Modeling PBL turbulence parameters by neural network to improve meteo stations

P. Agnello, C. Gariazzo, A. Pelliccioni
Italian Institute for Occupational Safety and Health (ISPESL)- Via Urbana 167, Roma (ITALY)

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1 Introduction

The evaluation of boundary layer parameters is a key factor to study the atmospheric dispersion of pollutants. In particular mechanic and thermic turbulence have a great influence on air pollution dispersion in the Planetary Boundary Layer (PBL). PBL parameters can be derived by turbulence fluxes analysis using sophisticated and expensive instruments such as ultrasonic anemometer, often not available at conventional meteorological stations. On such stations atmospheric stability is usually classified in classes, using semi-empirical relationship (Pasquill, 1974).
This methodology is often far to be complete and sometimes misleading. There is a general need to have a better knowledge of local atmospheric turbulence at lower cost.
A good cost/effective compromise seems to be the application of neural networks (NN) to estimate PBL parameters. NN represent a powerful tool in solving non-linear problems.
In environmental science, neural networks have been applied to forecast atmospheric pollution (Pelliccioni, 2000) and ozone concentrations at surface level (Hadjiiski, 2000).
The present work deals with application of a proper NN, the 3-Layer Perceptron, to reproduce turbulence parameters using as input conventional data, suggesting a way to improve meteorological stations.

2 Investigation area, experimental setup and turbulence parameters estimation

Meteorological measurements were carried out in a grape-growing area close to Monteporzio Catone, a village 24 km far from Rome. The area is hilly with a maximum height of 450 m asl. A field campaign has been conducted during summer 2000 using the ISPESL meteorological mobile laboratories. Meteorological surface parameters such as wind speed and direction at two different heights (3 and 10 m agl), absolute air temperature and its surface gradient (1.6 and 10 m agl), net and global solar radiation, pressure, relative humidity, were measured at 1Hz and averaged every 10 minutes. Wind measurements have been performed with a couple of GILL three axial sonic anemometers to measure the three cartesian wind components. For turbulence studies a different system has been used, which is connected to the digital output of the 10 m anemometer set at a sampling rate of 4Hz. Turbulence kinetic energy (*TKE*), friction velocity (u_*), average and standard deviation of vertical wind component *w*, were calculated at 15 min resolution.
Sensible heat flux (*H*) and Obukhov length (*L*), could not be measured by eddy correlation technique, due to experimental setup limitations. The former has instead been estimated using the gradient method, as suggested by Brotzge and Crawford (2000), which is based on temperature and wind speed vertical gradients. The Obukhov length has been derived using the gradient Richardson number *Ri* (Stull, 1989). The gradient method is robust and can be applied operationally. It doesn't require an explicit estimation of the roughness length z_0.
All meteorological parameters were averaged at 30 minutes resolution to smooth data variations and then used as input for modeling studies.
Among the data collected during the summer campaign, the August data were selected for model input. During this month the study area was characterized by a large scale high pressure system

located in the middle of Mediterranean sea. High temperatures above 30 °C, high insulation as much as 900 W/m^2 and relative humidity between 30% and 90% have been measured on this period which develop convective atmospheric conditions.
On such conditions the studied area was characterized by essentially three wind regimes: during nighttime a light wind from the top of hill (East) is prevailing. This wind regime can be ascribed to a katabatic wind which is correlated to a radiative cooling of the air adjacent to surfaces resulting in a cold downslope wind (Stull 1989). After sunrise, solar heating warms the air near the hill walls, causing warm upslope anabatic wind to come up (West-NorthWest). At midday high convective conditions are prevailing. The intensive solar radiation and subsequent warming of land surface triggers the development of a sea-breeze system. It starts at about 1400 CET coming from SouthWest with stronger wind up to 5 m/s till sunset. The latter regime was already been revealed by Melas et al. (2000).

