 500 M€/yr

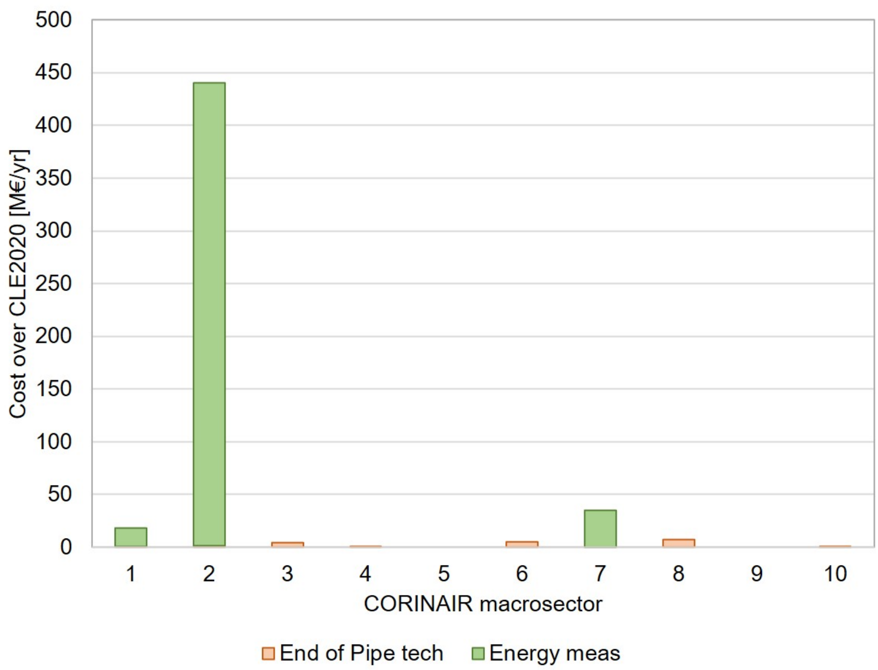

Figure 4.11: Emission abatement measures (energy and end of pipe) cost allocation per CORINAIR macrosector of the policy at 500 M€/yr

Energy efficiency measures are mainly applied, as it was discussed in 4.3.3, because there is more room for improvements compared to end of pipe technologies. Measures in macrosector 1 focuses on reducing fuel consumption and emissions

Table 4.7: Energy measures investments, energy savings and CO_2 equivalent emission reduction per CORINAIR macrosector, for the optimal policy at 500 M€/yr

MS	Energy measures cost [M€/yr]	Energy savings [M€/yr]	CO_2 emission reduction [kt/yr]
1	18	153	372 (-8.1%)
2	439	3540	2747 (-19.6%)
3	0	0	0
4	0	0	0
5	0	0	0
6	0	0	0
7	34.6	1465	2404 (-17.7%)
8	0	0	0
9	0	0	0
10	0	0	0
TOT	492	5158	5522 (-14.8%)

caused by heavy fuel oil and natural gas combustion in power plants, using both energy efficiency and end of pipe techniques.

In macrosector 2 only energy measures are reported, the most efficient way to abate primary particulate matter emissions from residential heating is the improvement of building energy efficiency, implementing building energy performance certifications, heat allocation approches and district heating. Also the ban of open fireplaces allows to reduce PPM emissions.

End of pipe measures are applied in industrial sectors (macrosector 3, combustion in manufacturing industry, and macrosector 6, solvent use for industrial paint application). Those measures lead to a reduction in combustion emissions and also an abatement of VOC emission due to the use of solvent-free powder coating systems.

In the road transport sector, measures aim to abate diesel fuel use, mainly with behavioral measures, such as walking, cycling or taking the bus instead of commuting driving diesel cars. Other mobile sources emissions (from railways and construction machinery) can be reduced applying end of pipe technologies.

4.3.5 Health impacts and Cost-Benefit analysis

Health impacts are computed in terms of mortality (YLL) due to $PM_{2.5}$ exposure, mortality due to NO_2 exposure and morbidity due to $PM_{2.5}$, that includes net restricted activity days, work loss days and minor restricted activity days. All the

Table 4.8: *End of pipe* and energy measures application rates variation and costs for the optimal policy at 500 M€ /yr

MS	Sector	Activity	Measure	Cost [M€/yr]	$\Delta\theta/\Delta\psi$ [%]
1	Power and district heat plants	Heavy fuel oil	*Combustion modification on existing oil and gas power plants*	0.3	31
			Low-energy street lighting systems	11.2	13
		Natural gas	Energy production by photovoltaic plants instead of regional thermoelectric ones	1.1	10
2	Fireplaces	Fuelwood	Improved fireplace	0.9	31
			Methane district heating	16.7	30
			Open fireplaces ban (information campaign+maintenance)	16.7	23
			Energy Performance Certificates for buildings	13.3	20
	Heating stoves	Fuelwood	Methane district heating	106.5	50
			Open fireplaces ban (information campaign+maintenance)	82.6	30
			Energy Performance Certificates for buildings	51.4	20
	Residential-commercial	Diesel	Heat costs allocation	49.6	20
		Natural gas	Heat costs allocation	55.7	16
3	Industrial furnaces	Derived coal	*Electrostatic precipitator: 1 field*	2.5	30
		Natural gas	*Combustion modification on oil and gas industrial boilers and furnaces*	1.3	16
6	Industrial paint use	Paint use	*Powder coating system (solvent free)*	4.8	10
7	Cars Extraurban	Diesel	commute by bus	0.2	11
	Cars Urban	Diesel	commute by bike	0.3	11
			commute by bus	0.3	11
			commute by walking	0.3	11
	LDV (Urban, extraurban, highway)	Diesel	*EURO 6a/b*	0.12	0.5
8	2-stroke engines	Gasoline	*Stage 2*	0.3	15
	Construction machinery	Diesel	*Stage 4*	5.5	28
	Railways	Diesel	*Stage 3B*	0.1	29
			Stage 3A	0.1	23

Table 4.9: Mortality due to air pollution exposure in the basecase scenario and optimal policy

Policy	Spatial average $PM_{2.5}$ YLL [months/pers]	$\Delta PM_{2.5}$ YLL [%]	Spatial average NO_2 YLL [months/pers]	ΔNO_2 YLL [%]
CLE2020	6.1	-	0.35	-
500 M€/yr	5.4	-11%	0.31	-11%

health savings, meaning the difference in external costs with respect to the basecase CLE2020, are plotted in the cost benefit space in Figure 4.12. The x-axis represents the cost over CLE2020, the y-axis reports the savings due to a reduced exposure to air pollution. The red dotted line is the cost-health benefit plan bisector, black line represents the optimal scenarios of the Pareto curve (Figure 4.7). All the scenarios (except MFR) lie in the area over the bisector, meaning that benefits are higher than costs. In the chosen optimal policy, a cost of 500 M€/yr leads to save 2003 M€/yr and 130 M€/yr because a reduction in mortality due to, respectively, $PM_{2.5}$ and NO_2 exposure. Furthermore 235 M€/yr savings in reduced morbidity caused by $PM_{2.5}$ concentrations, for a total savings in health impact of 2368 M€/yr.

The 500 M€/yr optimal policy mortality impacts are reported in Table 4.9 in terms of months per person and percentage variation with respect to CLE2020, $PM_{2.5}$ has higher impacts than NO_2 on mortality, $PM_{2.5}$ average YLL reach 11.2 months in the Paris metropolitan area at the basecase, as shown in Figure 4.14.

Benefits can also be analyzed in terms of savings due to the application of energy efficiency measures, whose effect is to reduce fuel consumption and, in turn, fuel costs. In Figure 4.13 policy costs and energy savings for the points of the pareto curve are reported (a focus between 0 and 15000 M€/yr). Also in this case all the optimal policies, except MFR, guarantee savings higher than costs, energy savings vary between 0 (CLE2020) and 20951 (MFR) M€/yr. When a 500 M€/yr budget is efficiently allocated in energy measures, savings can reach 5158 M€/yr.

