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A neural-network approach to radon short-range forecasting from concentration time series

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Summary. — The relevance of particulate radon progeny measurements for an estimation of the mixing height was recently established. Here, an attempt at a short-range forecast of radon concentration is presented using a neural-network model applied at a 2-hour based time series. This forecasting activity leads to useful predictions of the mixing height during stability conditions.

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1. – Introduction

Since late 70s, Fontan, Guedalia and co-workers recognised the relevance of radon progeny measurements to establish an index of the diffusion properties of the boundary layer [1-3]. More recently, an estimation of the mixing height through a box model using radon concentration data was successfully performed during stability conditions [4]. Furthermore, some qualitative relationships between radon concentration and the height of the mixed layer were shown also in advective situations [5].

Several groups performed new measurement campaigns during the last years, especially stressing observational features (vertical distribution, radon exhalation, etc.) [6-9]. Here, instead, we present an attempt at forecasting radon concentration by means of a neural-network model, in order to obtain useful short-range predictions of the mixing height through application of the cited box model.

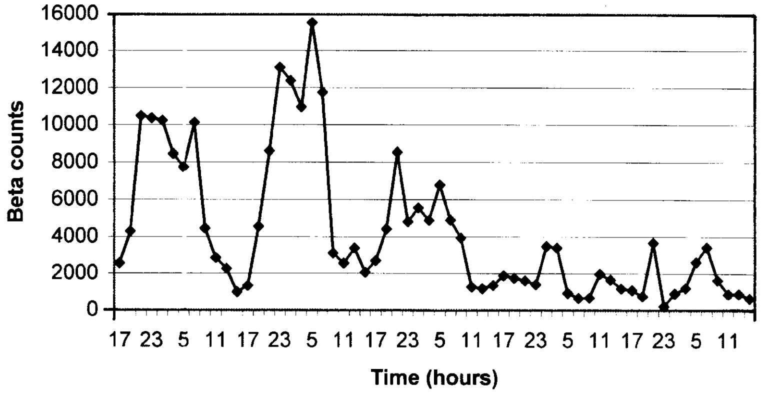

Fig. 1. – A subset of the 2-hour time series (3 October (h. 17)–8 October (h. 15) 1997). Note the transition from a stable condition to a moderate advective situation (after 5 October, 9 a.m.).

2. – Data set

The data set used in our analysis comes from a 1-year monitoring activity (1 January–31 December 1997) of radon detection on a 2-hour basis at Pratica di Mare, a site near Rome and very close to the Tyrrhenian Sea. The instrument used was a prototype similar to the ADM 9000 [4], specifically developed by CNR-IIA. This is a beta gauge monitor, which samples particulate on membrane filters and detects the short-lived radioactivity associated with particles by means of a Geiger-Müller detector.

3. – Brief statistical considerations

As in other studies (see, for instance, [10]), our time series of beta counts (directly proportional to radon concentration) shows the typical pattern with maxima and minima during stability conditions, due to the diurnal thermal cycle, and an asymptotic quasi-constant *plateau* during advective episodes (see fig. 1). Furthermore, an accurate analysis of our time series leads to recognise frequent bimodal structures in the nocturnal maxima and a Fourier analysis allows us to reveal the 24-hour peak of the diurnal cycle, but also several further peaks in the spectrum (see fig. 2), a clear sign of high-frequency periodicities. At the present stage of our study we are not able to determine the processes responsible for these further peaks, even if they should be identified in those physical processes in the PBL endowed with short evolution time.

Finally, an autocorrelation analysis shows that data at t: $\Delta t = t_0 - t = 20, 22, 24, 26,$ 28 hours reveal good correlation with data at time t_0. They are characterised by high-correlation coefficients, substantially comparable with those related to t: $\Delta t = 2, 4, 6$ (see fig. 3). In particular, this confirms the periodicity of 24 hours.

