

NEURAL NETWORK SURROGATE MODELS IN THE FRAME OF AIR QUALITY PLANNING AT REGIONAL SCALE

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Air pollution in the atmosphere derives from complex non-linear relationships that involve anthropogenic and biogenic precursor emissions. Due to this complexity, Decision Support Systems (DSSs) are important tools, to help Environmental Authorities to improve air quality reducing human and ecosystems pollution impacts in a cost efficient way. In this work seasonal air quality surrogate models (to be used in a DSSs) are presented. These surrogate models are able to model the nonlinear relation between emissions and air quality indexes considering also sub-yearly aggregation time horizons, usually not considered in integrated assessment models.

The decision problem formalization

The decision problem (in the case of application only of technical measures) can be formalized as follows [1], [2]:

$$\min_x J(x) = \min_x [AQI(E(x)) \quad C(E(x))] \quad (*)$$

$$s.t. \quad x \in X$$

Where

- x is the decision variable vector, in this case the level of application of a certain reduction technology;
- X is the feasible solution set;
- $E(x)$ are the emission, computed as a function of technology application
- AQI is the Air Quality Index [3], [4];
- C is the Cost Index.

Since the nonlinearity and complexity of relationship between AQI and emissions, $AQI(E(x))$ is usually computed by means of complex **Chemical Transport Model (CTM)**, that cannot be implemented in the solution of the optimization problem due to high computational time.

For these reasons, the relationship has to be implemented by **simplified model based on neural networks** computed starting from the results of a very limited number of CTM simulations.

The selection of the number and the features of the simulations to be performed is usually performed in the first phase of the project, named Design of Experiments (DoE), starting from the range of input variability needed for the solution of (*).

The Design of Experiments

To model the AQI objective just presented in the decision problem formalization, it is required at first to run a Chemical Transport Model on a set of emission reduction scenarios, considering a so called Design Of Experiment [3].

	AREAL AND POINT EMISSIONS					OUTSIDE REGIONAL DOMAIN
	NOX	VOC	NH3	PM	SO2	
1	B	B	B	B	B	B2 (cle2020)
2	L	L	L	L	L	B2 (cle2020)
3	H	H	H	H	H	B2 (cle2020)
4	H	L	L	L	L	B2 (cle2020)
5	L	H	L	L	L	B2 (cle2020)
6	L	L	H	L	L	B2 (cle2020)
7	L	L	L	H	L	B2 (cle2020)
8	L	L	L	L	H	B2 (cle2020)
9	H	H	L	L	L	B2 (cle2020)
10	H	L	H	H	H	B2 (cle2020)
11	H	L	H	L	L	B2 (cle2020)
12	H	L	H	L	H	B2 (cle2020)

As an example, in the previous table a set of 12 simulations have been selected. In the table B means the base case emission scenario (increased of 15%), H the maximum feasible scenario (decreased of 15%) and L the intermediate point. The idea of the Design of Experiment is to be able (with these B, L and H values) to cover the possible extreme variations of emissions (between minimum and maximum values) so that the source-receptor models (identified from these data) will be finally able to model a generic "emission to concentration" link.