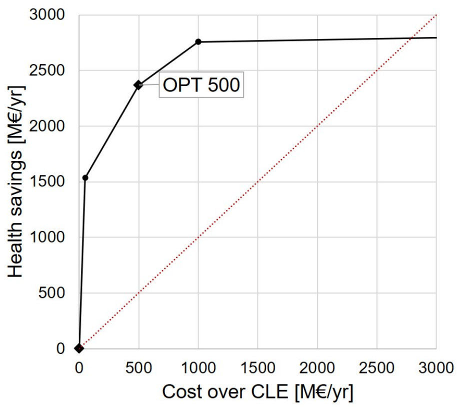

Figure 4.12: Cost benefit analysis: health savings

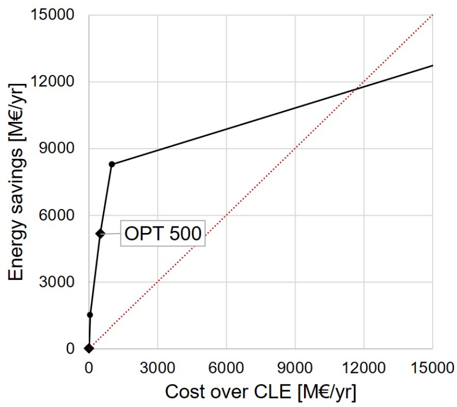

Figure 4.13: Cost-benefit analysis: energy savings

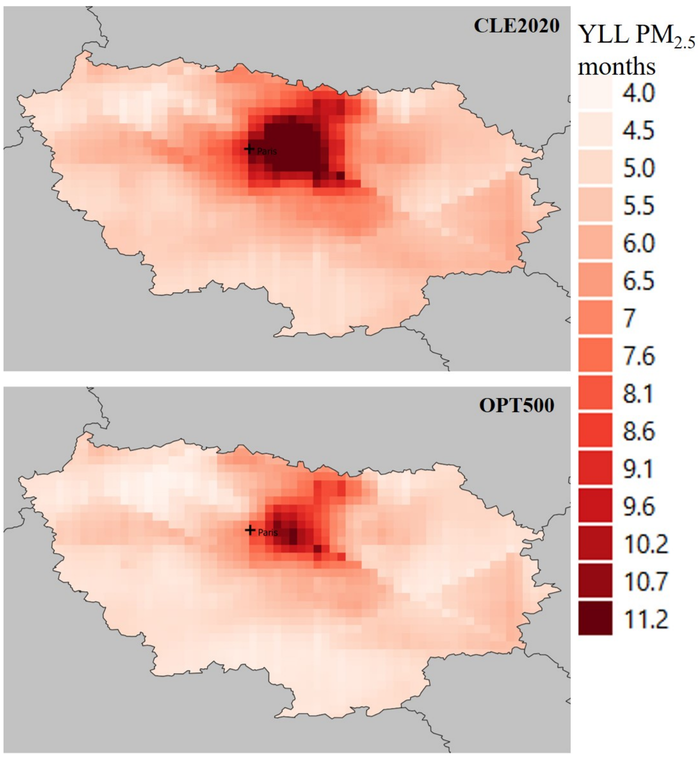

Figure 4.14: YLL due to $PM_{2.5}$ exposure

CHAPTER 5

Low emission road transport scenarios in Lombardy region

The decision problem defined in Section 2.2 has been implemented and tested for the Lombardy region (Figure 5.2). In this chapter the problem constrains are computed defining the electricity production projections and demand, solving the decision problem and studying three efficient solutions in terms of air quality, GHG emissions, health impacts, cost and savings [9].

5.1 Materials

Different energy production scenarios must be assessed to implement the case study: (1) the business as usual (BAU) electricity demand projection for 2030 and (2) energy scenarios to meet the electricity demand due to the BAU projection and the vehicle fleet electrification.

This chapter is based on E. De Angelis, C. Carnevale, G. Di Marcoberardino, E. Turrini and M. Volta, ”Low Emission Road Transport Scenarios: An Integrated Assessment of Energy Demand, Air Quality, GHG Emissions, and Costs,” in IEEE Transactions on Automation Science and Engineering, doi: 10.1109/TASE.2021.3073241.

5.1.1 Basecase Lombardy energy scenario: data and projections

The Italian energy plan provides the future energy scenarios according to European Commission 2050 Roadmap. Member states are committed to reduce GHG emission by 85-90% with respect to 1990 levels. To reach this objective an intermediate step for 2030 has been defined in the "Clean Energy Package for all Europeans", which states that 32% of final gross European energy consumption will be produced by Renewable Energy Sources (RES) [25]. The Italian plan for energy and climate (PNIEC) sets the RES objective for 2030 at 30% of final gross energy consumption, divided between electricity production, thermal energy and transport, as shown in Table 5.1 [33].

In 2018, Lombardy region produced 65.4% of electric power demand. The remaining electricity demand was covered by the other Italian regions for 4.6% and imported mainly from France and Switzerland, for 30.0% [82, 83]. The current energy production in Lombardy is based on fossil fuels (natural gas and coal), solid biomass, waste, solar energy and hydroelectric plants [83, 84].

The energy production from fossil fuels is estimated from the installed capacity of power plants. In Lombardy there are 15 combined cycle plants with an average value of equivalent production hours of 1600 hr/yr. Nine of them produce only electric energy with an efficiency assumed in η_E=0.55. Six plants produce both thermal and electric energy in cogeneration (η_E=0.50, η_T=0.40). The maximum energy production can be up to 7800 hr/yr [85], the reduction presumed for 2030 is 70% of current hours, 1120 hr/yr, as indicated by the Italian plan for Energy and Climate. Solid biomass and waste are mainly used to produce thermal energy but, in few cases, also electricity is produced in small plants through cogeneration.

The future of RES in Italy is mainly in the use of photovoltaic (PV), hydroelectricity and wind farms. Lombardy is not a suitable location for wind farms implementation due to frequent stagnant air conditions, but it is the Italian region with the highest number of installed PV plants and it covers the 27.2% of the Italian hydroelectric power. The maximum potential hydroelectric energy production is reported by Terna report [83] and in the PNIEC an increase of 7.0% of the hydroelectric energy consumption is expected nationwide. Solar photovoltaic can be improved installing new PV panels. Considering the regional area available (urbanized area equal to 2464 km^2 [86]) and the average solar energy potential, there is still room for improvements in PV implementation [87]. In fact, this is the RES for which the PNIEC expects the maximum increase. In Table 5.2, electricity production according to the MAQ model values and the data given by Terna e GSE are reported. In 2030, also considering a revamping of existing plants, the increase in hydroelectricity consumption can vary between 14% and 22% [88].

Table 5.1: RES penetration objectives in Italy in 2030 [33]

Sector	RES target at 2030
Electric energy	55.00%
Thermal energy	33.90%
Transport	22.00%

Also for centralized thermal power production the projections defined in the PNIEC are applied, resulting in a 33.9% of RES penetration for this sector. An important effort in thermal solar energy implementation is expected. Values are reported in Table 5.3.

Considering the future improvements expected in energy efficiency and the gradual electrification of different activities, the electricity demand will increase by 2.3%. On the other hand, thermal energy demand will be reduced especially because of improved energy efficiency in buildings. As shown in Table 5.6, the regional electricity production cannot satisfy the growing demand, producing an energy deficit equal to 28.2 PJ that could be covered increasing the import or further improving production, using RES available in the region that still have potential.

The electricity production sources distribution for the basecase scenario and the 2030 scenario are shown in Figure 5.1. In 2018 fossil fuels electricity was 66% of the total electricity produced in the region, in 2030 it will be only 44%. 56% of the production will be produced by RES.

Table 5.2: Electric power production scenarios given by the MAQ model database values and the PNIEC projections (percentage variation with respect to 2018 and values in PJ)

Fuel	Maximum Production [PJ]	Basecase 2018 [PJ]	Projection 2030 [%]	Projection 2030 [PJ]
Natural gas	759	136.3	-30.5	94.7
Coal	0	0.6	-100	0
Oil foss fuels	10.8	10.8	-30.5	7.5
Solid biomass	-	2	-18.7	1.6
Biogas	214.2	13.3	-18.7	10.8
Biofuels	-	1.3	-18.7	1
Waste	-	4.3	-18.7	3.5
Photovoltaic	986.7	11.4	197	34.1
Hydroelectric	64.3 ÷ 68.8[a]	52.7	7	56.4

[a] Improvements in the maximum hydroelectricity production can vary according to existing plants revamping (+14% - +22%).

Table 5.3: Thermal power production scenarios given by the MAQ model database values and the PNIEC projections (percentage variation with respect to 2018 and values in PJ)

Fuel	Basecase 2018 [PJ]	2030 scenario [%]	2030 scenario [PJ]
Natural gas	34.6	-30.5	24.1
Coal	2.8	-100	0.0
Oil fossil fuels	15.7	-43	8.9
Solid biomass	2.3	+3.8	2.4
Biogas	4.1	+3.8	4.3
Biofuels	1.5	+3.8	1.5
Waste	5.1	+3.8	5.2
Thermal solar	2.1	+259	7.7

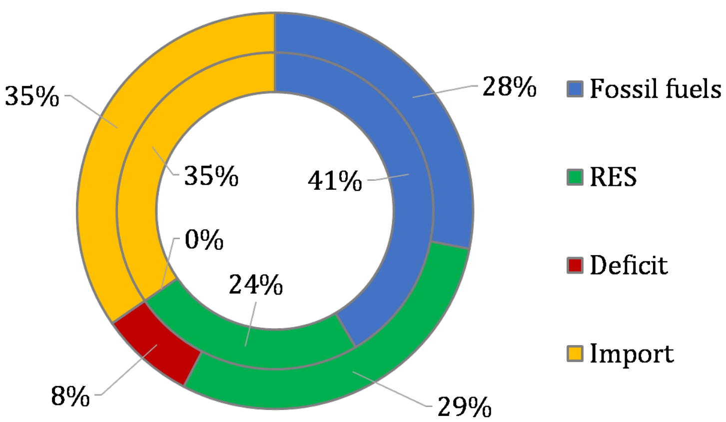

Figure 5.1: Electric power production and import in Lombardy in 2018 (inner circle) and projections for 2030 (outer circle) according to data reported by [83], GSE [84] and PNIEC [33]

5.1.2 Low emission road transport scenarios

In this work, a low emission road transport scenario is assessed: light duty vehicles, cars and mopeds are shifted to electricity and heavy-duty vehicles (HDV) are powered by biomethane. Electric mobility is growing fast, in 2018 the global electric car fleet exceeded 5.1 million units and the technological advancements are leading also to new vehicle models and cheaper batteries [89].

