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Development of a mobile dose prediction system based on artificial neural networks for NPP emergencies with radioactive material releases

Claudio M.N.A. Pereira [a,*], Roberto Schirru [b], Kelcio J. Gomes [a], José L. Cunha [b]

[a] Comissão Nacional de Energia Nuclear – IEN/CNEN, Rua Helio de Almeida, 75, Ilha do Fundão, 21941-906, Rio de Janeiro, Brazil
[b] Universidade Federal do Rio de Janeiro – PEN/COPPE/UFRJ, Ilha do Fundão, 21941-901, Centro de Tecnologia, Rio de Janeiro, Brazil

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ABSTRACT

This work presents the approach of a mobile dose prediction system for NPP emergencies with nuclear material release. The objective is to provide extra support to field teams decisions when plant information systems are not available. However, predicting doses due to atmospheric dispersion of radionuclide generally requires execution of complex and computationally intensive physical models. In order to allow such predictions to be made by using limited computational resources such as mobile phones, it is proposed the use of artificial neural networks (ANN) previously trained (offline) with data generated by precise simulations using the NPP atmospheric dispersion system. Typical situations for each postulated accident and respective source terms, as well as a wide range of meteorological conditions have been considered.

As a first step, several ANN architectures have been investigated in order to evaluate their ability for dose prediction in hypothetical scenarios in the vicinity of CNAAA Brazilian NPP, in Angra dos Reis, Brazil. As a result, good generalization and a correlation coefficient of 0.99 was achieved for a validation data set (untrained patterns). Then, selected ANNs have been coded in Java programming language to run as an Android application aimed to plot the spatial dose distribution into a map.

In this paper, the general architecture of the proposed system is described; numerical results and comparisons between investigated ANN architectures are discussed; performance and limitations of running the Application into a commercial mobile phone are evaluated and possible improvements and future works are pointed.

1. Introduction

The prediction of spatial dose distribution due to an atmospheric dispersion of radionuclide is key to support decision makers guiding people and environment protection during a Nuclear Power Plant (NPP) emergency with radioactive material release. Such task involves simulation of complex and computationally expensive physical models, such as: source term prediction, wind field calculations, plume dispersion, radionuclide deposition and equivalent doses prediction. The quality of such simulations depends on how realistic and refined are the computational models. However, to achieve the adequate quality, powerful computers are required.

In this work, we propose an approach aimed to give extra support to emergency field teams when the communication with the NPP information systems is not available. The idea is to provide handheld approximate prediction of spatial dose distribution based on typical accident situations (plant status, release paths and inventory) and current meteorological conditions. To overcome the need for huge computational efforts, allowing systems execution on limited resources hardware, such as mobile phones, the precise dedicated NPP atmospheric dispersion system is substituted by a set of artificial neural networks (ANN) (Hayking, 1999) previously trained.

The ANNs are trained offline, using data generated by precise realistic simulations using the NPP atmospheric dispersion system. Then, trained ANNs are integrated into an Android application, allowing it to run on commercial mobile phones.

The main objectives of this work are the following:

i) describe the general system's architecture and functionalities;
ii) evaluate the efficiency of different ANNs architectures in learning and its accuracy in dose prediction;

* Corresponding author.
E-mail addresses: cmnap@ien.gov.br (C.M.N.A. Pereira), schirru@lmp.ufrj.br (R. Schirru).

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iii) investigate appropriated training dataset selection and preprocessing;
iv) evaluate the performance of running the proposed system as an Android application on a commercial mobile phone.

To accomplish that, several ANN architectures have been investigated in order to evaluate its efficiency in learning and accuracy in the prediction. Selection and preprocessing of an appropriate training dataset has also been studied. Once trained, selected ANNs were integrated into the mobile dose prediction Android application and their performance were evaluated.

The remainder of this paper is organized as follow. Section 2 presents related works and contextualization. Section 3 describes the process of dose prediction and the NPP atmospheric dispersion system used in this work. An overview of the proposed approach is described on Section 4. Section 5 details the development and evaluation of several ANN architectures and their integration on an Android application. Finally, concluding remarks are presented in Section 6.

2. Related works and contextualization

In this section is focused on contextualizing two main features proposed in this work, which are: i) use of ANNs in radiation and atmospheric dispersion prediction; and ii) mobile support systems for NNP emergency. Some important works about these issues are, therefore, comment here.

2.1. ANNs in radiation prediction and atmospheric dispersion modeling

Nowadays, a wide variety of ANN applications are found in almost all fields of knowledge, including nuclear engineering. This section, however, has the focus on ANN applications on radiation predictions and atmospheric dispersion modeling.

Timonin and Savelieva (2005) applied General Regression Neural Networks (GRNN) for spatial predictions of radioactivity, concluding that GRNN is a promising tool for automatic spatial prediction of radioactivity in both routine and emergency situations.

