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FOG FORECAST FOR THE INTERNATIONAL AIRPORT OF MACEIÓ, BRAZIL USING ARTIFICIAL NEURAL NETWORK

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The different types of fog are defined in a general way as condensed water droplets in suspension in the atmosphere, very near the ground and able to decrease the horizontal visibility to less than 1km (INMET, 1999). In order to enhance fog forecast, It is important to know the several problems related to low visibility and the occurrence of fogs. Aeronautic operation restrictions in the airports, automobile accidents, health problems (especially when mixed the toxic residues and breathed) and many other problems are frequently caused by fog (Silveira, 2003; Oliveira, 1998). Had to the low computational and financial cost and the possibility of generation of trustworthy results using a meteorological station (a time that a good distribution of stations together with its generated information rare is accessible), a system for fog forecast is presented in this work in the International airport Zumbi of Palmares Maceió-Al, based in Artificial Neural Nets (RNAs) and in historical data, such as direction and speed of the wind, temperature and temperature of the dew point, visibility, etc, gotten in the meteorological station of the airport, being these used to validate and to construct a forecast model aiming at better to characterize and to identify this phenomenon. "RNA" consists of one technique of Artificial Intelligence, being its elaboration inspired in the cerebral structure human being and its capacity to assimilate very with the experience being used as regulating of function and recognized of standards. Therefore, in this work they had been used a description of hourly data during the year of 2004. The developed methodology revealed applicable standing out the how much bigger fact of the description and the quality of the best data the efficiency of the synthecized system of forecast.

Different authors, Tubelis & Nascimento (1983) and Varejão-Silva (2000), have the same definition for fog, as being microscopical small a visible set of small drop of water liquid, in suspension in the atmosphere together to the ground, diminishing the horizontal visibility for less than 1 km (one kilometre). Some classifications exist how much to the type of fog, the most used it is the one that divides them in four main types (Woillett, 1928; Byers, 1959; Jiusto, 1981) is they: 1)Fog of radiation; 2)Fog of advection; 3)Fog frontal and 4)Others. Each type still presents subdivision that differentiate how much its gênesis.

Amongst the main physical processes to analyze a forecast of formation of the fog they are distinguished the increase of the relative humidity of air, to put cooling or for addition ofvapour of water until the Temperature of the dew point (Td) becomes equal the Temperature of the air (T). In accordance with Peterssen (1940), the majority of fogs is produced by the cooling of air in contact with the surface of the Land. Peterssen noticed that the necessary conditions for the occurrence of one of these types of fog (of radiation) involve: high relative humidity, clean sky (or lightly cloudy), absence of wind and steady stratification of the atmosphere.

On this work the classification of fogs was based on the horizontal visibility, being able to still classify them how much its intensity, in the following way:

- Weak Fog: visibility between 1 km and 500m;
- Moderate Fog: visibility between 500 100m;
- Strong Fog: inferior visibility 100m.

The reduction of the visibility observed had to the fog can cause accidents in the airports mainly. With the formation of the fog, the reduction of the visibility is a factor of risk for the diverse modalities of transports, as for example: aerial, closing airports, dislocating routes and provoking delay of the flights; marine, restricting the visibility; terrestrial e, causing accidents in the roads. In the industrial areas, the fog mixed toxic residues can provoke damages to the health. In agriculture the fog is favorable to the species of plants that need high relative humidity. Of this form, the forecast of the processes of formation of this phenomenon becomes in general essential for the planning of an organized and developed society and for the security of the transports.

Amongst the transport pursuing, the most affected for the fog formation it is aviation. Aviation is extremely sensible to the weather conditions and its variations. A meteorological forecast of short term for the airports, with a good index of rightness, becomes essential in the monitoration of the responsible adverse phenomenos for the main occurred tribulation in the airports.

The meteorological models for the weather forecast require onerous computational tools that allied to the classic sinotic analyses determine the

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forecasts of the varied adverse phenomena. One of the crucial points for a good meteorological forecast is a good net of distributed accessible data in diverse representative points, what rare it occurs. The development of models of forecast for aerodrome using artificial neural nets, trained with the great existing mass of data, can represent an advance in this intention.

The Artificial Neural Nets (RNA's) consist of a mathematical tool for application in diverse branches of science, also meteorological forecasts, having as great advantage low computational cost and the probability to get trustful results using data of an only source. The RNA's is inspired in the cerebral structure human being (behavior of the neurons) and that they possess the capacity to learn through the experience. A RNA is constituted of units of simple processing, the neurons, that have the natural aptitude to store experimental knowledge and to become it available for the use. This knowledge is acquired from the environment through a process of learning (Almeida et. al.; 2004).

The objective of the work is the application of Artificial Neural Nets in the fog forecast in the International Airport Zumbi of the Palmares-AL (AIZP-Al), having as indicating parameter the horizontal visibility, thus generating a tool of lower applicable financial and operational cost in any aerial terminal.