Different studies have been made to estimate the electric vehicle sales projection. Among these, the percentage of EVs over the total vehicles sold in 2030 is uncertain and it can vary between 5% and 50% [90]. Furthermore, the Italian RES share goal of 30% can be achieved considering the transport sector, as shown in Table 5.1. In addition to the fleet electrification, the PNIEC [26] considers also the application of biomethane, especially for heavy duty vehicles. In Europe biomethane is emerging as an interesting solution for HDV sector [91, 92, 93], even if in Italy is not yet significantly exploited.

The objective of the case study is to evaluate the maximum benefit achievable in terms of air pollution and GHGs emissions from a low emission road transport scenario and how the energy mix used to produce electricity can impact on the results. Road transport emissions include non-exhaust emissions due to tyres, use of brakes and road abrasion. These emissions are estimated to not be modified by the electrification of the fleet and the fuel switch in HDV.

The impacts of shifting the whole HDV fleet on biomethane is shown in Table 5.4. In order to compute the electricity demand due to the fleet electrification, the activity level for each road transport vehicle class and fuel and the corresponding internal combustion engine (ICE) efficiency η are needed. The ICE efficiencies considered depend on the fuel and class of vehicles. They are equal to the mean value among all the vehicles belonging to a fuel-class. Moreover, the amount of electricity requested by the fleet must consider the electric engine efficiency (higher than ICE efficiency) and the losses due to electricity production and distribution. This latter value is given at national level by the Italian Energy Authority (ARERA). It defines the conversion factor of electric energy in primary energy, therefore the production and distribution efficiency is equal to 46%. The values computed from the MAQ model databases data are reported in Table 5.5, where the net energy includes the engines efficiencies (ICE and electric) and the final electricity demand takes into account also electricity production and distribution efficiency. Eventually the final energy demand is computed (506.4 PJ) adding to the 2030 energy demand projection, reported in Table 5.6 (363.8 PJ), the increase due to vehicle fleet electrification (142.6 PJ).

Table 5.4: Heavy Duty Vehicles biomethane fuel consumption

Fuel	Activity Level [PJ]	η [-]
Diesel	66.2	0.4
Natural gas	0.1	0.3
Total	66.4	
Net energy considering engine efficiency on biomethane	88.4	

Table 5.5: Electricity demand due to vehicle fleet electrification (cars, LDV and motorcycles)

Fuel	Activity Level [PJ]			η [-]
	Cars	LDV	Mopeds	
Diesel	97.5	9.8	0	0.4
Gasoline	27.9	0.6	0.7	0.3
LPG	20.6	0	0	0.3
Natural gas	3.7	0.2	0	0.3
Gross electric fleet energy	160.9			0.9
Net energy	65.6			
Electricity demand	142.6			

Table 5.6: Regional electric energy production, demand and import

	Basecase 2018	Projection 2030	Low emission traffic scenario 2030
Energy demand	355.7	363.8 (+2.3%)	506.4
Production	232.6	209.6	209.6
Import	123.1	125.9	175.2
Production+Import	355.7	335.6	384.8
Deficit	0	28.2	121.6

5.1.3 Scenarios design and implementation

The electricity deficit of 121.6 PJ is distributed among the k different energy sources, varying the share of increase in electricity demand that can be produced by each source ($\varepsilon(k)$ in Eq. 2.17), according to the regional electricity production upper and lower bounds. The lower bound is the value defined by the PNIEC projection and the upper bound depends on the production feasibility of each power source, computed according to data reported in the previous sections.

MAQ model simulation domain is composed by 5890 cells 6x6 km^2 (Figure 5.2). Energy production variation is applied to Lombardy region (pink cells) and resulting emission variations for each scenario are applied in the whole Northern Italy domain (light blue cells). According to the enumeration approach defined in section 2.2.3, twenty-two scenarios are identified randomly varying the control variables, meaning the sources electricity production, within the feasible set (detailed values for all scenarios are reported in Appendix B):

- 13 scenarios respect the 55%-45% percentage distribution between RES and fossil fuels, Italian objective for 2030;
- in 5 scenarios there is an increase in RES share, up to a 80%-20% ratio;
- 4 scenarios have the ambitious goal of 100% RES production.

In Figure 5.3 electricity production distribution of the 22 scenarios is presented for the different sources. There is no evident variation in fossil fuels: coal is always 0, as expected past 2025 due to coal plants decommissioning. The renewable energy sources have still room for improvement, except hydroelectric, where, according to data collected, only a maximum increase of 12.4 PJ is feasible.

5.2 Results and discussion

Defined all the decision problem elements, MAQ model is applied to the simulation domain, to assess the cost and the impacts on air quality and greenhouse gases emissions of selected scenarios.

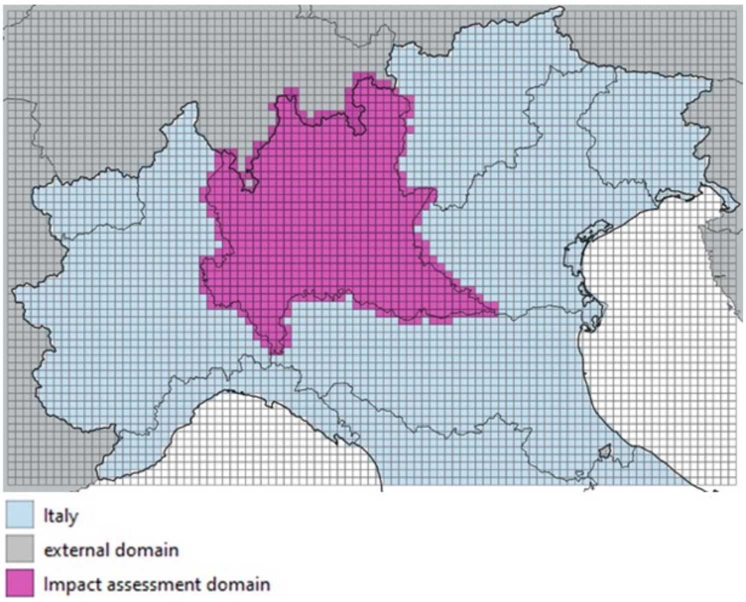

Figure 5.2: MAQ model domain, scenarios analysis results are evaluated over Lombardy region (pink cells), the policy is applied on the whole Northern Italy (light blue cells)

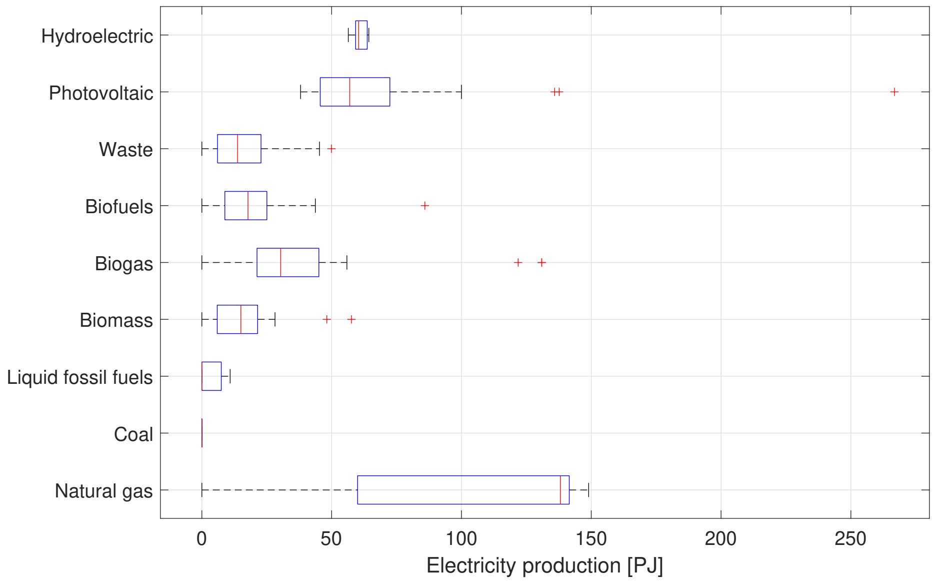

Figure 5.3: Electricity production distribution in PJ among the sources available in the region

5.2.1 Electricity production scenarios

The 22 scenarios assessed with MAQ are plotted in the 3 objective spaces, scenarios highlighted in red are the non-dominated solutions in each objective space.