4. – Neural and box models

The ability of neural networks to grasp the dynamical content hidden in a time series was extensively recognised in several fields (see [11] for a general reference). Recently, attempts at neural forecasting applied to time series of atmospheric variables appeared in the literature [12, 13]. Due to the features briefly discussed in the previous section,

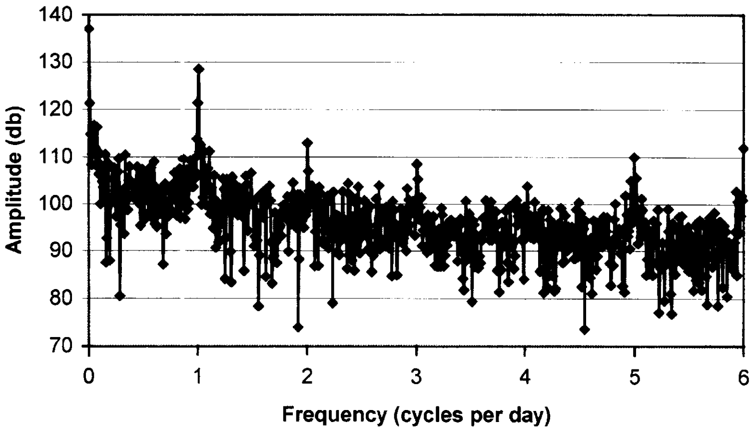

Fig. 2. – Fourier spectrum of our time series.

in particular the evidence of a complex dynamical content in our data, it is interesting to test the ability of a neural network in forecasting radon concentration (some steps ahead). Soon afterwards, the results of this forecasting activity will be used as inputs for the box model described in [4], in order to obtain useful short-range predictions of the height of the nocturnal stable layer.

The neural model used in the present application was extensively described in [14]. Here we stress that in our model we use a feed-forward neural network with standard back-propagation training and weight updating, performed *via* a generalised Widrow-Hoff rule containing both gradient descent and momentum terms (see [15, 16] for general introductions to this kind of networks).

Unlike our previous application (see, for instance, [14]), when we used input patterns coming from a synchronous set of meteorological observations, in the present approach time-delayed truncated series of radon data are considered as input patterns, in order to test if the information contained therein is sufficient for allowing good forecasts in this particular problem. The alternative multivariate approach used in [14], when the input represents an "initial state" of the PBL formed by several variables at the same

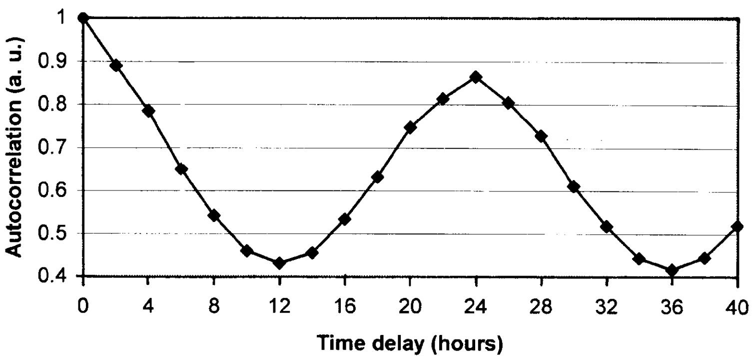

Fig. 3. – Autocorrelation graph.

time t_0, is now under test for radon forecasting and the results of its implementation will be presented in a forthcoming paper. Furthermore, due to the recognition of a seasonal change effect on forecasting results, in the present attempt we use a moving window training, as in [14]. Here, we fix a "2-month memory" of training cases and update it at every new forecast, thus limiting the training to the same "season" of any forecast case.

As far as the box model using radon concentration data is concerned, its comprehensive description and application in order to estimate the height of the nocturnal stable layer are presented in [4]. Here, we remember that, under some simplifying hypotheses (valid for periods of nocturnal stability), the model allows us to estimate an equivalent mixing height h_e that was shown to be strongly correlated with an independent meteorological estimation of the mixing height, thus giving us a new method for monitoring the nocturnal stable layer depth. The equivalent mixing height at the time t can be estimated by the relation

$$h_\mathrm{e}(t) = \frac{\Phi \Delta t}{C(t) - C_0}, \tag{1}$$

where Φ is the radon flux at the surface, Δt is the time from the start of the accumulation, $C(t)$ is the radon concentration at time t and C_0 is the radon concentration at the beginning of accumulation. At present, a consistent effort is devoted to improve this model by considering some effects previously neglected, such as radon decay and entrainment from the top of the box in cases of nocturnal fluctuations. This improvement leads to a better estimation of nocturnal PBL depth fluctuations, whose fingerprint is very evident in radon patterns as well as in the concentrations of several pollutants [17].