This work has as objective main to investigate the use of the application of the RNA's in the fog forecast in the AIZP-AL. Was opted to the choice of the use of neural nets with architecture feedforward, investigating the possible scenes, algorithm of training, pre and post-processing of data and structure of the neural nets in general (number of layers and knots). In relation specifically to the possible scenes of entrance and exit of the net for the architectures feedforward, investigated it use of the used lengths of memory, which according to literature is determinative for the success of the use of the RNA's.

Theoretically, the application of neural nets for functional approach can be analyzed using the theorem of Wierrstrass Haaser (1971). This theorem affirms, basically, that any continuous function of real values defined in limited interval can be approached by a polynomial. If the function of activation of each element of the neural net will be a continuous function of real value, it also it could be approached by a polynomial and consequently the functional relation of entrance and exit of the net could also be approached by a polynomial. Thus being, it will be always possible to define a neural net of multiple layers to act as approach of a specific not linear mapping.

The net is capable to establish associations between known entrances and exits (pairs of enter-exit of data system), through the experimentation of a great number of situations. Informations of entrance are placed in a net of nodules that interact mathematically between itself. Based in these informations a mapping appears of the macrocospic model input/output waited, or either, the interactions between the nodules are well defined and adjusted until the desired relations input/output appropriately are gotten.

The nodes in artificial neural nets processing sufficiently simple are inspired by its biological similars (cerebral neurons). Figure 1 shows the anatomy of this element of processing where the majority of the calculations are effected.

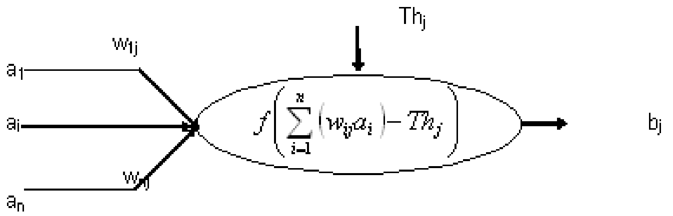

Figure 1 - Anatomy of the J-ésimo nodule (artificial neuron)

The values of the components of the vector-entered “a” have a effect on exit "b" of the neuron, but some components you add of the nodule also affect b, the (Wij) that is corresponding to the component of ai of entrance of j-ésimo nodule. Each entrance is multiplied by its respective ponderal factor and this ponderal entrance is used for the next calculations. These factors you ponder, or weights can assume inhibitors or excited effect. If Wij is adjusted such that the Wijai product is positive (and of great preference), the trend is of excitement of neuron j. If Wijai will be negative, this ponderal entrance will inhibit the nodule. If Wijai assume a very small value in relation to the other signals (or ponderal entered Wijai), the effect will be very small or null on the nodule.

The internal residual activity of the J-ésimo nodule, Th_j, controls the total activation of the nodule, and also it is known as bia neural. The first nodule calculates the somatório of all the ponder entrances and later it calculates the total activation for the subtraction of the internal residual value:

$$\text{Total Activation} = \sum_{i=1}^{n}\left(w_{ij}a_i\right) - Th_j \qquad (1)$$

If Th_j has great and positive value, the nodule has a high internal residual activation, what it inhibits the excitement of the same. In contrast, if Th_j will be null or assume negative values (in some cases), the artificial neuron has low an internal residual activation, suffering excitement more easily; if no internal activation will be specified, must be assumed null Th_j.

It is verified then that the artificial neuron carries through its calculations based on its information of entrance. It makes the somatório of the product enters the vectors a and w_J, deducts the internal residual activation and then he passes this result for a functional form, f( ), or either:

$$f\left(w_j A - Th_j\right) = f\left(\sum_{i=1}^{n}\left(w_{ij}a_i\right) - Th_j\right) \qquad (2)$$

The activation function precedes the transference function and has for attribution repass the signal for the exit of the neuron. Usually, the activation function is the proper function of addition of the ponderal entrances of the neuron. Already the transference function can have many forms. Amongst the most used, the linear functions can be cited, of the type slope and sigmóide. The transference defines and sends for out of the neuron the value passed for the activation function.

The weights are values that represent the degree of stimulate of the connections among the neurons. The weights can be seen, mathematically, as a vector of values $\left(w_1, w_2, w_3, \ldots w_n\right)$. When the entrances $\left(a_1, a_2, a_3, \ldots, a_n\right)$ are presented for the neuron, they are multiplied by the weights and the addition of these results is the signal of excitement in the neuron.

The nets need a considerable amount of historical data so that they obtain satisfactorily extract the existing relevant characteristics in the data set. If trained correctly, the net is capable to not only catch the relation statistics many times implicit between the variable, but also to generalize, providing correct exits for entrances not presented previously.

The neural nets have been used mainly in problems where the relation between variable is not total known, in problems of difficult modeling, in problems where small alterations in the entrance data do not produce great changes in the results, and mainly in problems where a great amount of data is available for learning or simulation. Perhaps the great advantage of the use of neural nets is the shape possibility of a physical phenomenon without knowing the intrinsic theory to the problem, being for these called characteristics of Free Models or Black Box.

A very relevant application of the neural nets is its use in temporal systems. It is through the information of the time in the operation of a neural net that it is enabled to follow the statistical variations in not stationary processes as the signals of speak, signals of radar, fluctuations in price of market of action etc.

