

NON LINEAR DECISION MODELS TO MITIGATE AIR QUALITY EFFECTS ON HEALTH IN NORTHERN ITALY

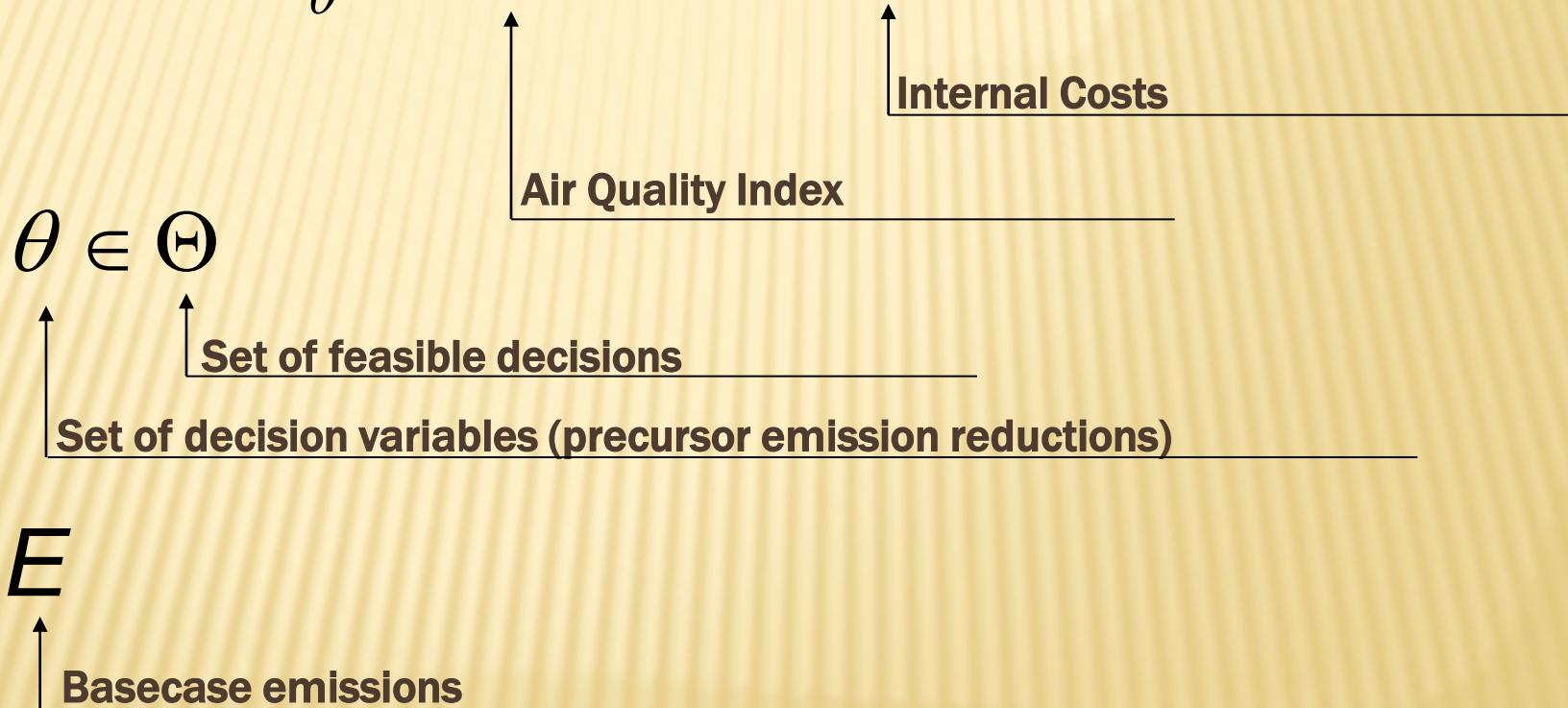
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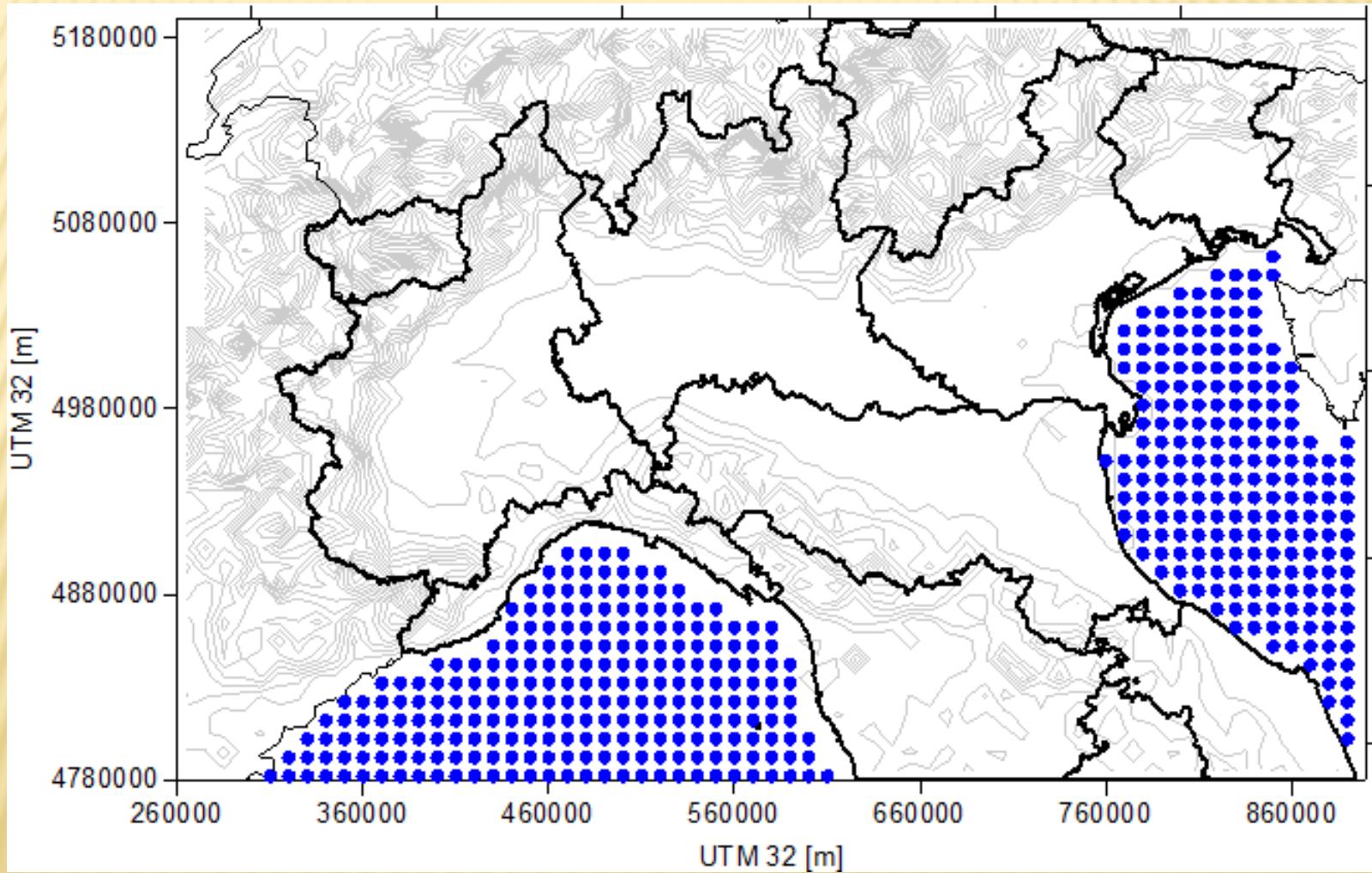
² Atmospheric Pollution and Economic Development Program, IIASA, Austria