Mól et al. (2011) also applied a GRNN for dose prediction in the area of the Argonauta research reactor located at Intituto de Engenharia Nuclear/CNEN (Brazil). In this work, prediction was done as a function of reactor operating power and spatial position (x, x).

Sarwat and Helal (2013) proposed the use of a GRNN for estimating radiation workers internal dose. They pointed to GRNNs as good ANN for continuous functions mapping and concluded that they have good possibilities in the proposed application.

Cao et al. (2010) applied ANN in prediction of short-term concentration distributions of aerosols released from point sources. He concluded that the performance of the neural network model was comparable or better than predictions from two Gaussian-based puff models.

Lauret et al. (2013), investigated the use of ANN in atmospheric gas dispersion concluding that the stationary ANN model gave good agreement with CFD software with the advantage of faster processing.

Hossain (2014) applied ANN to predict concentration of carbon monoxide and particulate matters in urban atmospheres using field meteorological and traffic data. The conclusion was that ANN models based on both meteorological and traffic variables are capable of resolving patterns of pollutant dispersion to the atmosphere for different cities.

2.2. Mobile support systems for NNP emergency

Mobile monitoring systems as well as mobile communication systems are widely used by emergency teams. However, the use of mobile apparatus such as smart-phones to run decision support systems is still uncommon.

Silva et all 2013 developed a system to support first responders to deal with radiological emergencies using cognitive task analysis techniques. According to the authors, the main benefits are the overall control of the response, more instantaneous updates of information, and their verification, and agility to conduct the response.

Maybe until now, decision support systems based on smart-phones are underutilized in nuclear industry, however, due to the exponential evolution of such "mobile computers", authors believe it will grow very fast and sooner.

3. Dose prediction and the NPP atmospheric dispersion system

Dose prediction due to atmospheric dispersion of NPP releases are made by means of dedicated systems (Atmospheric Dispersion Systems – ADS), comprised by complex physical models which generally run on powerful computers.

This work considers, as reference, the ADS used in Brazilian CNAAA NPP (SCA, a Portuguese abbreviation meaning Environmental Control System). The SCA is basically comprised by 4 modules: i) Source Term prediction module; ii) Wind Field module; iii) Plume Dispersion and dose calculation module; iv) Plume Projection module. Fig. 1 shows a simplified schematic diagram of SCA.

The Source Term module receives information about the NPP status (including monitored process variables, accident diagnosis and inventory) and calculates the amount and rate of nuclear material released (source term). The Wind Field module uses topographical and meteorological information to produce a divergent-free wind field. Then, the Plume Dispersion module uses the outputs of Source Term and Wind Field modules to simulate the plume dispersion and calculate equivalent doses. The Plume Projection module makes projections of the plume dispersion for 1 and 2 h after accident start.

4. The mobile dose prediction system

The proposed mobile approach for dose prediction is primarily designed for standalone operation, in other words, it must be able to work without any network connection. The system must give an approximate spatial dose distribution considering the following information:

i) current accident (previously identified): variable as input;
ii) meteorological conditions: variable as input;
iii) time after accident starts: variable as input;

To accomplish that, a set of ANNs is developed and trained, for each postulated accident, considering a wide range of meteorological conditions. The training dataset is generated by simulations using the precise NPP ADS, shown if Fig. 1.

4.1. The ANN architecture

In order to enhance performance in the learning process, 4 ANN have been used for each postulated accident. Each one is applied for a specific range of wind direction (North-ANN, South-ANN, East-ANN and West-ANN). Fig. 2 shows the scope of prediction of each one. The doted rectangle limits the area of training data, while the angle marked in bold black lines defines the range of wind directions preferable to the specific ANN. For example, the North-ANN is trained with dose distribution in the upper part of the map and its scope of application is for winds which directions

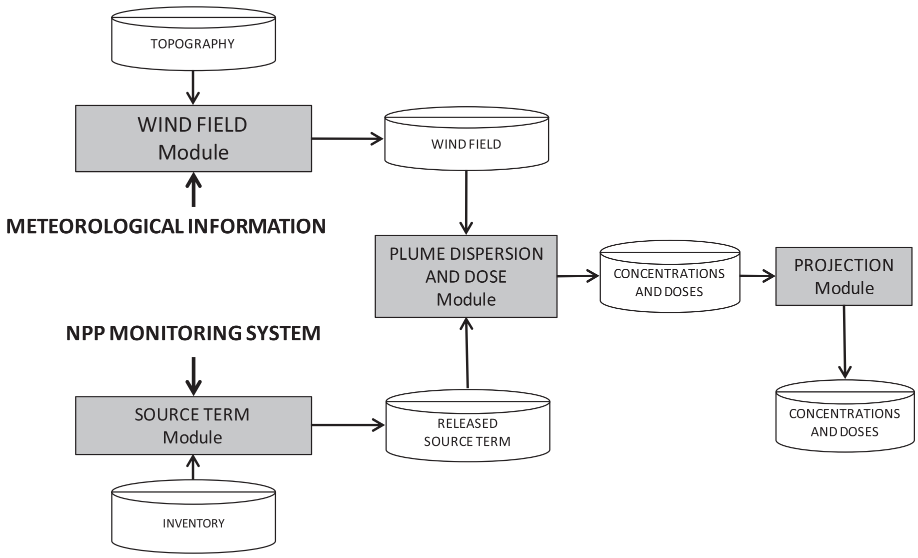

Fig. 1. Schematic diagram of the ADS used in this work.