3 Multi-Layer Perceptron model description

The Multi-Layer Perceptron (MLP) is a modeling forecasting tool that uses a neural network to model data (Rojas, 1996) (Haykin, 1999). The back-propagation algorithm used in the MLP is the Conjugate Gradient algorithm, the most common supervised learning algorithm which measures the gradient of the error surface after each pass.
MLP consists of a number of simple processing elements (neurons or nodes) arranged as layers. The inputs to each processing element are usually fully connected to the outputs of previous layer.
In this work we apply a 3-Layer Perceptron architecture (3-LP) where the three layers are: the input layer with input variables, the hidden layer (to perform non-linear mappings) and the output layer (reproduced values of the target variables). The hidden layer increases the learning power of the 3-LP. This architecture is able to reproduce non-linear data, without a-priori assumptions. 3-LP consists of two different phases: training of the network and running through the trained net.
Training phase proceeds initializing the weights in the network to small random values. The output from any neuron is the product of its input and a weighting. Given any input pattern, the 3-LP produces a set of output values that, via the transfer function, are then fed to neurons in the following layer.
A procedure which minimizes the difference between target variable and its model reproduction, is applied in order to obtain the best network. This procedure is achieved by tuning network parameters such as learning rules and activation functions.
The obtained best network is then used for the running phase using as input a new data set without the target variable that instead has to be forecast. The goodness of results depends on the type of input parameters selected and on the ability to choose a proper training data set which contains all meaningful situations in the studied process.
The model implementation has been done using the SPSS package Neural Connection (SPSS, 1999). It is a software system that allows to build applications for solving complex and/or non-linear problems using neural computing.

4 Modeling setup

Since the modeling procedure consists of two different phases, training and running, a proper data set must be chosen. For the training phase, five days of August were selected, namely August 10, 11, 13, 28, 31 for a total of 240 records. The first two days were selected because they contain all three recognized wind regimes. August 13 and 28 were chosen due to their belonging to episodic partially cloudy days. On such conditions weaker convection is revealed which is better monitored by a lower vertical wind variance and surface vertical temperature gradient. August 31 was selected because a passage of a front was monitored which is characterized by cloudy conditions with high wind speed (up to 7 m/s) and lower temperature gradient (up to -0.033 °C/m). In this day mechanic turbulence dominates in the atmosphere. Even a low-level jet was revealed in the same day. These five days should guarantee that all possible meteorological phenomena, occurring in the analyzed month, are considered, which in turn should undertake a proper data selection for the 3-LP learning phase.

As far as the modeling of PBL turbulence is concerned, the parameter used as input for the 3-LP model should contain the actual information which is required to describe the turbulence processes. Furthermore in order to keep the number of input parameters as low as possible and widely available to any meteorological station, some important meteo parameters, such as vertical wind speed (w), its variance (σ_w) and vertical wind speed gradient (du/dz), haven't been selected as input. Among the available measured variables, wind speed (u), standard deviation of wind direction (σ_θ), air temperature (T), solar global radiation (SGR) and surface temperature gradient (dT/dz) were selected as model input. Standard deviation of wind direction and vertical temperature gradient are usually considered to evaluate the atmospheric stability (Zannetti, 1990). Wind speed has been considered due to its high correlation with mechanical turbulence, while temperature and solar global radiation are indicators of free convective conditions when buoyancy term of turbulence kinetic energy (*TKE*) dominates with respect to mechanical one.

As target (or output) variables Obukhov length L, turbulence kinetic energy *TKE,* sensible heat flux H and friction velocity u_*, were assumed during the learning phase and reproduced at running time.

For the running phase we have used 20 days of August for a total of 960 records.

To optimize the target variables prediction we trained four different 3-LPs, one for each target variable.

First network reproduces $1/L$ using 7 neurons in the hidden layer and the Hyperbolic Tangent as activation function. The latter provided best results with respect to Sigmoid Function, conventionally used.

The other three 3-LP architectures, reproducing *TKE*, H and u_*, have respectively 7, 10 and 9 neurons in the hidden layer, and utilize the Sigmoid as activation function.

5 Results and discussion

The modeled turbulence variables ($1/L$, *TKE*, H, u_*) are presented on Figures 1 a, b, c, d respectively. In general they show good agreement with correspondent observed values.

In order to quantify the degree of reproducibility, the statistical indexes Normalized Bias (*nbias)*, Normalized Mean Square Error (*nmse)* and R^2 were used. Their values are shown on Table1.

Table 1 Statistical indexes.