PROBLEM FORMULATION

$$\min_{\theta} J(\theta) = \min_{\theta} [AQI(E(\theta)) + C(E(\theta))]$$



CASE STUDY



OBJECTIVE 1: AIR QUALITY INDEX

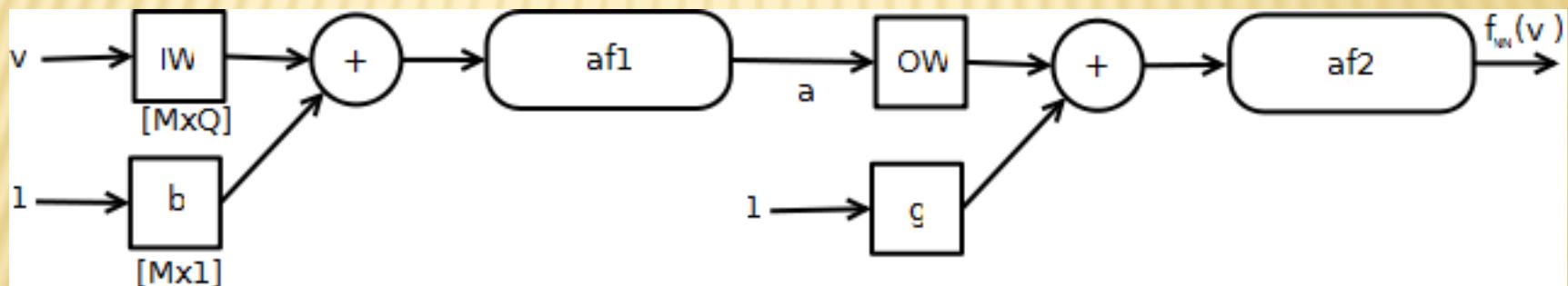
- ✖ Air Quality Index: PM10 mean concentrations
- ✖ Emission-concentration = nonlinear link
- ✖ Source-Receptor models:
 - ✖ Artificial Neural Networks (ANNs)
- ✖ Identification dataset: TCAM simulations

CARNEVALE C; FINZI G; PISONI E; VOLTA M. (2009). Neuro-fuzzy and neural network systems for air quality control. *ATMOSPHERIC ENVIRONMENT*. 4811-4821. 43

CARNEVALE C; DECANINI E; VOLTA M. (2008). Design and validation of a multiphase 3D model to simulate tropospheric pollution. *SCIENCE OF THE TOTAL ENVIRONMENT*. 166-176. 390

ANNS ARCHITECTURE

- ✖ Feed Forward network
- ✖ Input: (ring of cells) precursor emissions
- ✖ Output: (cell) AQI



ANNS IDENTIFICATION

✗ Emission reductions [%]:

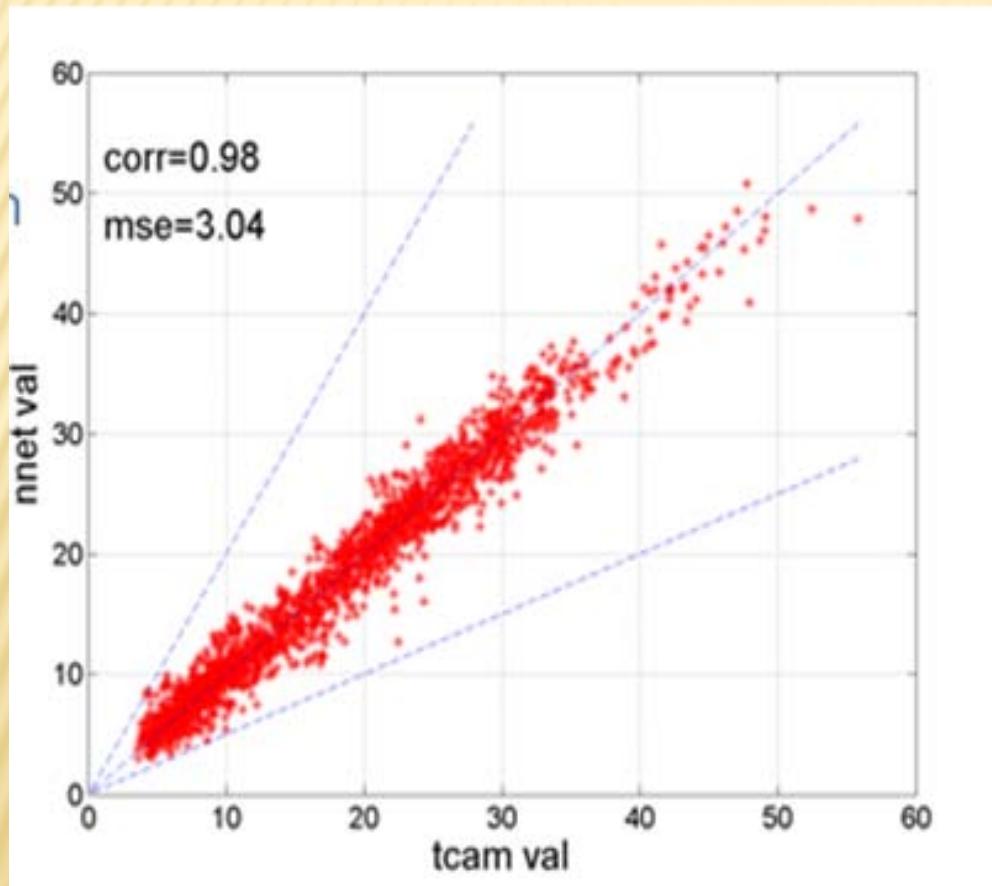
- ✗ C&Epackage MRR (2020)
- ✗ NEC2007BASELINE

SCENARIOS	NOX	VOC	NH3	PM	SO2
1	30.89	27.26	21.45	26.70	35.85
2	61.78	54.52	42.90	53.40	71.70
3	61.78	27.26	21.45	26.70	35.85
4	30.89	54.52	21.45	26.70	35.85
5	30.89	27.26	42.90	26.70	35.85
6	30.89	27.26	21.45	53.40	35.85
7	30.89	27.26	21.45	26.70	71.70
8	30.89	54.52	21.45	53.40	35.85
9	61.78	54.52	21.45	53.40	71.70
10	61.78	27.26	42.90	26.70	35.85

✗ 11 TCAM simulations:

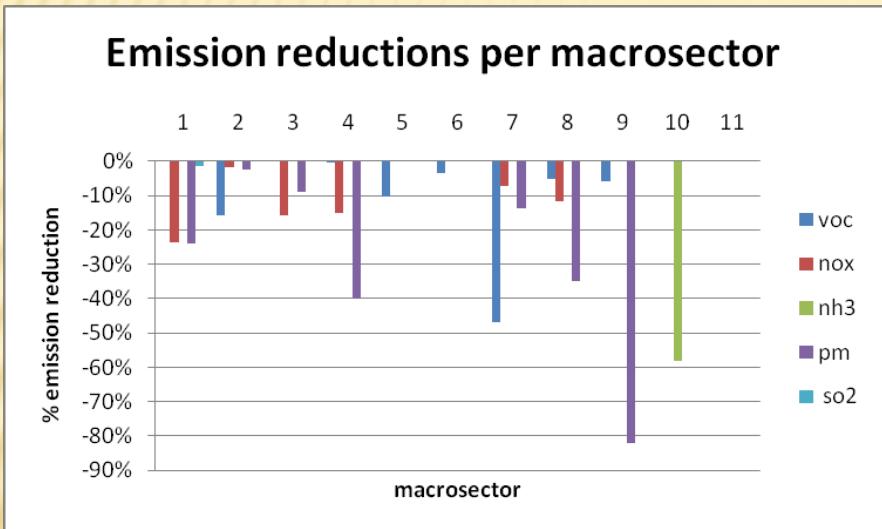
- ✗ 2004
- ✗ 10x10km²

SOURCE-RECEPTOR MODELS: RESULTS

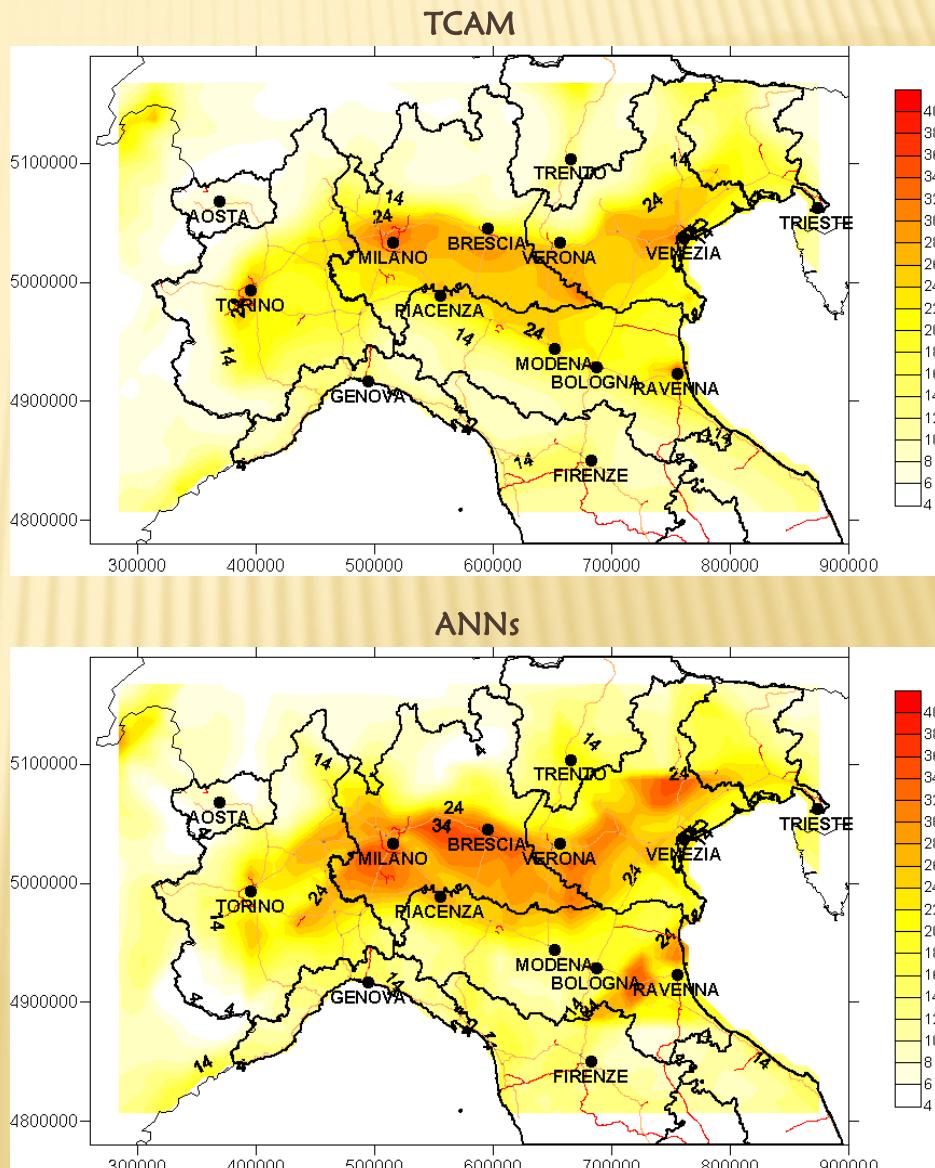


TCAM mean ($\mu\text{g}/\text{m}^3$)	17.63
ANNs mean($\mu\text{g}/\text{m}^3$)	17.59
correlation	0.98
Mean Error ($\mu\text{g}/\text{m}^3$)	-0.05
Mean Absolute Error ($\mu\text{g}/\text{m}^3$)	1.31
Normalized Mean Absolute Error	0.07

SOURCE RECEPTOR MODELS: RESULTS



	TCAM (mg/m ³)	ANNs (mg/m ³)
Mean PM	13.33	15.29



OBJECTIVE 2: INTERNAL COSTS

- ✖ Internal costs: precursor emission reductions
- ✖ Technical measures
- ✖ Macrosectors
- ✖ Emission-cost functions
 - + Artificial Neural Networks (ANNs)
- ✖ Identification dataset:
 - + 1000 scenarios simulated by GAINS for Italy

EMISSION-COST MODELS

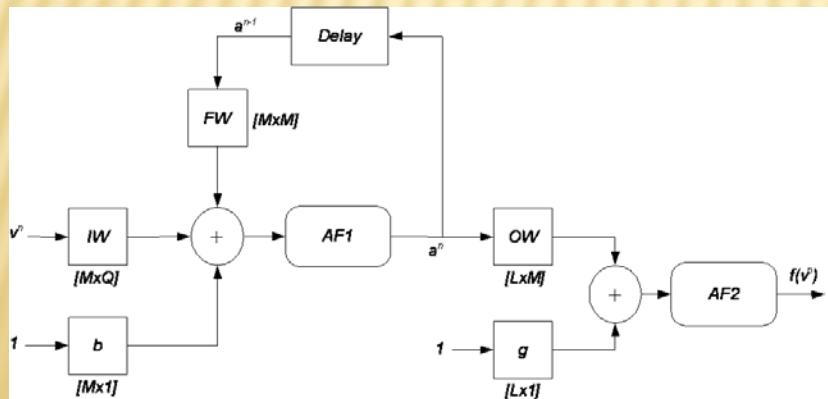
× ANNs Input:

- + Optimized emissions [kton] of the 5 precursors, sampled using a uniform distribution, between CLE2020 and MFR2020

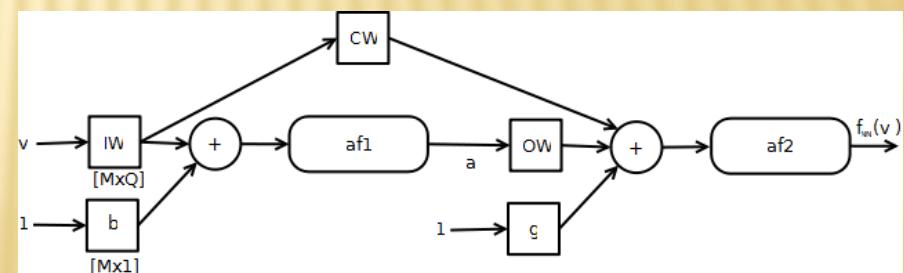
× ANNs Output:

- + Optimal costs over CLE2020 [Meuro/ton]

Elman NN



Cascade-forward



BEST PERFORMING ANNS ARCHITECTURE

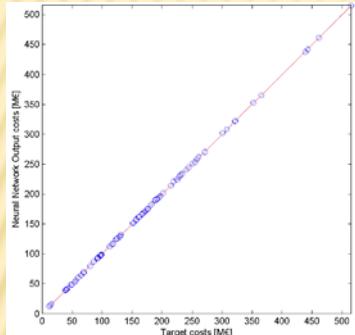
<i>MACROSECTOR</i>	<i>INPUT FUNCTION</i>	<i>OUTPUT FUNCTION</i>	<i>TRAINING</i>	<i>NEURONS</i>	<i>ANNs input (EMISSIONS)</i>
1	poslin	poslin	trainlm	19	SO2, NOx, pPM, NH ₃
2	tansig	poslin	trainlm	17	SO2, NOx, pPM, NH ₃ , VOC
3	logsig	poslin	trainlm	25	SO2, NOx, pPM, NH ₃
4	poslin	poslin	trainlm	17	SO2, NOx, pPM, VOC
5	logsig	poslin	trainbfg	15	pPM, VOC
6	poslin	poslin	trainlm	17	VOC
7	logsig	poslin	trainlm	17	NOx, pPM, NH ₃ , VOC
8	poslin	poslin	trainbfg	25	SO2, NOx, pPM, NH ₃ , VOC
9	tansig	poslin	trainlm	21	SO2, NOx, pPM, NH ₃ , VOC
10	poslin	poslin	trainlm	20	SO2, NOx, pPM, NH ₃ , VOC