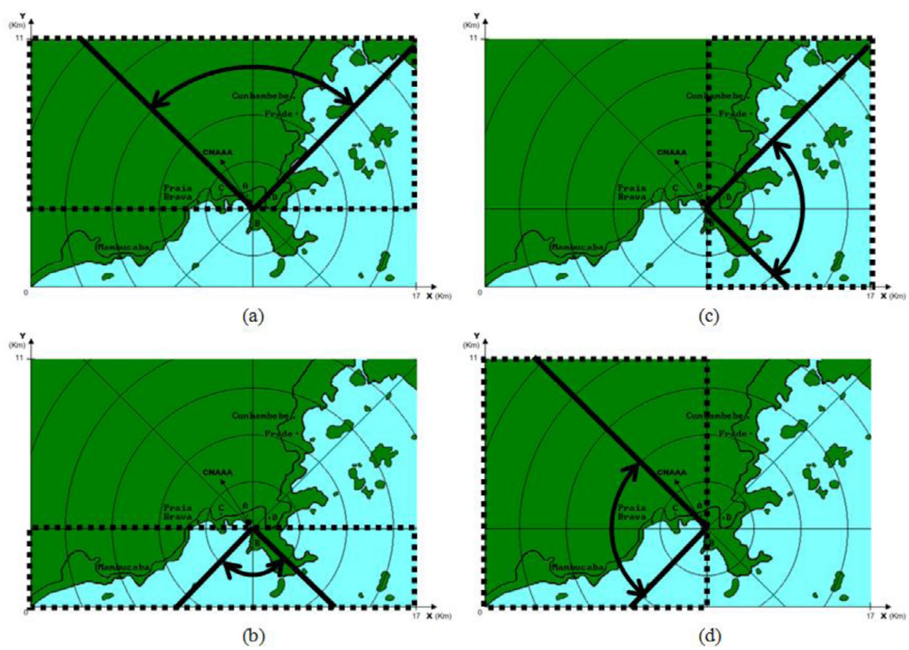

Fig. 2. Scope of prediction of each ANN: a) North-ANN; b) South-ANN; c) East-ANN and d) West-ANN.

range from 315° to 45° (OBS: the North axis is the 0° direction and the angles increase clockwise).

Each ANN is trained to predict doses based on spatial position (X, Y) and meteorological conditions. Many meteorological conditions could be used as input, such as: i) wind velocity; ii) wind direction; iii) wind stability; iv) temperature; v) temperature gradient; vi) rainfall index; among others. Similarly, several possible outputs could be used: i) equivalent doses; ii) effective doses; iii) dose rates etc. However, in this work a reduced set is used to illustrate and validate our approach. As a preliminary investigation, the variables in Table 1 have been used as ANN inputs/outputs.

Fig. 3 shows the ANN approach proposed. According to the identified accident and the wind direction, the control module decides

Table 1
ANN inputs and output.

Inputs	Wind velocity
	Wind direction
	Position X
	Position Y
Output	Dose rate

Table 2
Ranges and distribution of training set.

Name	Range	Values	Step
Wind velocity (m/s)	1–5	5	1
Wind direction (degrees)	135–225	5	22.5
Position X	1–65*	17	4
Position Y	10–42*	9	4

* Computational domain is discretized into 65 × 42 cells of 250 × 250 m.

which ANN will be applied. Then, the inputs are passed to the ANN chosen and it is fired, producing the predicted dose rate as output.

Note that a single dose rate is output. In order to reconstruct the spatial dose distribution, the ANN must be executed for each spatial position.

4.2. The mobile dose prediction application

At the present stage of our research, we are focused in evaluating the accuracy of the prediction and the performance/limitation of running such system on commercial smart-phones. To accomplish that, a simple Android based prototype have been developed, comprising basically one view, in which user can input the current accident and meteorological information and visualize, as output, the dose distribution map. Fig. 4 shows the proposed Users' Interface (UI).

As input, the user must chose: i) the accident in course; ii) the kind of dose/dose rate to be predicted; iii) time after accident starts; iv) wind direction and v) wind velocity. Note that 4 inputs are considered for the ANNs: wind direction, wind velocity and position (x, y). Due to the size of the dataset required to train and test the ANNs (described in Section 5.2), at this point of our research, the time after accident starts is not considered as ANN input (it would increase the dataset by at least 5 times). So, a separate ANN is trained for each time-step of 15 min. Future work may investigate the introduction of this variable. Our expectation is that deep learning and parallel training algorithms shall be required.