1. Cost – mean yearly NO_2 concentrations (Figure 5.4): scenarios 1, 3, 6, 8, 11,

19 and 20 are non-dominated.

2. Cost – mean yearly $PM_{2.5}$ concentrations (Figure 5.5): scenarios 1, 3, 6, 8, 11, 19 and 20 are non-dominated.

3. Cost – mean yearly CO_{2eq} emissions (Figure 5.6): scenarios 8, 16, 19, 20 and 22 are non-dominated.

Scenarios 1, 3, and 6 are efficient in the objective space 1 and 2 but they are dominated in objective space 3. Scenario 22 is efficient accordingly to CO_2 and cost but is dominated in the air quality objective spaces. Non-dominated scenarios for all objectives are 8, 19 and 20. The selected scenarios have different activity levels distribution over the electricity production sources, scenario 8 has the minimum electricity RES production objective for 2030 (55%), while in scenarios 19 and 20 production is totally from RES. Detailed distribution of the power production is shown in Figure 5.7.

5.2.2 Emissions

In Table 5.7 the percentage emission reductions with respect to the base case scenario are reported. The main reductions are in NO_x and SO_2. NO_x are emitted from fuel combustion, therefore they are caused by energy production plants and, mainly, by vehicles internal combustion engines. SO_2 is emitted by power production plants, combustion in industries and, to a lesser extent, by road transport. Primary particulate matter emissions are mainly due to residential/commercial heating (that account for the 58% of total PPM emissions).

In the road transport sector PPM is emitted by exhaust and non-exhaust activities: non-exhaust emissions are assumed to be unchanged by the electrification of the fleet, while exhaust emissions are reduced by 46%. The vehicle fleet electrification and the biomethane use in HDV abate the road transport sector NO_x emission by 95.9% and SO_2 emission by 100%. The total emission reductions depend on the electricity production sources used. In scenario 19 and 20, the abatement of NO_x and SO_2 is maximum, because the electricity is produced mainly with “clean” RES,

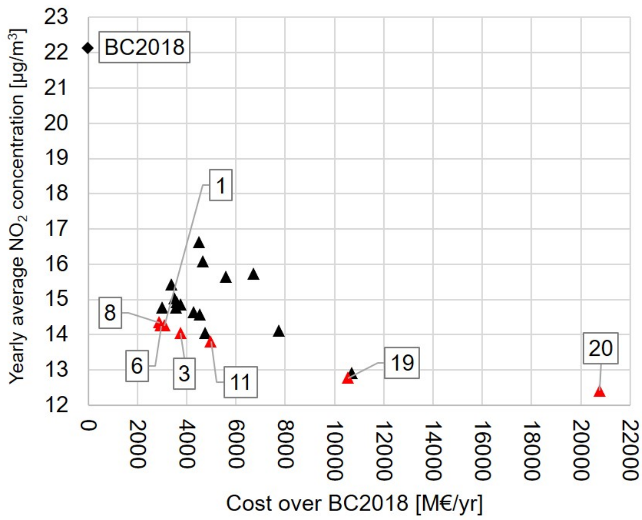

Figure 5.4: Objective space 1: Policy cost - NO_2 concentrations

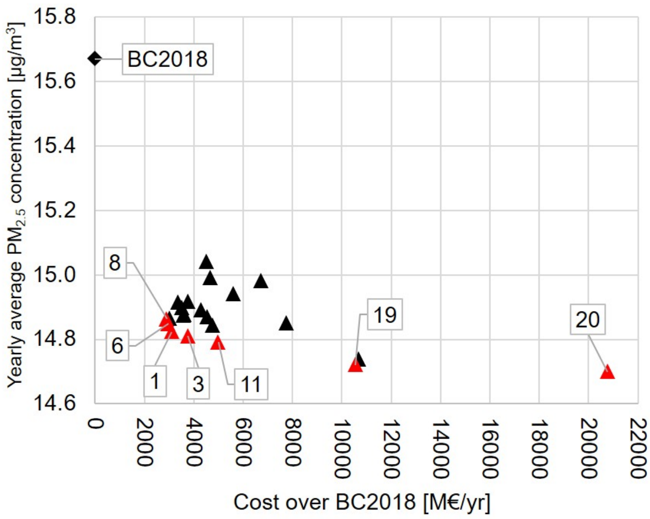

Figure 5.5: Objective space 2: Policy cost - $PM_{2.5}$ concentrations

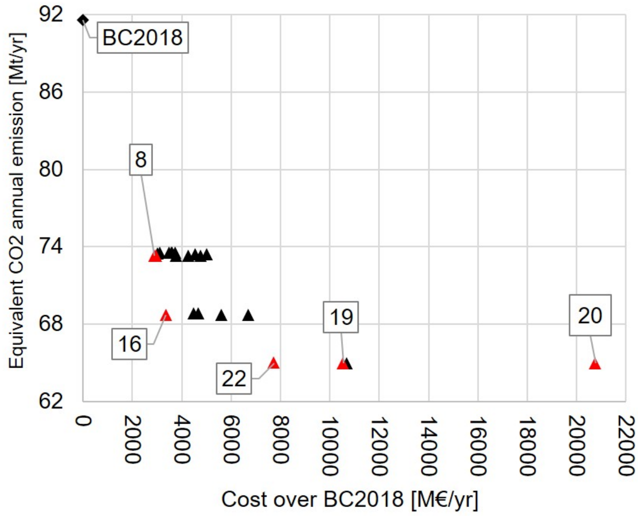

Figure 5.6: Objective space 3: Policy cost - CO_2 concentrations

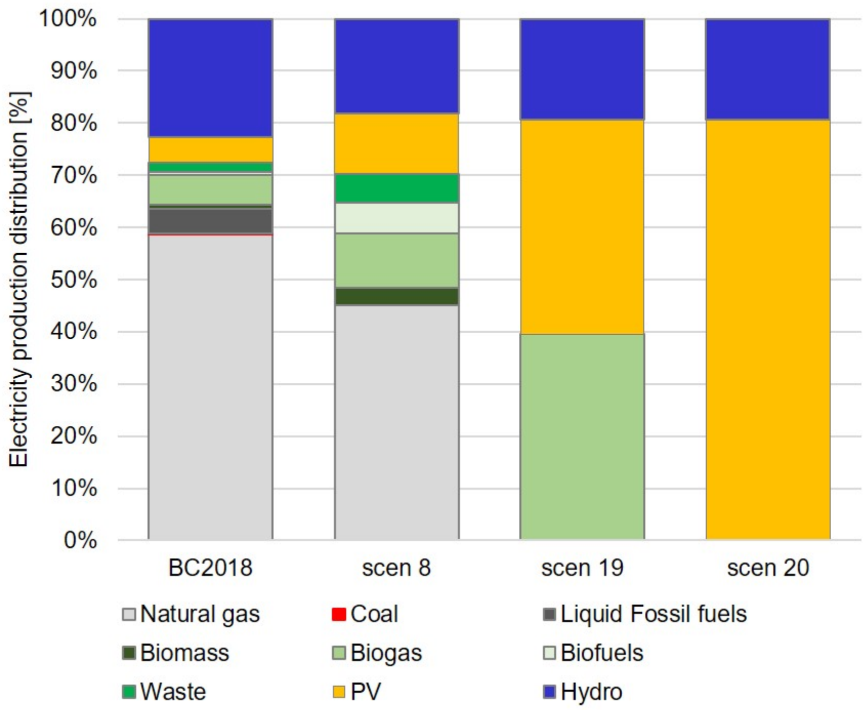

Figure 5.7: Percentage electricity production distribution among the sources for the selected solutions

hydroelectric and photovoltaic, that do not have direct pollutant emissions, furthermore biogas and natural gas a have low NO_x emission factor (0.03÷0.06 kt/PJ in modern power plants). In scenario 8, NO_x emissions strictly depend on the use of biofuels, biomass and waste.