COST ANNS: RESULTS

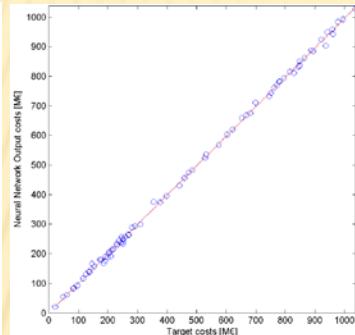
MACROSECTOR	Normalized Mean Error [%]	Normalized Mean Absolute Error [%]
1	-0,23	0,65
2	0,15	2,05
3	0,13	1,05
4	0,03	0,06
5	0,002	0,003
6	0,22	1,52
7	-0,27	2,13
8	0,44	7,55
9	-0,50	1,78
10	-0,06	0,52

COST ANNS: MACROSECTOR RESULTS

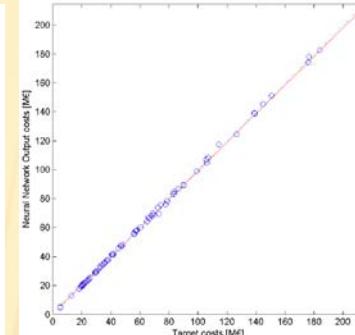
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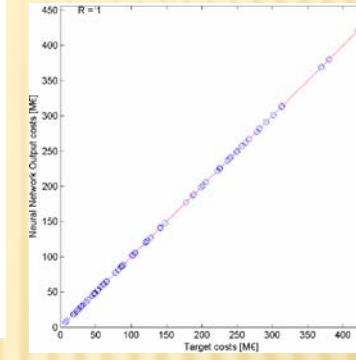
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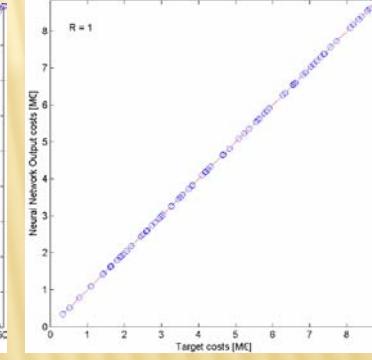
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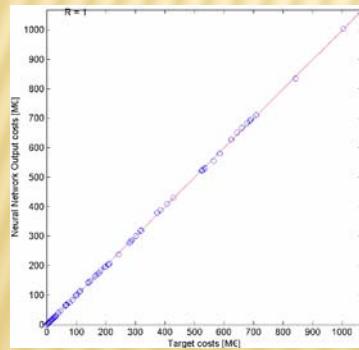
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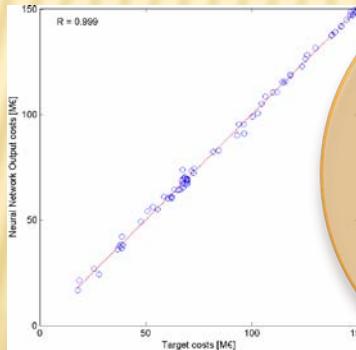
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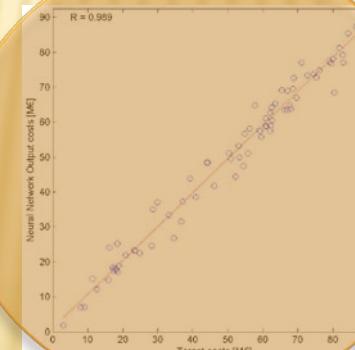
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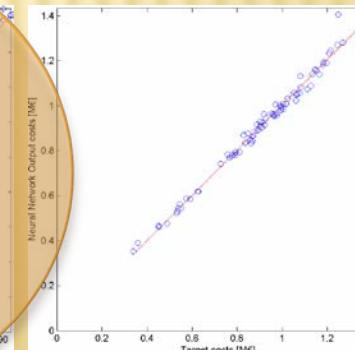
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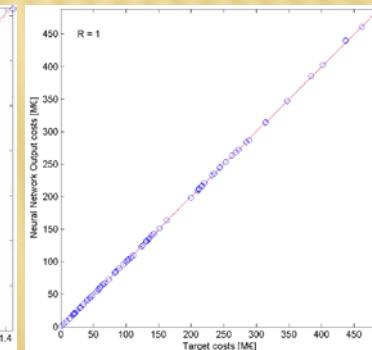
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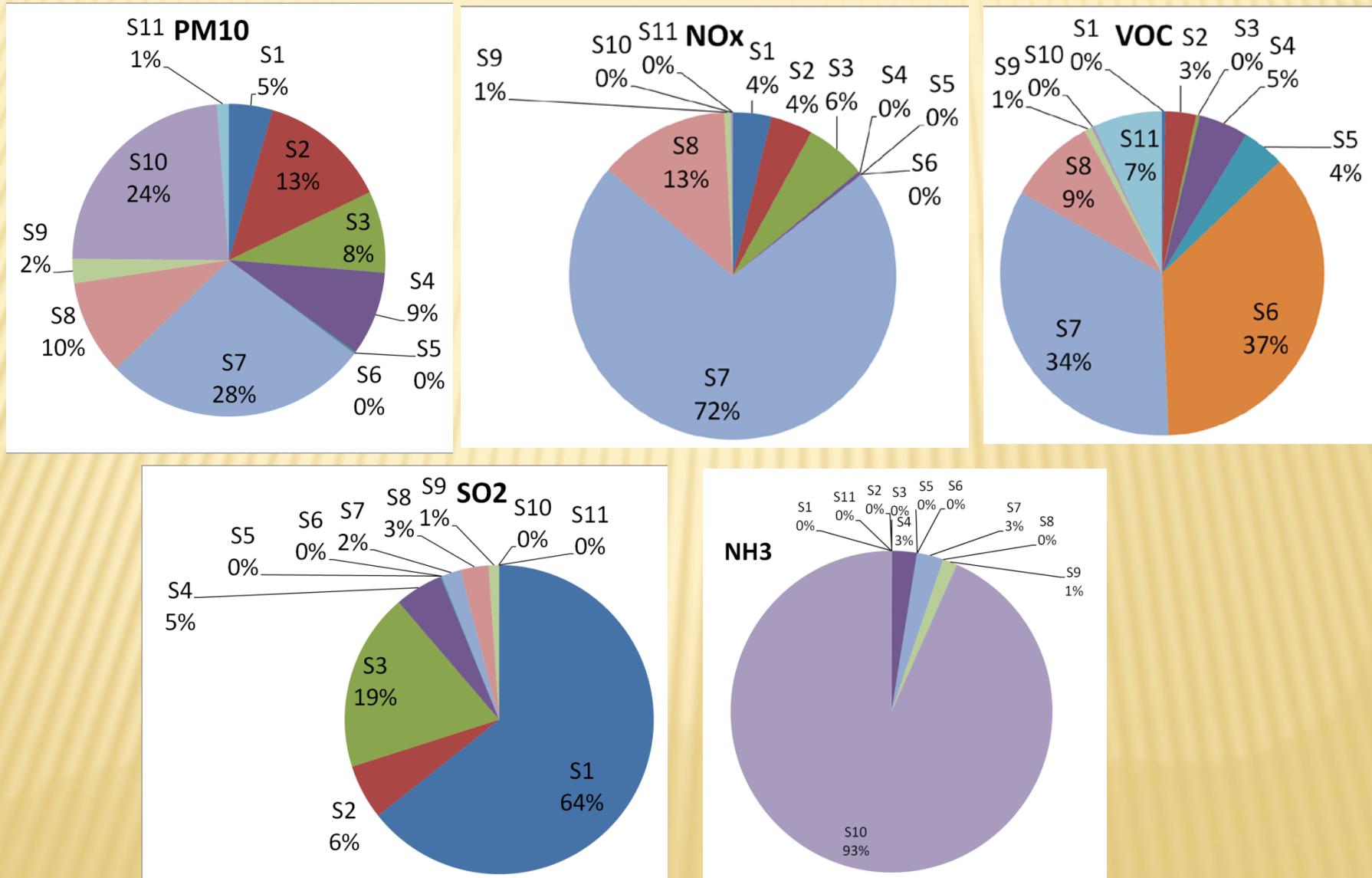
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10