After choosing the input information and clicking button "Predict", the adequate ANN is chosen and fired for each cell of the computational domain (2881 position in the map). The generated dose distribution is then plotted on the map. The application also comprises some other functionalities, such as: i) showing the current position and dose of the user and ii) showing the dose on a clicked position of the map.

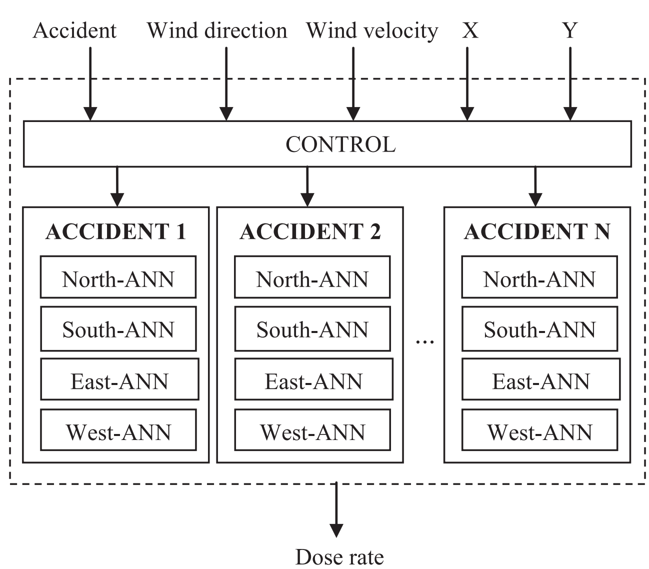

Fig. 3. The ANN approach.

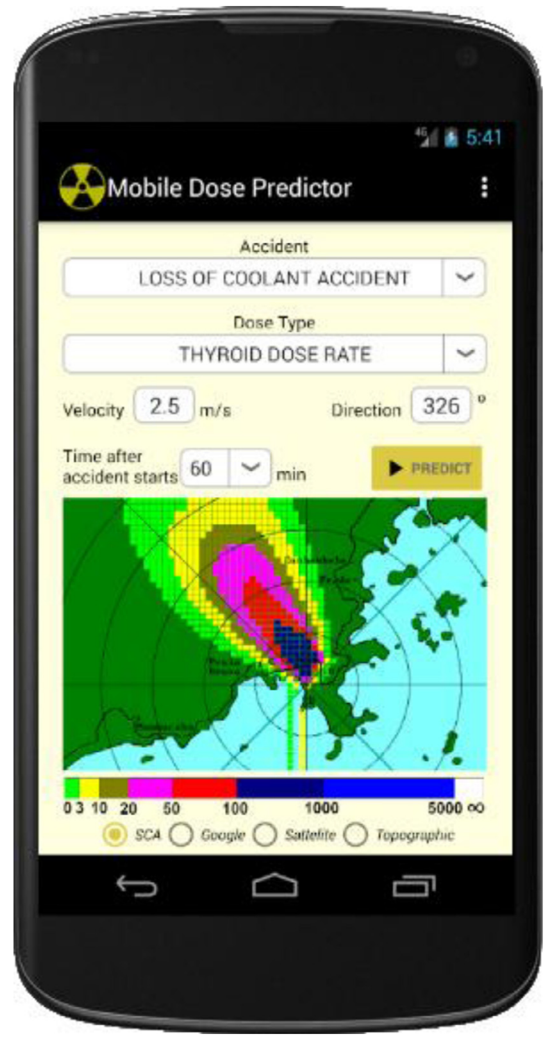

Fig. 4. Prototype of the mobile dose prediction applet.

5. Artificial neural networks design and application

5.1. Artificial neural network architectures

Artificial neural networks (ANN) [1] are mathematical models inspired in the human brain, which have the ability of learning by examples. There are many different approaches for ANNs. In this work, we consider those that use supervised learning (input/output learning) and are skilled for interpolation and prediction. According to literature, Backpropagation Multilayer Perceptrons (MLP) [1] and General Regression Neural Networks (GRNN) [2] present such characteristics.

It is well-known the ability of backpropagation MLPs for generalization and prediction, however, training might be very time-consuming. On the other hand, GRNNs are fast to train and are pointed in literature (Timonin and Savelieva, 2005) as promising tool for spatial prediction of radioactivity. Preliminary comparative work (Pereira et al., 2016) ratified this points. In that work, a 5-layers MLP was presented the best accuracy while the GRNN presented slightly worst results but with a very faster training. In that work the 3-layers MLPs were the worst ones. Hence, in the present work, we emphasize investigations on GRNN and 5-Layers MLP in order to improve them to be used in the mobile dose prediction system.