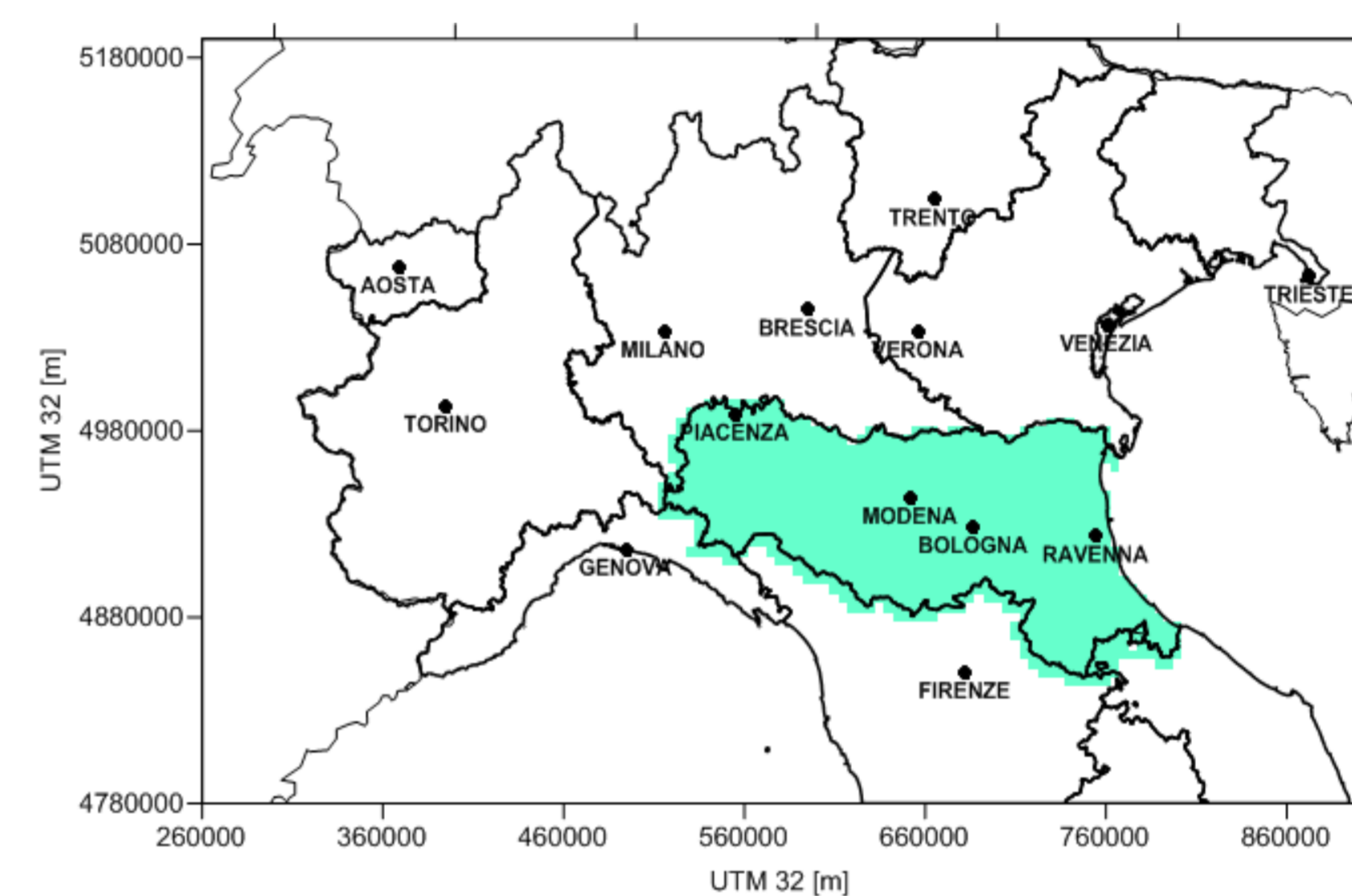
The surrogate model results

The input-output patterns provided by the CHIMERE CTM simulations on the DoE scenarios have been used to train seasonal Artificial Neural Networks (ANNs) [3]. These ANNs are able to consider yearly, winter (October to March) and summer (April to September) time horizons, linking the temporally (summed up) aggregated emissions with the yearly/seasonal targets. The input/output structure is shown in the following Figure.