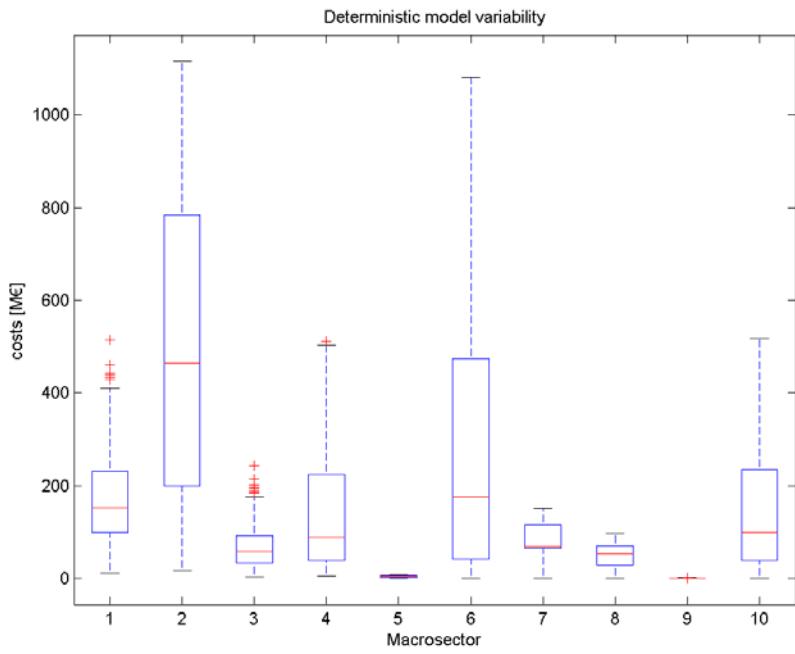


MACROSECTOR EMISSIONS

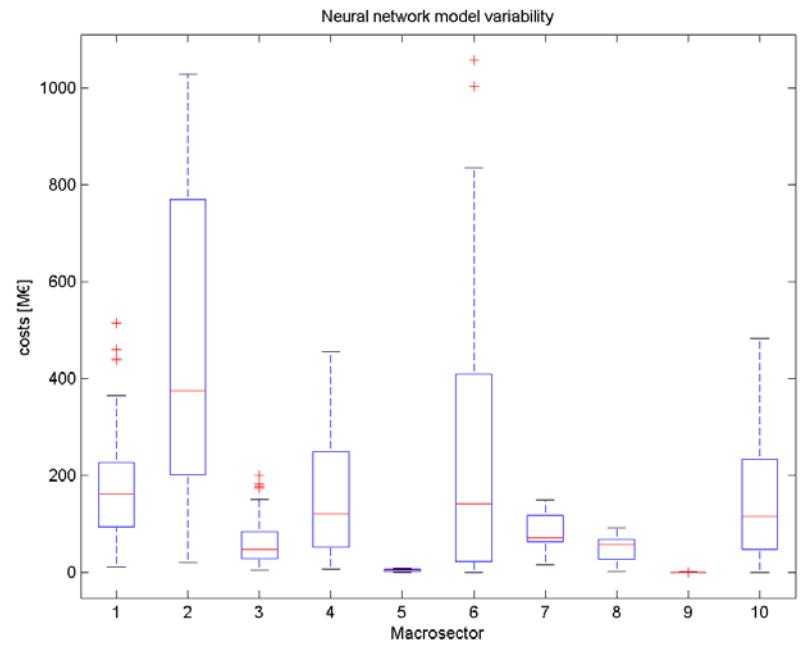


COST ANNS: RESULTS

GAINS



ANNs



DECISION PROBLEM SOLUTION

- Weighted sum method:

$$\min_{\theta} J(\theta) = \min_{\theta} [\alpha \cdot AQI(E(\theta)) + (1 - \alpha) \cdot C(E(\theta))]$$

$$0 \leq \alpha \leq 1$$

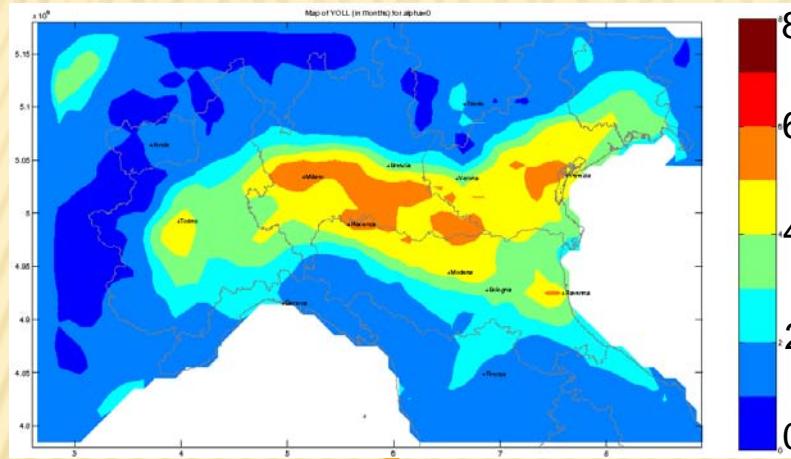
- Constraints:

	1	2	3	4	5	6	7	8	9	10	11
VOC	0,00	0,66	0,00	0,37	0,02	0,35	0,00	0,00	0,06	0,90	0,00
NOx	0,52	0,27	0,58	0,50	0,00	0,00	0,62	0,77	0,50	1,00	0,00
NH3	0,41	0,02	0,76	0,00	0,00	0,00	0,08	0,47	0,00	0,34	0,00
PM10	0,65	0,75	0,20	0,50	0,00	0,00	0,00	0,00	0,29	0,78	0,00
SO2	0,70	0,22	0,42	0,61	0,00	0,00	0,00	0,77	0,36	1,00	0,00

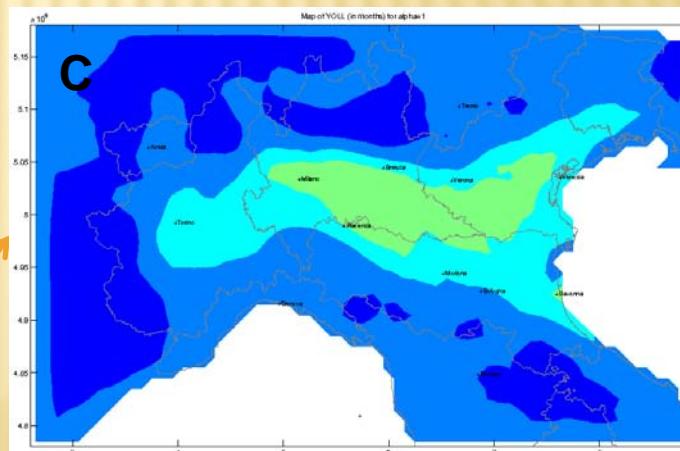
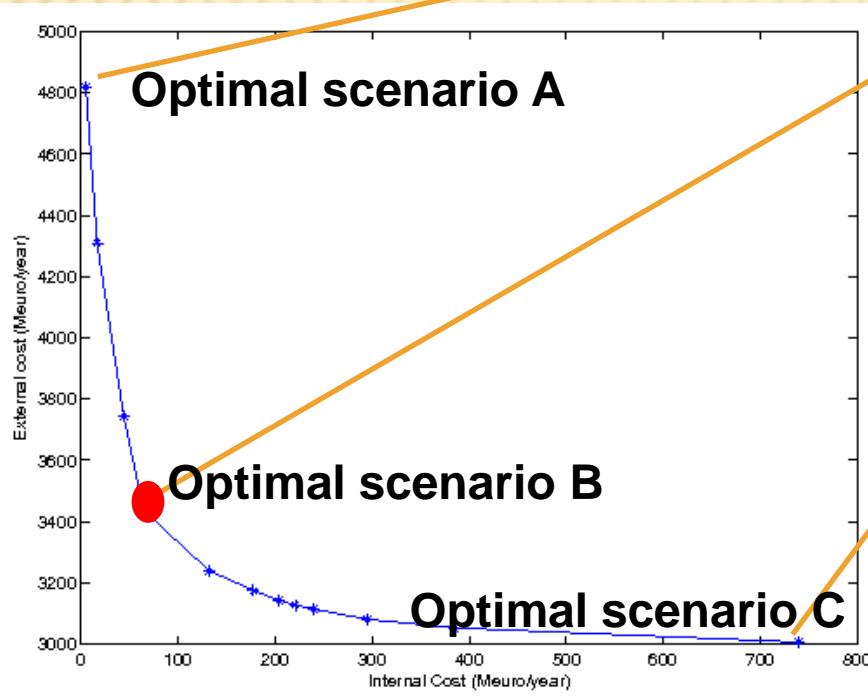
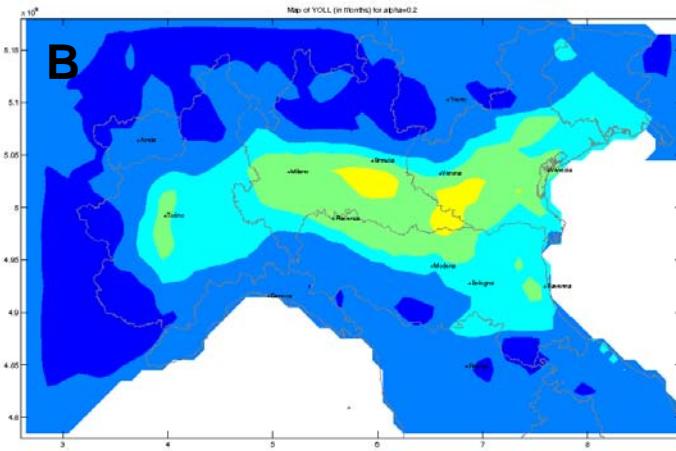
- Multi-pollutant technologies