5.1.1. Backpropagation Multilayer Perceptrons

Backpropagation Multilayer Perceptrons (MLPs) are ANN comprised by layers of neurons, in which the input signals always propagates forward, from input to output. They present: i) an input layer, which receives the input data, ii) an output layer, which provides the ANN output and iii) one or more hidden layers. The number of neurons in the input layers is equal to the number of inputs of the problem. As well, the number of neurons in the output layer is equal to the number of outputs. The number of neurons in the hidden layer(s) is flexible and is responsible to provide the ability of non-linear adaptation of the ANN. The activation function of neurons may be non-linear (generally logistic or tanh) for complex adaptations. The training algorithm used is the backpropagation [1], which is a gradient-descendent algorithm aimed to minimize the ANN squared error by tuning the synaptic weights iteratively as the training patterns are presented. The training may be very time-consuming according to the number of patterns, complexity of the correlations and number of neurons.

5.1.2. General Regression Neural Network

Preliminary investigations were done in order to select an adequate ANN architecture and training strategies. Several multi-layer perceptrons (MLP) architectures with backpropagation training algorithms were tried without success. The General Regression Neural Network (GRNN) (Specht, 1991) optimized by Genetic Algorithm (GA) (Goldberg, 1989) produced, by far, the best results. This observation agrees with literature, in which some authors (Timonin and Savelieva, 2005; Mól et al., 2011 and Sarwat and Helal, 2013) also used GRNN due to its skill for estimation of continuous variables.

According to Specht (1991), GRNN is "a memory-based network that provides estimates of continuous variables and converge to the underlying (linear or nonlinear) regression surface". It uses a one-pass learning algorithm that provides smooth transitions between training patterns even with sparse data in multidimensional spaces.

The GRNN uses the concepts of consistent estimators proposed by Parzen (1962). The estimated output (Eq. (1)) is a weighted average of all training patterns.

$$\hat{Y}(X) = \frac{\sum_{i=1}^{n} Y^i \exp\left(-\frac{D_i^2}{2\sigma^2}\right)}{\sum_{i=1}^{n} \exp\left(-\frac{D_i^2}{2\sigma^2}\right)} \tag{1}$$

$$D_i^2 = \left(X - X^i\right)^T \left(X - X^i\right) \tag{2}$$

where $\hat{Y}(X)$ is the estimated output; X^i and Y^i are the training patterns inputs and outputs, respectively; X is an observed value to which an estimation is required; and σ is the smoothing factor.

High values of σ leads to more smooth function. To find optimum value for σ, optimization procedures can be used in order to minimize the least squared errors for a test set. In this work a Genetic Algorithm (GA) (Goldberg, 1989) have been used.

5.2. Training, test and production dataset preparation

All training, test and production patterns were generated using the CNAAA NPP atmospheric dispersion system, which (in simulation mode) can be used to simulate customized scenarios for the whole set of postulated accidents and observed meteorological conditions. Tables 2 and 3 show the ranges and distribution of each variable of training and test sets.

In order to test the ANN with patterns different from those used in training and test set, a wide production dataset was generated uniformly spread along the computational domain. The total number of patterns generated for each usage is shown in Table 4. These patterns comprise more than 80 plumes (dose distribution maps) generated in the simulator.

In order to improve the ANNs efficiency in learning the training patterns, data have been normalized according to Eq. (3).

$$X_N = \frac{(X - \overline{X})}{S}, \tag{3}$$

where X_N is the normalized value; X is the original value; $\overline{X}$ is the average and S is the standard deviation.

Table 3
Ranges and distribution of test set.

Name	Range	Values	Step
Wind velocity (m/s)	1.5–4.5	4	1
Wind direction (degrees)	146–214	5	22.5
Position X	1–65*	17	4
Position Y	10–42*	9	4

* Computational domain is discretized into 65 × 42 cells of 250 × 250 m.

Table 4
Quantity of training, test and production patterns.

Usage	Quantity
Training	3825
Test	2448
Production	6120

Table 5
ANN characteristics.

ANN architecture	Characteristics
GRNN	- Layers: 4 - Input layer: 4 neurons (distribution) - Pattern layer (hidden): 3825 neurons (Gaussian) - Summation layer (hidden): 2 neuron (sum) - Output layer: 1 neuron - Smoothing factor optimization: genetic algorithm
5L-MLP	- Layers: 5 - Input layer: 4 neurons (linear) - Hidden layer 1: 40 neurons (logistic) - Hidden layer 2: 40 neurons (logistic) - Hidden layer 3: 40 neurons (logistic) - Output layer: 1 neuron - Training: backpropagation

Table 6
Statistics of the GRNN training.

	Training set	Test set	Production set
Number of patterns	3825	2448	6120
Mean absolute error	0.011	1.810	1.217
Max absolute error	1.088	74.060	98.538
Correlation coefficient	1.0000	0.9822	0.9882
Generations (population = 20)	31		
Training time	00:19 h		

Table 7
Statistics of the 5 L-MLP training.