	1/L	*TKE*	H	u_*
nbias	0.59	0.01	0.08	0.02
nmse	14.28	0.09	0.44	0.18
R^2	0.3	0.9	0.9	0.6

On the average the $1/L$ results exhibit an overestimation with poor values of R^2 and *nmse*. Comparison between observed and modeled values is shown on Figure 1a. The model is able to reproduce both nighttime stability (L>0) and daytime instability (L<0) values except in some extreme situations. As far as the degree of stability/instability of the atmosphere is concerned, we are not interested in an exact prediction of $1/L$. On the contrary it is important that, during daytime and nighttime, the predicted $1/L$ lie within a specific interval which characterize atmosphere stability. According to this evaluation methodology we should consider that $1/L$ prediction is good. Furthermore we have to highlight that observed $1/L$ values are based on gradient Richardson number R_i. The latter is estimated as a function of temperature and wind speed vertical gradients, where only the former is included as input to 3-LP model. So, probably the predictions could suffer of this lacking.

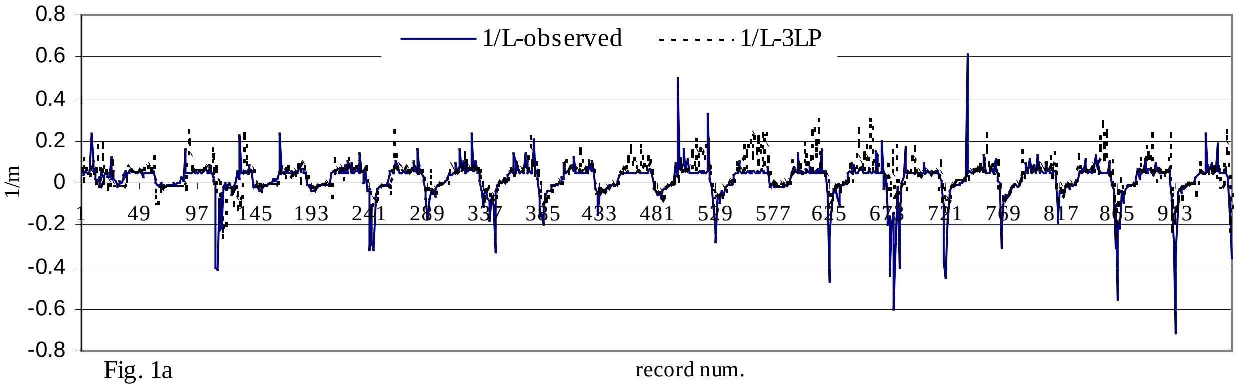

Fig. 1a

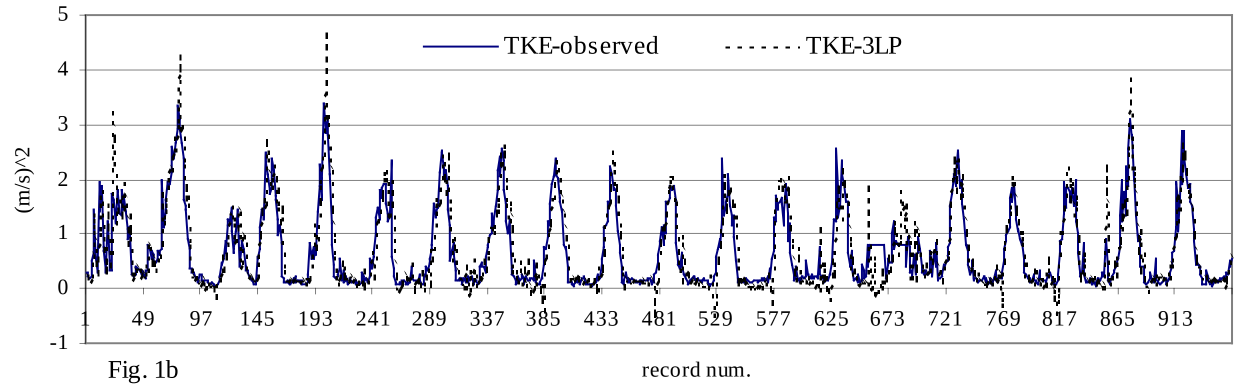

Fig. 1b

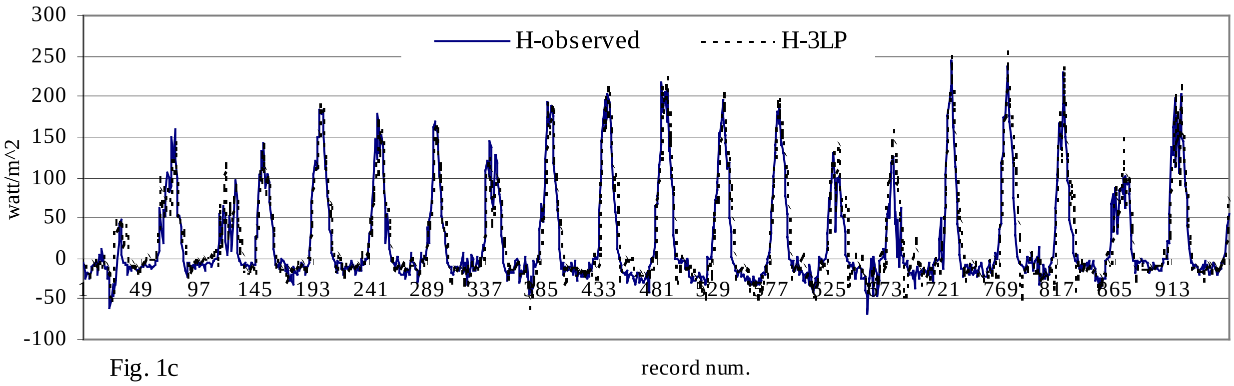

Fig. 1c

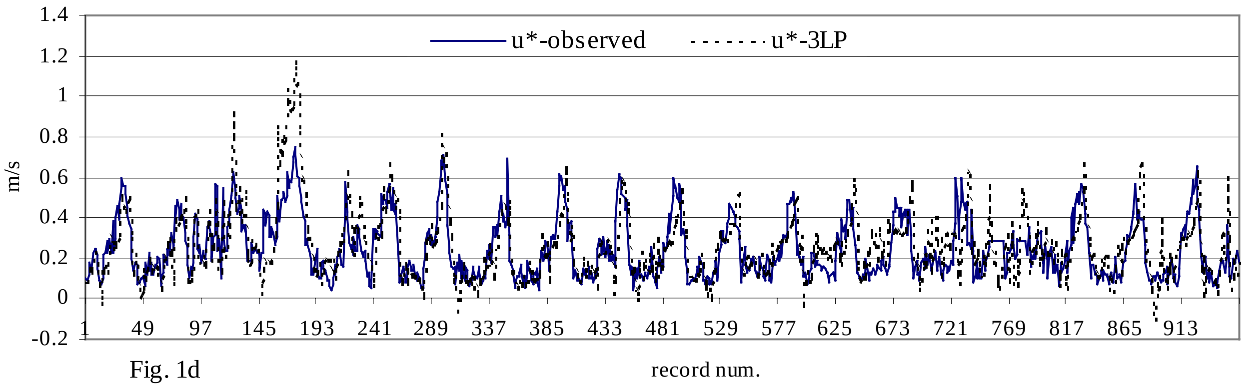

Fig. 1d

Figure 1 a, b, c, d: observed and reproduced turbulence parameters during 20 days of August 2000 (960 records).