Table 5.7: Air pollution precursors percentage emission reduction with respect to the base case 2018 for the selected scenarios

Scenario	NO_x	VOC	NH_3	PM_{10}	$PM_{2.5}$	SO_2
scen 8	-46.8%	-1.8%	-0.5%	-4.7%	-5.8%	-15.2%
scen 19	-53.4%	-3.4%	-0.6%	-6.1%	-7.3%	-21.8%
scen 20	-55.0%	-3.4%	-0.6%	-6.1%	-7.4%	-22.0%

5.2.3 Analysis of road transport meta-emission factors

A comparison between the scenarios can be performed computing an average road transport meta-emission factor for NO_x, primary PM_{10}, primary $PM_{2.5}$ and CO_2 equivalent that includes cars, light duty vehicles and mopeds. The meta-emission factor mEF linearly depends on the activity level of the sources used to produce electricity in each scenario. All scenarios have meta-emission factors values drastically reduced for all the pollutants. Scenario 8 shows minor reductions because it includes waste, biomass and biofuels in the energy mix. Even so, there is an abatement in NO_x and CO_{2eq} of respectively 37% and 52%. PPM meta-emission factors decrease by 84% (83% for $PM_{2.5}$) in scenario 8 and 100% in scenario 19. Scenario 20 describes an electricity production coming only from "clean" sources, meaning solar and hydroelectric, that don't have direct pollutant emissions, therefore mEF are equal to zero for all pollutants. Natural gas and biogas, mainly used in scenario 8 and 19, have very low primary PM emissions; however this has negligible impacts on the $PM_{2.5}$ annual average concentrations (Table 5.9). This is due two main reasons, (1) the main source of PPM (both PM_{10} and $PM_{2.5}$) is the residential/commercial heating sector, that is not examined in this study, but it is proven to be a key challenge to reduce PM population exposure in urban areas and (2) it must also be taken into account the important role of secondary particulate matter formation in this area [94, 95, 96].

Table 5.8: Meta-emission factors for cars, LVD and mopeds in the selected scenarios compared to the basecase (derived by INEMAR 2017 [97])

Scenario	NO_x mEF [mg/km]	PM_{10} mEF [mg/km]	$PM_{2.5}$ mEF [mg/km]	CO_{2eq} mEF [g/km]
BC 2018	426.5	53.6	43.4	146.5
scen 8	267.3	8.7	7.6	70.9
scen 19	14.6	0.1	0.1	30.3
scen 20	0.0	0.0	0.0	0.0

5.2.4 Air quality and GHG objectives

Air quality indexes, GHG and costs are reported in Table 5.9, expressed respectively in percentage variation with respect to the basecase and cost in M€/yr. Air quality impacts are significant for NO_2 concentrations, this is related to the abatement of NO_x emissions. The best result is obtained for scenario 20, with a 44.0% reduction corresponding to a maximum spatial average reduction of 9.8 $\mu g/m^3$.

$PM_{2.5}$ reductions vary between 5.1% and 6.2%, meaning a maximum reduction of 1.0 $\mu g/m^3$. $PM_{2.5}$ concentration impacts are negligible, compared to NO_2. The concentrations over the domain are mainly due to primary particulate matter (PPM_{10}

and $PPM_{2.5}$) emitted by residential heating sources, and to secondary PM formation caused by NO_x, VOC, NH_3 and SO_2 emissions. While NO_x and SO_2 emissions are considerably reduced, VOC and NH_3 emissions have negligible reductions in the scenarios analysed.

Scenario 8 reduces CO_2 equivalent emissions by 20%, while scenario 19 and 20 increase the GHG abatement to 29.1%, but the policy implementation cost in these two scenarios is one order of magnitude higher. The use of RES already implemented in the domain, such as biomass and biofuels, allows to reduce greenhouse gases emissions at a moderate cost. In scenario 8 natural gas is used for the 45%, RES are mainly solar, hydroelectric and biomethane. These sources have low emission factors for air pollution precursors, but natural gas CO_2 emission factor is higher, equal to 55.8 kt/PJ.

In Figure 5.8 concentration maps over the domain are reported for NO_2. The fleet electrification allows a diffuse reduction of concentration exposure, that is critical at the base case, especially in the highly urbanized area Milan-Bergamo-Brescia. Even if scenario 8 still presents some critical hot spots, especially in the Milan metropolitan area and the western border, the policy allows to contain the average annual concentrations below the European limit value, 40 μg/m^3, in the most part of the domain.

Table 5.9: Cost over base case 2018 and objectives reduction with respect to the base case for the selected scenarios

Scenario	Cost over BC [M€/yr]	$\Delta PM_{2.5}$	ΔNO_2	ΔCO_2
scen 8	2905	5.3%	35.3%	20.0%
scen 19	10550	6.2%	42.4%	29.1%
scen 20	20773	6.3%	44.0%	29.1%

5.2.5 Health impacts and Cost-Benefit analysis

Benefits in terms of energy savings and health impacts are computed for all scenarios. Health costs include mortality due to $PM_{2.5}$ and NO_2 exposure, morbidity due to PM_{10} , $PM_{2.5}$ and NO_2. In terms of mortality (Table 5.10), expressed as average spatial YLL (in months per person), there is an important decrease of NO_2

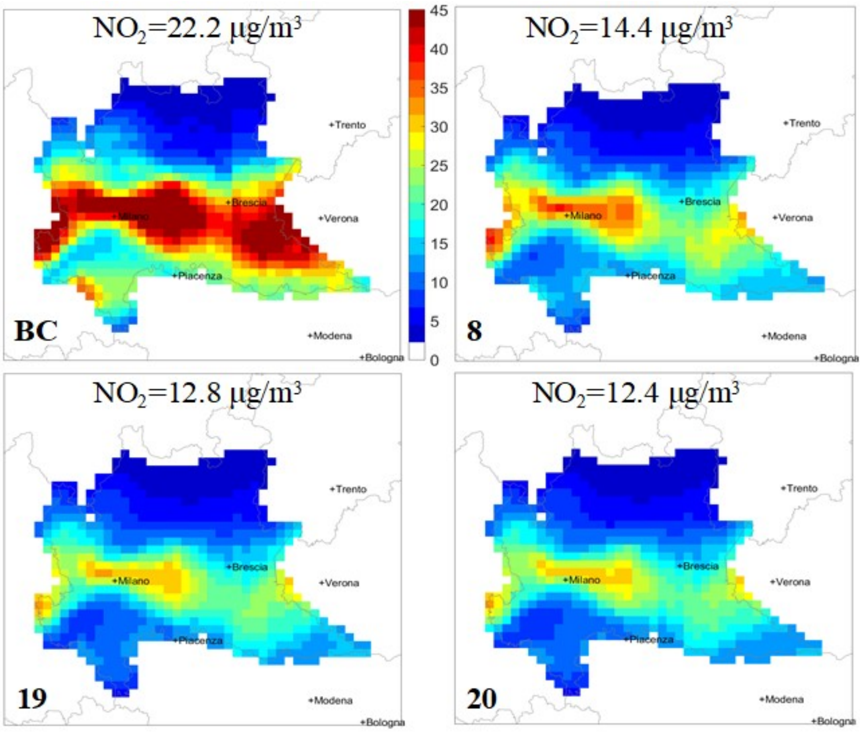

Figure 5.8: NO_2 average concentration in μg/m^3 in the selected scenarios and the base case 2018

Table 5.10: Mortality in terms of YLL of the basecase and the selected scenarios

Scen	Cost	$PM_{2.5}$ YLL		NO_2 YLL	
	M€/yr	months	%	months	%
BC	0	9.9	-	1.3	-
8	2905	9.5	-4.8%	0.86	-35%
19	10550	9.4	-5.8%	0.76	-42%
20	20773	9.4	-5.8%	0.74	-44%

YLL, because it is the pollutant mainly impacted by the low emission road transport policy, varying between -35% and -44%. On the other hand, it must be considered that, even if spatial concentration reductions seem negligible, $PM_{2.5}$ YLL can be reduced up to 0.5 months. Reduction in air pollution exposure leads to less morbidity costs, as shown in Table 5.11.

The abatement of light vehicle fleet fuel consumption and the different electricity production mixes lead to a reduction in energy costs. It is worth to mention that in this study it is not taken into account the cost of buying electricity to power electric vehicles, the cost of the primary fuel used (natural gas, biogas, ecc) it is considered instead.

Table 5.11: Costs and savings of the basecase and the selected scenarios

Scen	Cost	Mortality $PM_{2.5}$	Mortality NO_2	Morbidity	Health savings	Energy savings	Total savings
BC2018	0	8673	1681	10017	0	0	0
scen 8	2905	8202	1142	9471	1555	3229	4784
scen 19	10550	8085	1004	9389	1893	4275	6169
scen 20	20773	8070	975	9383	1943	5874	7817

Conclusions

Low carbon transition and air pollution are highly interconnected and decision makers have the task to develop win-win policies that reduce the pressures that human activities have on the environment. The Integrated Assessment approach can help in the comprehensive evaluation of environmental, energy, economic and demographic factors in order to define efficient policies aimed at tackling both climate change and air pollution drivers. This research focuses on the formalization, implementation and solution of two decision problems that aim at defining efficient air quality and low carbon policies, in an Integrated Asessment approach, including in the decision process technological, health and economic aspects. The integrated Assessment Modeling tool used is the Multi-dimensional Air Quality system, MAQ.