	Training set	Test set	Production set
Number of patterns	3825	2448	6120
Mean absolute error	0.691	1.113	1.050
Max absolute error	28.772	82.884	98.065
Correlation coefficient	0.9980	0.9906	0.9909
Learning epochs	40,000		
Training time	04:30 h		

5.3. ANN application and evaluation

As already mentioned, in this work we emphasize the investigations to find improved ANN architectures for the proposed application, starting from the results obtained in preliminary investigations (Pereira et al., 2016). Ratifying previous results, after some dozens of experiments, with different number of layers (from 3 to 5), neurons per layers, and activation functions, a 5-layers MLP achieved the best accuracy while the GRNN presented the fastest training. Their characteristics are summarized on Table 5.

5.3.1. Statistics of the ANNs training

Tables 6 and 7 shows some statistics obtained applying the GRNN and the 5L-MLP, respectively, to each dataset.

The correlation coefficients and errors on Tables 6 and 7 are quite good, specially for the production set, demonstrating very good generalization (ability to predict untrained patterns) of both ANN.

Note that the 5L-MLP was slightly better on test and production datasets. On the other hand, the GRNN got a very good fitting on the training set. This is an expected characteristic of GRNNs due to the fact that the pattern-layer activation functions (Gaussians) are centered on each training pattern. The smoothing factor is, then, optimized to fit the test patterns. Notably, the GRNN presented a great advantage in terms of training time.

5.3.2. Prediction of the spatial dose distribution

In order to achieve the final objective, which is to obtain the dose distribution map, the ANNs were fired for each spatial position.

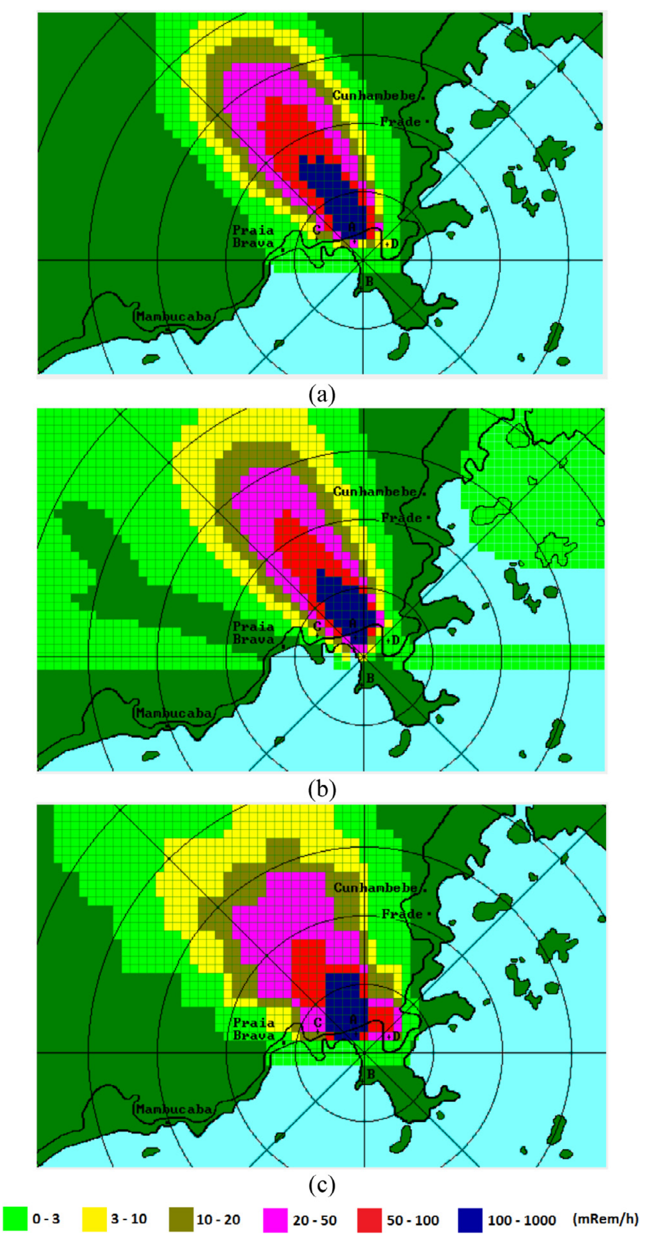

Fig. 5. Comparisons between (a) simulator; (b) MLP predictions and (c) GRNN predictions for spatial dose rate distribution 1 h after a occurring the accident, considering wind velocity = 2.5 m/s and wind direction = 326°.