5. – Results

When dealing with multi-layer neural-network models, an important activity is the choice of the optimal architecture, both in terms of number and kind of inputs and in terms of number of hidden neurons and layers. The aim is to choose a topology which leads to a good representation of the underlying function that we want to reproduce and, at the same time, allows us to avoid the phenomenon of overfitting, often using an early-stopping method, too. Here, for lack of space, we do not discuss about this activity, but present directly the optimal architecture found for our forecasting problem.

After several attempts and following theoretical and empirical rules (see [18] for a review of such methods), we chose a network endowed with one hidden layer with 8 neurons, one output neuron and N inputs in the input layer (N chosen as the number of delayed data with a correlation higher than 0.65 in the autocorrelation graph). An early-stopping rule was also applied, in order to prevent overfitting.

In order to test the forecasting performance of the model, we calculate the linear correlation coefficient R between observed and forecast data and a Generalisation Coefficient (GC), calculated as follows (see [14]: now we have only one output unit):

$$\mathrm{GC} = 1 - \sqrt{\frac{\sum_{\mu=1}^{M} [(O^\mu - T^\mu) - \overline{(O^\mu - T^\mu)}]^2}{M}}, \tag{2}$$

where M is the total number of test patterns, O^μ and T^μ are the output (forecast value) and the target (verification value: detected) respectively, for every pattern μ, and

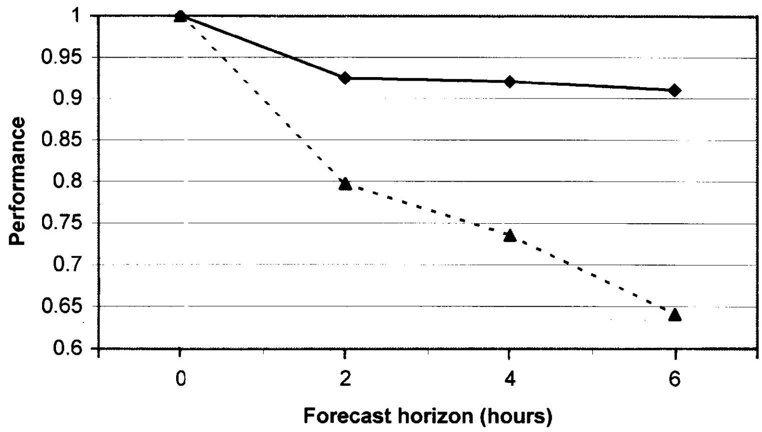

Fig. 4. – Performance of the neural model on the test set (1 March–31 December 1997) as the forecast horizon increases: in terms of GC (solid line) and R (dotted line).

$\overline{(O^\mu - T^\mu)}$ is the systematic error of the network (usually very low). Note that, as usual in neural modelling, input, target and output values are normalised between 0 and 1. Therefore, $0 \leq \mathrm{GC} \leq 1$ and the closer it is to 1, the better are the forecasts of the neural network.

The performance of neural forecasts is presented in fig. 4 for 3 steps ahead ($t+2$, $t+4$ and $t+6$ hours). Each forecast is obtained by a long step method, and for the second and the third step we directly forecast radon concentration starting from purely detected data. An alternative recursive method, performing always a $t+2$ hours forecast, *via* insertion of forecast values into the input patterns for the $t+4$ and $t+6$ hours forecast, leads to lower performance in our case, as also properly supposed from theoretical considerations [19].

These results bear witness to the good general forecasting properties of our model, of course with a moderate decrease in performance as the time horizon increases. Furthermore, a more accurate analysis leads to recognise a satisfying behaviour even in specific cases of physical relevance as shown in fig. 5, where one can see as nocturnal fluctuations are correctly grasped by the model.

Finally, for the stability periods shown in fig. 5, an estimate of the nocturnal value of h_e has been calculated by means of the box model previously described, both from detected and forecast values of concentration. The relevance of this model for a correct estimation of the nocturnal mixed layer depth from detected values was shown elsewhere [4]. Here, the calculation of h_e from forecast values shows that it is possible to obtain a useful forecast of this variable by means of application of neural and box models (see fig. 6).