This work has the following objectives:

1. formulation of decision problems that include both end of pipe measures and energy efficiency policies, aimed at decreasing air pollutants precursors emissions mainly reducing the activity levels causing those pressures;

2. formalization and solution of a multiobjective air quality decision problem where an air quality index and the policy cost are minimized;

3. formalization and solution of a multiobjective decision problem where two air quality indexes, GHG emissions and the policy cost are minimized;

4. formalization of a methodology that allows a cost-benefit analysis of efficient policies in terms of policy implementation costs, health external costs and energy savings;

5. definition of the Multi-dimensional Air Quality system MAQ and all its components. The modularity of the systems allows to implement and solve specific decision problems setting domain and spatial resolution, objectives, decision variables and constraints;

6. design of a decision problem to define efficient measures to reduce $PM_{2.5}$ population exposure over the Île-de-France.

7. Design of a decision problem aimed at evaluating renewable and non renewable electricity sources needed to power the electrification of traffic fleet in Lombardy region.

In the first case study (Chapter 4), the solution of an air quality multiobjective problem shows the benefits of the inclusion of energy efficiency measures in air quality planning. The problem is solved considering a combination of end of pipe and energy measures. The solution shows that this measure dataset allows to reach a reduction of 25% in $PM_{2.5}$ exposure if we consider a policy implementation cost equal to 500 M€/yr.

Investment costs are mainly allocated in the implementation of energy efficiency measures, because at the CLE2020 (the basecase) end of pipe measures are already widely diffused and there is not so much room for improvement, while energy efficiency measures diffusion can be still implemented in all macrosectors. Furthermore energy efficiency technologies are more expensive and need a budget allocation higher than end of pipe measures. It is also worth to mention that behavioral measures can be included, they reduce the activity levels changing population habits: in this study active mobility measures are included in the database, meaning commuting by walking, by bike or bus instead of using private cars. These measures can reduce the fuel consumption, lowering the average kilometers driven.

Furthermore, the importance of energy efficiency measures is highlighted by a

GHG emissions reduction, equal to 15% in the optimal policy described that allows to reach substantial energy savings, showing the important role of the MAQ system in identifying effective win-win polices.

The second case study presented (Chapter 5) can help in the evaluation of costs and benefits, through a quantitative estimation of the impacts on air quality, GHG emissions and costs taking into account the economic, demographic and technological projection of this domain. Results suggest what are the optimal energy mixes possible and which are the renewable energy sources to invest on, showing, as expected, that the reduction of internal combustion engines fuel consumption of the current fleet has a great impact on NO_2 concentrations. The NO_2 annual average concentration is estimated to decrease over the whole domain while PM concentrations, often discussed because of the chronic exceedances of the European limit values in this area, are minimally impacted by the scenarios analysed.

Furthermore, the case study focuses on alternative electric power sources and how the energy mix used can change the impacts on air quality and CO_2 equivalent emissions. The use of renewable energy sources is still limited but it is growing fast, and clear paths are defined by European and National regulation. RES include biomass, waste and biofuels, emitting less CO_2 respect to natural gas but more PPM, VOC and SO_2, therefore negative impacts on air quality can arise from their application. On the other hand, the use of fossil natural gas has a detrimental impact on GHG emission but a higher effect on air pollution concentration reduction. ”Cleaner” solution, such as photovoltaic panels and hydroelectric plants have limitations due to the implementation cost (for the photovoltaic panels) and revamping feasibility and costs (hydroelectric plants).

This thesis stresses the role of Integrated Assessment Modeling approaches and tools in the design and implementation of decision problems for complex systems control, when policies impact on different processes (air quality and climate change) and dimensions (economy, technological innovation, human and ecosystem health). Further research on this approach might consider both methodological and implementation developments, such as:

- focusing on the *decision variables* set, more behavioral measures in the databases, considering also their social acceptability, can be included;
- in the *ex-post analysis* methodology impacts on ecosystems, for example the critical load exceedance for nitrogen, can be formalized;
- new methods for the multiobjective *decision problem solution* can be tested, for example genetic algorithms;
- further study on the *surrogate models* implemented in the IAM tools can include:
  - more study on their ability to describe emission-concentration relationship both in the identification/validation process and in the optimization phase;
  - inclusion of other surrogate models in the MAQ system.

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Methodology nomenclature

Variables

af: attributable fraction [-]

agf: age group fraction [-]

al activity level [alu, Activity Level Unit]

AQI: air quality index [μg/m^3]

C: Cost [M€/yr]

crf: concentration-response function [1/μg/m^3]

D: electricity demand [PJ/yr]

e: emission [t/yr]

hi: health impact [years]

nr: non-renewable sources electricity production [PJ]

mEF: road transport meta emission factor [mg/km, for GHG g/km]

ϕ: application rate of fuel switch measures [-]

pop: population in the domain [inhabitants]

ψ: application rate of energy efficiency measures [-]

r: renewable sources electricity production [PJ]

TC: Total policy cost [M€ /yr]

θ: application rate of end of pipe measures [-]

u: imported electricity [PJ]

$\mathbf{x}$: decision variables

yll: years of life lost [years]

Sets

A: set of air quality indexes considered in the health impacts

G: greenhouse gases

K: activities

P: air pollutants

Φ_k: set of fuel switch measures applicable to the activity k

Ψ_k: set of energy efficiency measures applicable to the activity k

S_k: set of fuel switch measures applicable to the activity k

Θ_k: set of end of pipe technologies applicable to the activity k

W: set of considered road transport vehicles types

X: generic decision variables feasible set

Y: set of vehicle fuels

Parameters

α: renewable energy sources share required [-]

ayl: average years of life lost due to air pollution exposure [years]

β: relative risk [-]

ce: fuel consumption reduction efficiency [-]

δ: income elasicity [-]

ef^g: emission factor for greenhouse gas g [kt/alu]

ef^p: emission factor for air pollutant p [t/alu]

ε: share of the total increase in energy demand that can be produced by a source [-]

η_e: efficiency of the electric engine [-]

η_{pd}: electricity production and distribution efficiency [-]

η_y: efficiency of the fuel y internal combustion engine [-]

in: average income [€]

inc: natural mortality rate of the population [-]

lb^{nr}: production lower bounds for non renewable electricity sources [PJ]

lb^r: production lower bounds for renewable electricity sources [PJ]

n_n: total number of non renewable energy sources [-]

n_r: total number of renewable energy sources [-]

n_t: total number of energy sources [-]

re: removal efficiency [-]

rgf: risk group factor [-]

td: total kilometers driven [km]

ub^{nr}: production upper bounds for non renewable electricity sources [PJ]

ub^r: production upper bounds for renewable electricity sources [PJ]

uc: unit cost [M€]

uc_u: imported electricity cost [M€/PJ]

wtp: willing to pay health impacts value [€]

Acronyms and abbreviations

ANN: Artificial Neural Network

AQI: Air Quality Index

ARERA: (*in italian*) Autorità di Regolazione per Energia, Reti e Ambiente

CH_4: methane

CLRTAP: Convention on Long-range Transboundary Air Pollution

CO_2: carbon dioxide

CTM: Chemical Transport Model

EMEP: European Monitoring and Evaluation Program

EPEC: Equilibrium Problem with Equilibrium Constraints

EV: Electric Vehicle

F_{gases}: Fluorinated gases

GAINS: Greenhouse gas - Air pollution Interactions and Synergies

GHG: greenhouse gases

GSE: (*in italian*) Gestore Servizi Energetici

GWP: Global Warming Potential

HRAPIE: Health Risks of Air Pollution in Europe

HDV: Heavy Duty Vehicle

IIASA: International Institute of Applied System Analysis

ICE: Internal Combustion Engine

IPCC: Intergovernmental Panel on Climate Change

LDV: Light Duty Vehicle

lpg: Liquefied Petroleum Gas

MAQ: Multi-dimensional Air Quality system

N_2O: nitrous oxide

NH_3: ammonia

NO_2: nitrogen dioxide

NO_x: nitrogen oxide

PM_{10} : particular matter with aerodynamic diameter less or equal to 10 μm

$PM_{2.5}$: particular matter with aerodynamic diameter less or equal to 2.5 μm

PNIEC: (*in italian*) Piano Nazionale Integrato Energia e Clima

PAD: Policy Application Domain

PPM_{10}: Primary PM_{10}

$PPM_{2.5}$: Primary $PM_{2.5}$

PRIMES: Price-Induced Market Equilibrium system

PV: Photovoltaic

RES: Renewable Energy Sources

SO_2: sulphur dioxide

SR: Source-Receptor model

TIAM: TIMES Integrated Assessment Model

TIMES: The Integrated MARKAL-EFOM System

VOC: non-methane Volatile Organic Compounds

YLL: Years of Life Lost

Appendix A

In this appendix are reported the detailed results of the ANN training for the Île-de-France domain.