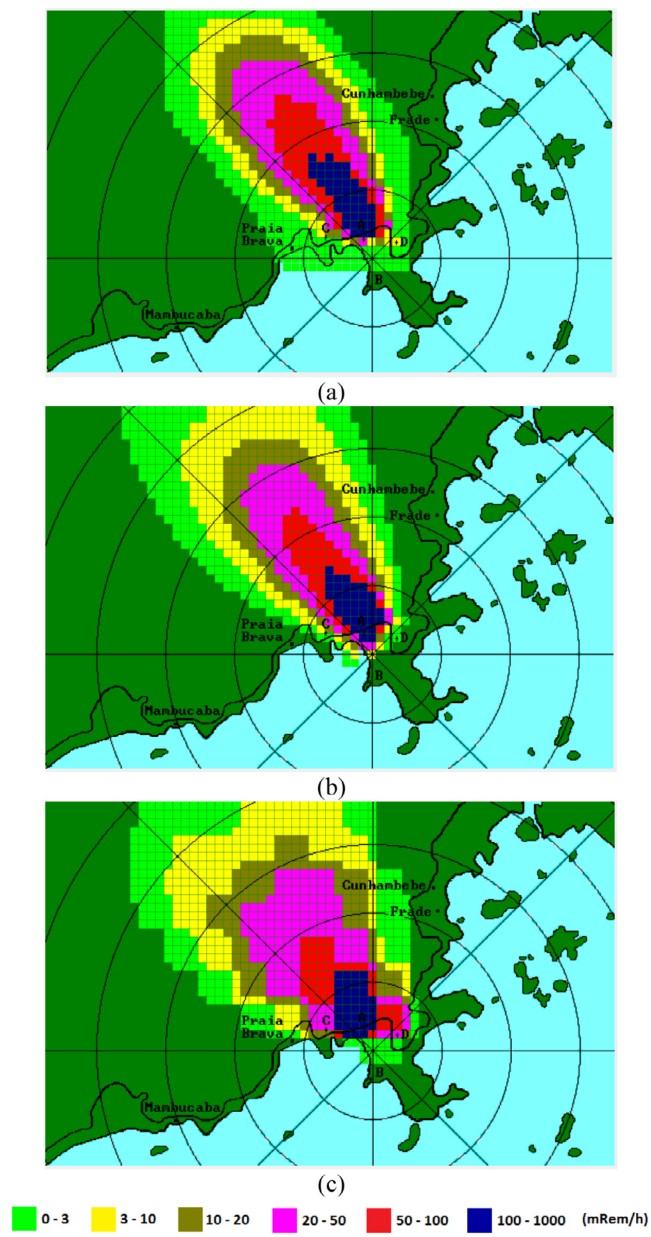

Fig. 6. Comparisons between (a) simulator; (b) MLP predictions and (c) GRNN predictions for spatial dose rate distribution 1 h after a occurring the accident, considering wind velocity = 2.5 m/s and wind direction = 326°, applying the threshold of 0.5 mRem/h to consider null doses.

Table 8
Execution time of the dose map reconstruction using GRNN and 5 L-MLP.

	Execution time (s)
5L-MLP	5
GRNN	25

Fig. 5(a) shows the map generated by the NPP atmospheric dispersion simulator (used here as reference) for a 2.5 m/s and 326° wind for a hypothetical nuclear accident (source term). It must be emphasized that it comprises only untrained (production) patterns. Fig. 5(b) and (c) shows predictions obtained by the 5L-MLP and the GRNN respectively. Values bellow 10^{-2} mRem/h were considered zero.

Note that, although the statistics of trained ANNs seems to be very good and similar for both ANNs, many different discrepancies appear. On the 5L-MLP predicted spatial dose map (Fig. 5(b)), too many points in the map, supposed to have null dose rate, present small values (see the light green regions), inclusive in improbable regions. On the other hand, high dose rate regions (other colors) present satisfactory prediction. In the case of the GRNN, discrepancies occur in regions of high dose. It doesn't seem to interpolate with smooth transitions leading to a poor resolution. On the other hand, the GRNN is more coherent in predicting the limits of the plume (it does not "spread" small values in improbable regions in which of dose rates are supposed to be null).

Considering such limitation on the ANNs prediction, some adjustments are proposed. Aiming to eliminate the false dose indication in regions supposed to have null dose rate, a threshold has been defined to consider the dose rates equal to zero. Empirical experiments demonstrated that 0.5 mRem/h (less than 0.1 percent of the maximum output value in the training dataset) was adequate. The result of applying this cutoff in shown in Fig. 6.

Note that although some discrepancies can be observed between simulated and predicted maps, the information is qualitatively important to support field teams decisions if NPP information systems are no available. The prediction of the 5L-MLP seems to be more similar to the simulated map.

5.4. Running the system on an Android phone

In this section we show results of the performance evaluation of the ANNs running on an Android mobile system. Here, we used a commercial smart-phone Samsung J5 (Quad Core com 1.2 GHz e 2 Gb de RAM). Table 8 shows the execution time of each ANN on the specified system to reconstruct and plot the dose rate distribution. Remember that, the ANN needs to be fired 2881 times (once for each position).