PARETO BOUNDARY (OVER CLE2020)

A

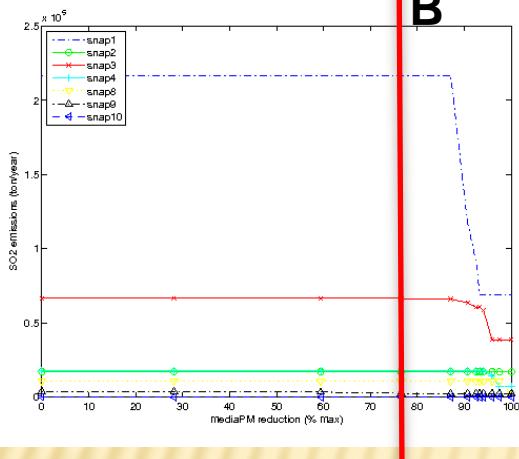


months of lost life

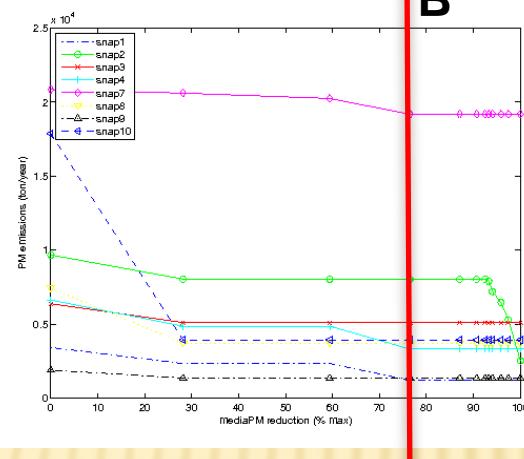


OPTIMAL POLICIES (OVER CLE2020)

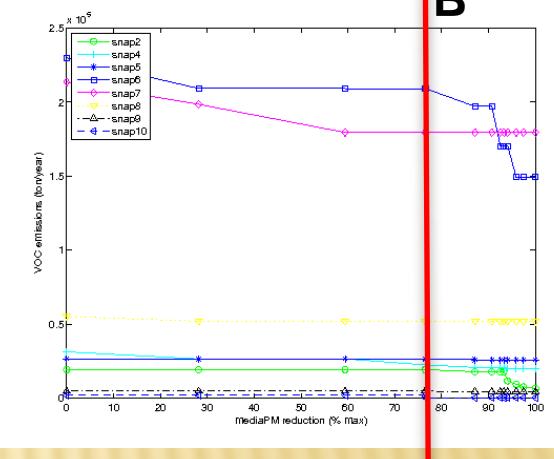
S02



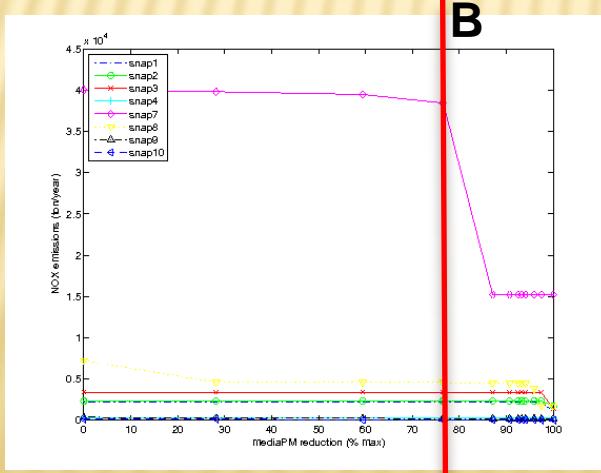
PM10



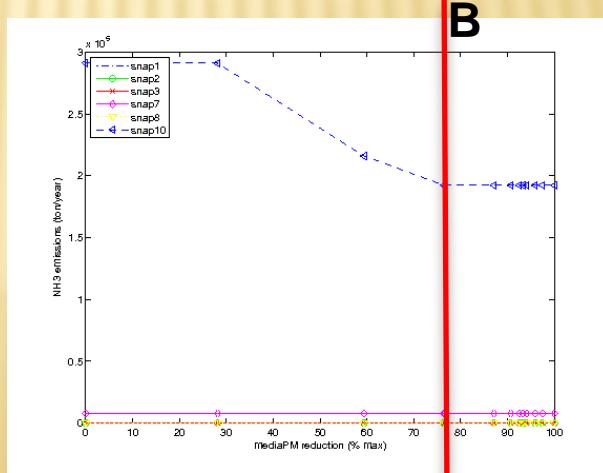
VOC



NOx



NH₃



CONCLUSIONS

- ✖ A decision model has been formalized to control PM10 exposure in Northern Italy
- ✖ Emission-AQI and Emission –Cost: non-linear functions
- ✖ AQI and internal costs are simulated by ANNs
- ✖ TCAM (11) and GAMES (1000) simulations
- ✖ Optimal policy analysis
- ✖ Comparison between the solutions of the proposed methodology and the GAINS ones?

SENSITIVITY ANALYSIS

1. the **sensitivity** of the effective policies to
 - ✓ uncertainty of the inputs
 - ✓ different problem formulations, optimization algorithms, planning objectives, emission-concentration relationships, spatial scales ...
2. the definition of a set of **indexes** and a **methodology** to **measure the sensitivity** of the decision problem solutions.

the absolute “optimal”
policy is not known

intercomparison

indexes

3. methods and tools to **support** air quality authorities in the application of IAMs