TKE predictions are close to the perfect value. The reproduction of the observed values is very good both on peak and valley data. Episodic overestimation of peak values is sometimes present though on average the prediction is very good as shown by the *nbias*, *nmse* and R^2 values. This best result can be explained by a good choice of input parameters, in particular the wind speed which has an high degree of correlation with *TKE*.
The *H* results are shown on Figure 1c. Daylight and nighttime cycles are well reproduced. As for *TKE*, the statistical index values are good though *nmse* is one order of magnitude higher. It's important to highlight that on both sunny and cloudy days the modeled *H* values are in agreement with the observed values. A light overestimation is seen as well.
The u_* results are a bit worse than to *TKE* and *H*. While *nbias* is good, *nmse* shows that model results are sometimes a bit different from the observed values. In fact looking at the Figure 1d, either under or overestimation is occasionally recognized. This is also confirmed by a lower R^2 value.

6 Conclusion

Turbulence parameters can be derived by turbulence fluxes analysis using sophisticated and expensive instruments such as ultrasonic anemometer, often not available at conventional meteorological stations.
In order to overcome this problem a 3-LP model has been used to derive these parameters starting from conventional meteo data. Results demonstrate that 1/*L*, *TKE*, *H*, and u_* can be calculated with reliable accuracy, using application of the 3-LP to improve the capabilities of conventional meteorological stations and providing an estimation of turbulence parameters otherwise not available.

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