Table A.1: $PM_{2.5}$ Artificial Neural Networks tested - EMI-CONC class - net features

Net name	Input shape	Layers	Neurons	Activation function	Output function	Radius of influence (cells)
PM2.5_D_a	Slice	2	20	logsig	tansig	6
PM2.5_D_b	Rings	2	20	tansig	purelin	2-10-20-60
PM2.5_D_c	Ring+slice	2	20	logsig	purelin	2-10-20-60

Table A.2: $PM_{2.5}$ Artificial Neural Networks tested - DELTA class - net features

Net name	Input shape	Layers	Neurons	Activation function	Output function	Radius of influence (cells)
PM2.5_D_a	Slice	2	20	tansig	purelin	6
PM2.5_D_b	Rings	2	20	tansig	purelin	2-10-20-60
PM2.5_D_c	Ring+slice	2	20	logsig	purelin	2-10-20-60

Table A.3: $PM_{2.5}$ Artificial Neural Networks tested - statistics

Net name	r	e max	rmse	expl var
PM2.5_EC_a	0.98	0.41	0.44	0.87
PM2.5_EC_b	0.98	0.37	0.33	0.95
PM2.5_EC_c	0.98	0.48	0.37	0.94
PM2.5_D_a	0.99	-0.89	0.01	0.98
PM2.5_D_b	0.99	-0.53	0.01	0.98
PM2.5_D_c	1.00	-0.25	0.01	0.99

Table A.4: NO_2 Artificial Neural Networks tested - EMI-CONC class - net features

Net name	Input shape	Layers	Neurons	Activation function	Output function	Radius of influence (cells)
NO2_EC_a	Slice	2	20	logsig	tansig	4
NO2_EC_b	Rings	2	20	tansig	purelin	2-10-20-60
NO2_EC_c	Ring+slice	2	20	logsig	tansig	2-10-20-60

Table A.5: NO_2 Artificial Neural Networks tested - DELTA class - net features

Net name	Input shape	Layers	Neurons	Activation function	Output function	Radius of influence (cells)
NO2_D_a	Slice	2	20	tansig	purelin	4
NO2_D_b	Rings	2	20	logsig	tansig	2-10-20-60
NO2_D_c	Ring+slice	2	20	tansig	purelin	2-10-20-60

Table A.6: NO_2 Artificial Neural Networks tested - statistics

Net name	r	e max	rmse	expl var
NO2_EC_a	0.97	1.85	1.03	0.92
NO2_EC_b	0.97	0.66	1.01	1.22
NO2_EC_c	0.99	0.79	0.69	1.09
NO2_D_a	1.00	-0.15	0.01	0.99
NO2_D_b	1.00	-0.15	0.01	1.00
NO2_D_c	1.00	-0.13	0.01	1.00

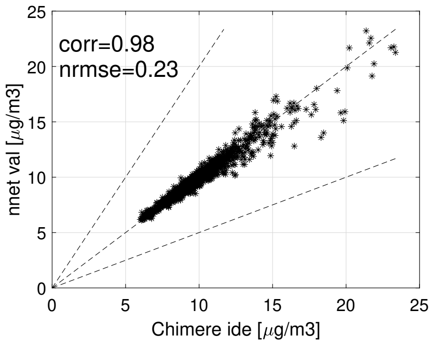

Figure A.1: $PM_{2.5}$ ANN EMI-CONC input slice - validation scatterplot

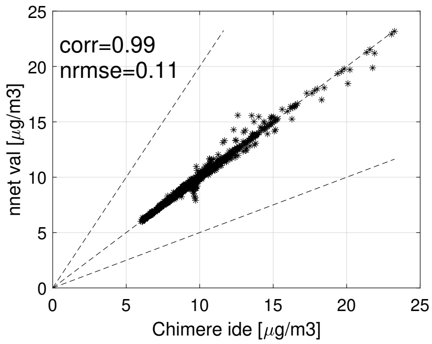

Figure A.2: $PM_{2.5}$ ANN: DELTA input slice - validation scatterplot

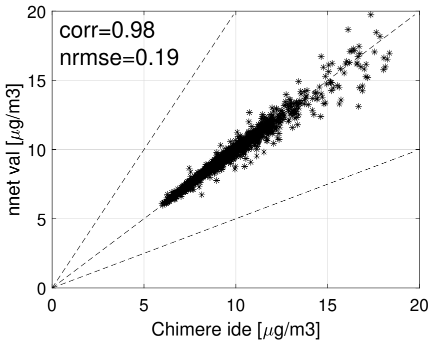

Figure A.3: $PM_{2.5}$ ANN: EMI-CONC input rings - validation scatterplot

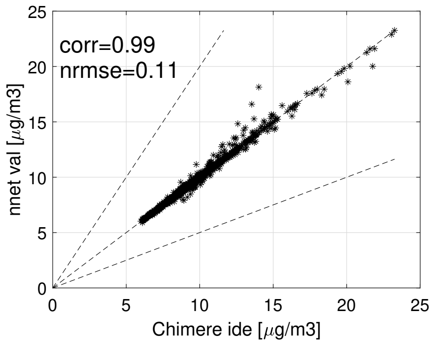

Figure A.4: $PM_{2.5}$ ANN: DELTA input rings - validation scatterplot

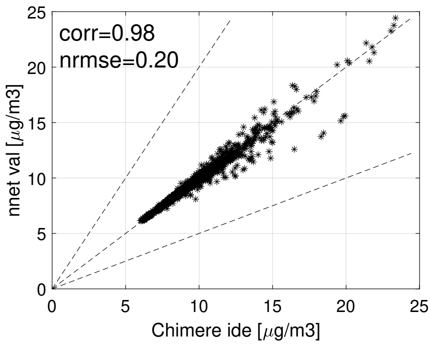

Figure A.5: $PM_{2.5}$ ANN: EMI-CONC input slice+rings - validation scatterplot

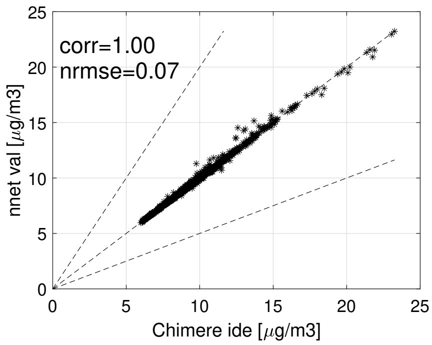

Figure A.6: $PM_{2.5}$ ANN: DELTA input slice+rings - validation scatterplot

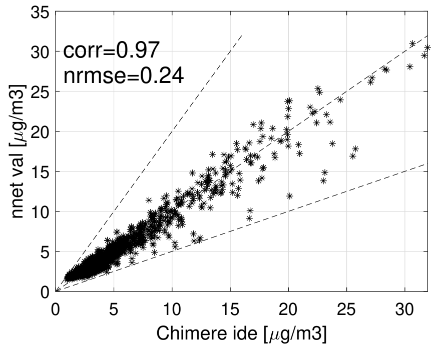

Figure A.7: NO_2 ANN: EMI-CONC input slice - validation scatterplot

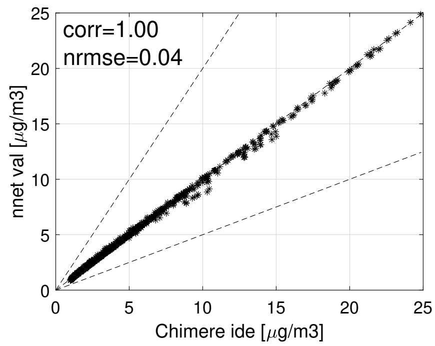

Figure A.8: NO_2 ANN: DELTA input slice - validation scatterplot

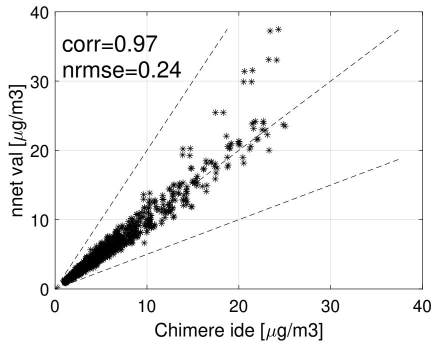

Figure A.9: NO_2 ANN: EMI-CONC input rings - validation scatterplot

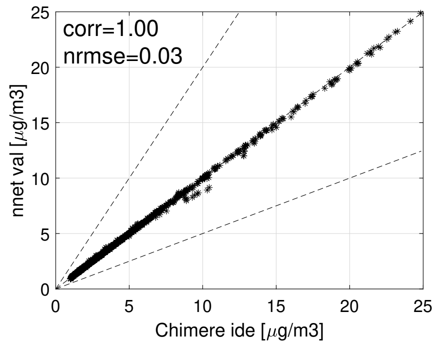

Figure A.10: NO_2 ANN: DELTA input rings - validation scatterplot

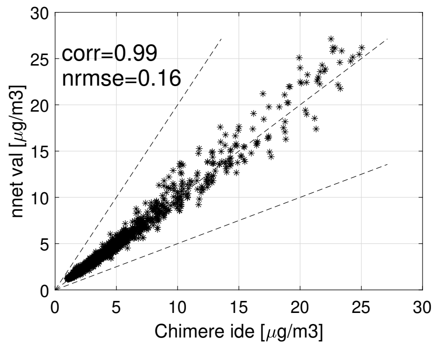

Figure A.11: NO_2 ANN: EMI-CONC input slice+rings - validation scatterplot

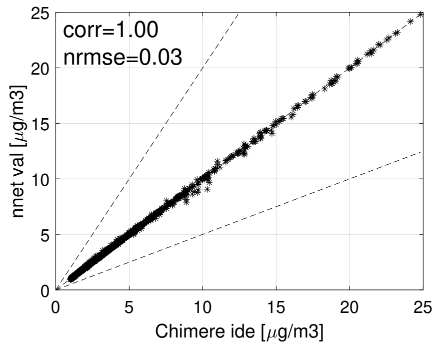

Figure A.12: NO_2 ANN: DELTA input slice+rings - validation scatterplot

Appendix B

In this appendix are reported the detailed results for all 22 scenario simulated for Lombardy in the case study ”Low emission road transport scenarios in Lombardy region”.