As a preliminar comment to this figure, we can say that the range of nocturnal fluctuations, even in the estimations from detected radon values, seems sometimes too wide for physical consistent oscillations of the stable layer depth: this effect is due to the simple form of the box model adopted here and it is greatly reduced in applications of a refined model (now under development [17]), where radon decay and entrainment from the top of the box are included in its theoretical formulation. In spite of this, qualitatively the patterns of nocturnal fluctuations are well predicted, even if sometimes with amplitudes different from those estimated by measures. Furthermore, due to its structure, the box model is more sensitive to errors of the neural model in predicting medium-low radon

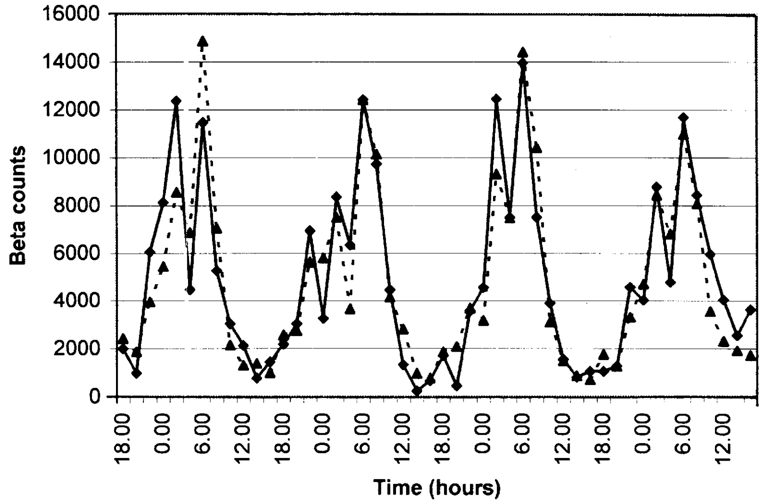

Fig. 5. – Detected data (solid line) *vs.* forecast data (dotted line) for the period 9–13 September 1997.

concentrations, rather than to errors in the range of high radon concentration values. Therefore, while there are some discrepancies in the results for high values of h_e, the most acute episodes (very low h_e) are always well forecasted.

6. – Conclusions and perspectives

Following previous works [1-5], which claim the relevance of radon progeny measurements for estimating the physical features of the PBL and, in particular, the nocturnal stable layer depth, in this note we present an original application of a neural-network model to evaluate short-range forecasts of radon concentration at the surface. Accord-

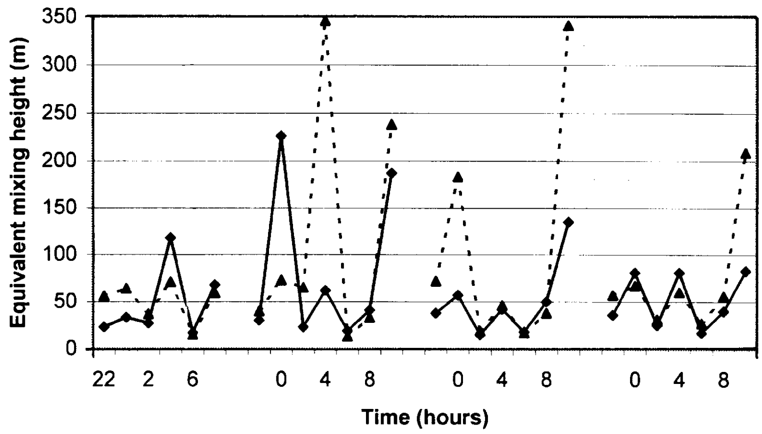

Fig. 6. – Nocturnal Equivalent Mixing Heights as calculated by the box model using detected data (solid line) and forecast data (dotted line).

ingly, the obtained results are encouraging and, after the further application of a box model, lead to accurate short-range forecast of the nocturnal mixed layer depth.

We have shown that our time series of radon concentration on a 2-hour basis contains sufficient information for its short-range forecasting. Nevertheless, as a perspective of further studies, attempts at including other physical observations (related to the boundary layer) into the input layer seem to be promising for better characterise the initial state of the PBL and in order to achieve more accurate forecasts.

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