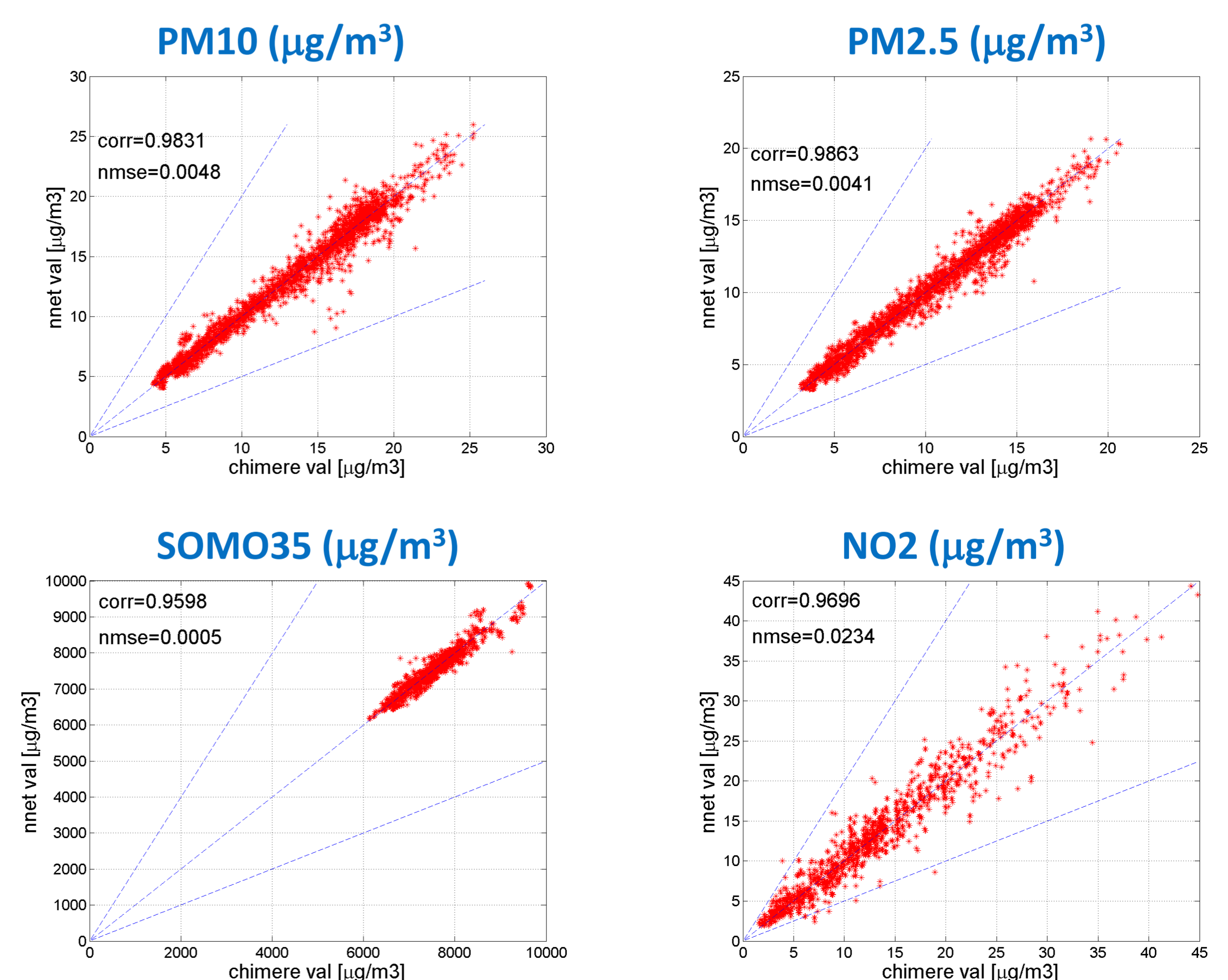
ANNs inputs: quadrant precursor emissions ANNs output: AQI



In this case study, the ANNs identification has been done considering the Emilia Romagna domain, as shown in the following Figure (see light blue cells).



The results in terms of validation scatter plot are shown in the following Figure for winter PM10 (top left figure); winter PM25 (top right); summer SOMO35 (bottom left); and winter NO2 (bottom right). As shown in these Figures, the ANNs are able to properly model the seasonal behavior for the various emission reduction scenarios and AQIs considered.



Acknowledgments

This study has been done in the frame of the OPERA (Operational Procedure for Emission Reduction Assessment) LIFE+ project (2010-2013, www.operatool.eu).

References

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