Table B.1: Air quality indexes, GHG and costs values for all scenarios

Scen -	PM_{10} $\mu g/m^3$	$PM_{2.5}$ $\mu g/m^3$	NO_2 $\mu g/m^3$	CO_{2eq} kt/yr	Cost M€/yr
BC	20.3	15.7	22.2	91589	0
1	19.1	14.8	14.3	73529	70920
2	19.2	14.9	14.9	73540	70931
3	19.1	14.8	14.0	73524	70915
4	19.2	14.9	15.0	73535	70925
5	19.2	14.9	14.8	73533	70924
6	19.2	14.8	14.3	73307	70698
7	19.2	14.8	14.1	73301	70692
8	19.2	14.9	14.3	73306	70697
9	19.2	14.9	14.9	73309	70699
10	19.2	14.9	14.6	73309	70700
11	19.1	14.8	13.8	73456	70847
12	19.2	14.9	14.6	73460	70851
13	19.2	14.9	14.8	73469	70860
14	19.4	15.0	16.6	68838	66229
15	19.3	15.0	16.1	68835	66226
16	19.3	14.9	15.4	68710	66101
17	19.3	14.9	15.6	68712	66103
18	19.3	15.0	15.7	68702	66093
19	19.0	14.7	12.8	64970	62360
20	19.0	14.7	12.4	64970	62360
21	19.0	14.7	12.9	64972	62363
22	19.2	14.9	14.1	64990	62381

Table B.2: Electricity production from each source in PJ

Scen	Natural gas	Coal	Liquid fossil fuels	Biomass	Biogas	Biofuels	Waste	PV	Hydro
BC	136.3	0.6	10.8	2.0	13.3	1.3	4.3	11.4	52.7
1	138.1	0.0	10.9	20.2	42.8	1.0	16.9	40.6	60.5
2	138.1	0.0	10.9	21.5	11.3	17.3	22.8	46.9	62.2
3	138.1	0.0	10.9	6.0	45.1	12.1	9.7	49.0	60.1
4	138.1	0.0	10.9	4.3	26.9	41.3	4.7	45.6	59.2
5	138.1	0.0	10.9	28.2	28.6	9.5	9.2	46.7	60.0
6	149.0	0.0	0.0	8.0	32.2	18.2	25.5	38.7	59.5
7	149.0	0.0	0.0	17.1	21.2	8.9	12.9	61.8	60.2
8	149.0	0.0	0.0	11.0	34.7	19.4	18.6	38.0	60.3
9	149.0	0.0	0.0	25.5	14.9	23.4	5.7	48.9	63.7
10	149.0	0.0	0.0	20.0	14.8	20.6	14.6	55.6	56.5
11	141.5	0.0	7.5	3.0	22.3	8.5	23.0	64.8	60.5
12	141.5	0.0	7.5	23.7	22.1	12.4	7.8	59.0	57.1
13	141.5	0.0	7.5	5.9	15.2	28.7	28.9	39.3	63.9
14	60.0	0.0	6.2	7.4	44.8	85.9	6.0	58.3	62.4
15	60.0	0.0	6.2	57.6	48.3	19.0	15.5	60.6	64.0
16	66.2	0.0	0.0	15.1	55.9	37.3	49.9	43.9	62.9
17	66.2	0.0	0.0	17.9	26.4	43.7	45.3	72.4	59.1
18	66.2	0.0	0.0	48.1	34.6	25.1	12.5	86.6	57.9
19	0.0	0.0	0.0	0.0	130.9	0.0	0.0	135.9	64.3
20	0.0	0.0	0.0	0.0	0.0	0.0	0.0	266.8	64.3
21	0.0	0.0	0.0	1.6	130.9	1.0	3.5	137.6	56.4
22	0.0	0.0	0.0	15.0	121.8	15.0	15.0	100.0	64.3

Table B.3: Percentage emission reduction with respect to the base case 2018

Scenario	NO_x	VOC	NH_3	PM_{10}	$PM_{2.5}$	SO_2
BC	-	-	-	-	-	-
1	-47.2%	-2.2%	-0.5%	-5.0%	-6.3%	-15.0%
2	-44.4%	-1.3%	-0.4%	-4.3%	-5.4%	-12.2%
3	-48.1%	-2.4%	-0.5%	-5.2%	-6.4%	-16.7%
4	-44.0%	-1.1%	-0.4%	-4.0%	-5.1%	-15.0%
5	-45.1%	-1.4%	-0.5%	-4.3%	-5.5%	-14.9%
6	-47.2%	-1.9%	-0.5%	-4.9%	-6.0%	-14.3%
7	-48.0%	-2.0%	-0.5%	-4.9%	-6.1%	-16.7%
8	-46.8%	-1.8%	-0.5%	-4.7%	-5.8%	-15.2%
9	-44.7%	-1.0%	-0.4%	-3.9%	-5.0%	-15.9%
10	-45.6%	-1.3%	-0.5%	-4.2%	-5.4%	-15.0%
11	-49.1%	-2.6%	-0.5%	-5.5%	-6.7%	-15.3%
12	-45.8%	-1.6%	-0.5%	-4.4%	-5.6%	-15.8%
13	-45.1%	-1.5%	-0.5%	-4.5%	-5.6%	-11.9%
14	-37.4%	1.2%	-0.3%	-1.9%	-2.9%	-10.7%
15	-39.6%	0.5%	-0.3%	-2.7%	-3.7%	-10.6%
16	-42.4%	-0.5%	-0.4%	-3.7%	-4.8%	-7.2%
17	-41.4%	-0.1%	-0.4%	-3.3%	-4.4%	-7.2%
18	-41.1%	0.3%	-0.4%	-2.8%	-3.9%	-12.3%
19	-53.4%	-3.4%	-0.6%	-6.1%	-7.3%	-21.8%
20	-55.0%	-3.4%	-0.6%	-6.1%	-7.4%	-22.0%
21	-52.8%	-3.3%	-0.6%	-5.9%	-7.2%	-20.9%
22	-47.8%	-1.8%	-0.5%	-4.7%	-5.9%	-16.0%

Table B.4: Policy cost, energy cost and energy savings for all scenarios

Scen	Cost M€/yr	Energy cost M€/yr	Energy savings M€/yr
BC	0	7657	0
1	3109	4496	3161
2	3602	4330	3327
3	3764	4468	3189
4	3497	4544	3113
5	3579	4487	3170
6	2962	4369	3288
7	4761	4196	3461
8	2905	4428	3229
9	3757	4358	3299
10	4278	4288	3368
11	4997	4129	3528
12	4545	4361	3296
13	3008	4323	3334
14	4493	4264	3393
15	4666	4144	3513
16	3364	4017	3640
17	5592	3749	3908
18	6702	3885	3772
19	10550	3382	4275
20	20773	1783	5874
21	10685	3422	4235
22	7747	3656	4000

Table B.5: Mortality costs, morbidity costs and health savings for all scenarios

Scen	Cost M€/yr	Mortality costs $PM_{2.5}$ M€/yr	Mortality costs NO_2 M€/yr	Morbidity costs ($PM_{2.5}$) M€/yr	Health savings M€/yr
BC	-	8673	1681	10017	-
1	3109	8181	1128	9456	1605
4	3602	8225	1189	9490	1467
5	3764	8162	1110	9440	1659
6	3497	8211	1197	9475	1487
7	3579	8203	1175	9470	1523
9	2962	8203	1134	9474	1559
11	4761	8182	1117	9455	1616
13	2905	8202	1142	9471	1555
14	3757	8217	1189	9479	1485
15	4278	8215	1169	9480	1507
21	4997	8167	1091	9447	1665
22	4545	8196	1160	9464	1550
23	3008	8225	1176	9491	1478
26	4493	8296	1341	9538	1195
27	4666	8281	1294	9530	1266
28	3364	8278	1237	9538	1318
31	5592	8287	1258	9544	1282
32	6702	8269	1266	9520	1316
33	10550	8085	1004	9389	1893
36	20773	8070	975	9383	1943
37	10685	8101	1017	9400	1853
40	7747	8190	1123	9462	1596