Note that the execution of the GRNN is very time consuming, when compared to the 5L-MLP. This fact was expected due to the great number of neurons required in the pattern (hidden) layer. The GRNN is comprised by 3832 neurons at all, while the 5L-MLP has only 125.

Although the 5L-MLP needs much more time for training (4:30 h), considering the predicted dose distribution map and the associated execution time to generate it, the 5L-MLP seems to be quite better than the GRNN.

6. Concluding remarks

In this work, a mobile system for dose predictions based on ANN has been proposed and evaluated. Preliminary investigations (Pereira et al., 2016) pointed to a 5 layers MLP and a GRNN as good options. Here, these two ANN architectures were improved and incorporated in a mobile system aimed to generate a dose distribution map for supporting decisions of emergency teams when NPP data and systems are no available.

As concluded in previous investigations, the statistics of both, 5L-MLP and GRNN seemed to be similar in terms of errors magnitude and correlation coefficients. However, it has been showed here that the dose distribution maps generated by each ANN are quite different. The 5L-MLP presented much more errors when dose rate values should be null, while the GRNN presented more errors in high values of dose rates. In order to enhance the predicted maps, a threshold of 0.5 mRem/h has been imposed to set the null dose points.

Comparing the maps generated for a production set (untrained data) with the simulated (reference) map, a better representation was produced by the 5L-MLP, while the GRNN did not interpolate training data with smooth transitions, leading to poor spatial resolution.

After evaluating the ANNs accuracy in their predictions, the execution times on an Android based commercial smart-phone were measured. Remember that, to generate one the dose distribution map, the ANN must be executed 2881 times. To accomplish that, the 5L-MLP took 5 s, while the GRNN needed 25 s. Such great difference in execution times was expected due to the 3832 neurons needed in the GRNN, while the 5L-MLP used only 125.

In summary, it could be concluded that the mobile dose prediction using a 5L-MLP achieved good accuracy in the prediction of the dose map, with fast execution time.

This work is the first step in investigations of the feasibility of developing a mobile dose prediction system for mobile phones, based on ANNs. The system would be more complete if other variables, such as the time after accident stars, temperature and other meteorological information, for example, were considered. However, to include more variables as ANNs inputs, the size of the dataset for training and testing the ANNs would increase in such a way that conventional ANNs may not be able to deal with. To overcome such limitations, the use of deep learning models, such as deep nets, together with the use of parallel processing techniques are under investigation.

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References

Hayking, S., 1999. Neural Networks: A Comprehensive Foundation. Prentice Hall.

Mól, A.C.A., Pereira, C.M.N.A., Freitas, V.G.G., Jorge, C.A.F., 2011. Radiation dose rate map interpolation in nuclear plants using neural networks and virtual reality techniques. Ann. Nucl. Energy 38, 705–712.

Sarwat, E., Helal, N., 2013. General regression neural networks for estimating radiation workers internal dose. Arab. J. Nucl. Sci. Appl. 46 (1), 374–380.

Timonin, V., Savelieva, E. Spatial Prediction of Radioactivity using General Regression Neural Networks. Applied GIS, vol. 1, n.2, Monash University EPress, 2005.

Specht, D.F., 1991. A general regression neural network. IEEE Trans. Neural Netw. 2 (6).

Lauret, P., Heymesa, F., Aprina, L., Johannetb, A., Dusserrea, G., Munierc, L., Lapébiec, E., 2013. Near field atmospheric dispersion modeling on an industrial site using neural networks. Chem. Eng. Trans. 31.

Hossain, K.M.A., 2014. Predictive ability of improved neural network models to simulate pollutant dispersion. Int. J. Atmos. Sci. (101155/2014/141923).

Cao, X., Roy, G., Hurley, W.J., Andrews, W.S., 2010. Modeling the concentration distributions of aerosol puffs using artificial neural networks. Bound.-Layer Meteorol. 136 (1), 83–103 (10.1007/s10546-010-9501-).

Silva, A.J.D., Santos, J.R., Pereira, C.M.N.A., Carvalho, P. V.R., A mobile computer system to support first responders to a radiological emergency. In: International Nuclear Atlantic Conference – INAC 2013, Brazil, pp. 24–29, 2013 (ISBN: 978-85-99141-05-2).

Goldberg, D.E., 1989. Genetic Algorithms in Search, Optimization and Machine Learning. Addison-Wesley, New York.

Parzen, E., 1962. On estimation of a probability density function and mode. Ann. Math. Stat. 33, 1065–1076.

Pereira, C.M.N.A., Schirru, R., Gomes, K.J., Cunha, J.L., Artificial Neural Networks for Radiation Dose Prediction in Nuclear Emergencies: Preliminary Investigations. Advances in Computer Science Research (ISSN 2352–538X), Atlantis Press, 2016.