The topology of RNA refers to the way as the artificial neurons are interconnected and organized in layer. In the literature, the topologies usually employed refer to the forms of the type: "feedforward"; completely appealing and appealing limited.

Accordant detached for Aguirre (2000), some necessary basic stages exist to treat temporary series in general ("identification of dynamic systems not linear"), where these can be summarized in the following way evaluation of the training data; selection of the structure; estimate of the model; validation of model.

In the project of models based on the presentation of data, in the case of neural nets, The generation stage and it collection of these data it still wins and importance larger, in a general way, these models type "box- black" has your prediction capacity very influenced by the quality of the entrance and exit data used in the training stage. As described previously, the data used in that work were consisted properly and obtained of the International Airport Zumbi of Palmares-AL (AIZP-AL) in the form of description horary_the group of data is corresponding to the year of 2004. It is worth to point out that the variable visibility is represented by values that are in the band above 1000m considered as good visibility and below this value bad visibility.

In agreement with Silveira (2003) and your forecast model for fog in the AIZP showed be observed in first place the season. In case it is winter to observe close to the state of Alagoas the influence of the subtropical anticyclone, it that influence is positive, it show be analyzed the vertical profile of temperature and temperature of the dew point and, being that inferior difference for 2°c (Ta-Tb<2°c) and the temperature to stay constant and the variation of the wind goes SE/N or null speed, there is great possibility of occurrence fog.

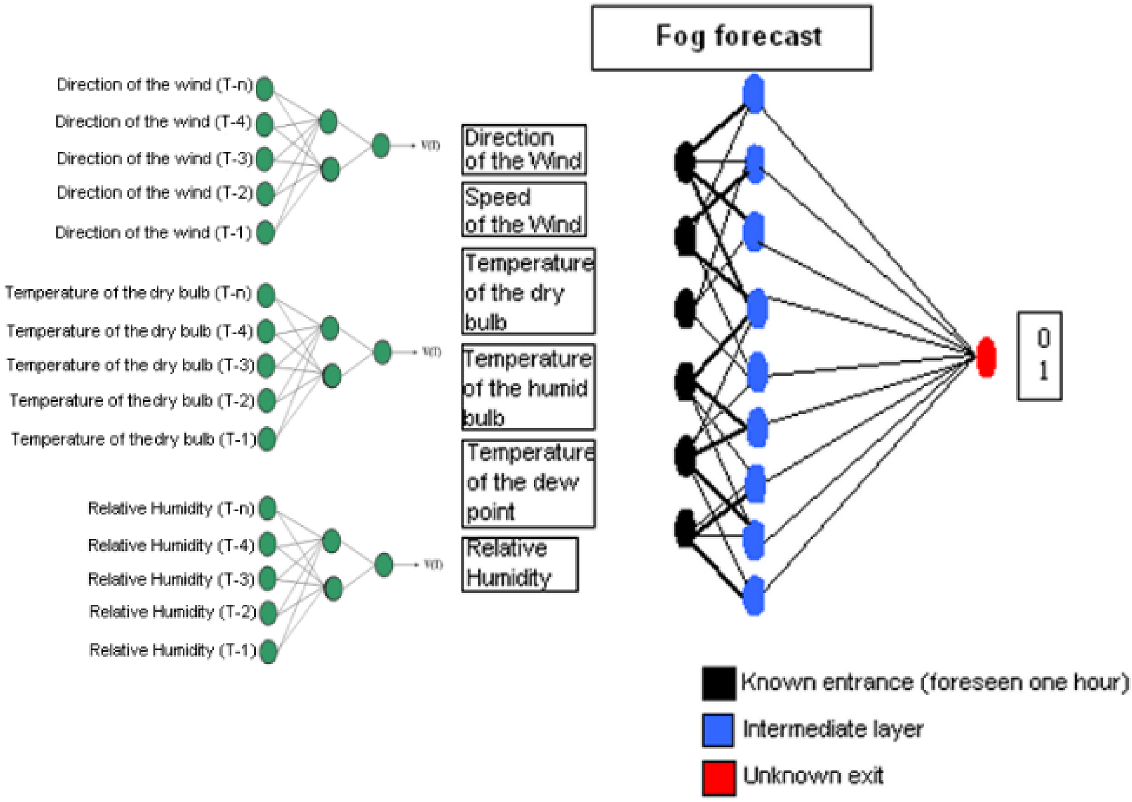

Figure 2. Models of architecture of the used RNA, scenes of forecast and scene of forecast for visibility. SOURCE: SOUSA and AIZP.

For series secular of direction of the wind, speed of wind, temperature of the dry bulb, temperature of the humid bulb, temperature of the dew point and relative humidity is verified that the same ones don't present tendency. This statement is important, once any doesn't exist type of movement ascending or descending in the tempory development of the series, what characterizes a stationary a treatment to eliminate the tendency.

According to HAYKIN (2001), two representations for the extension of the RNA "feedforward" for dynamic systems or temporary systems can be used: the implicit representation – where the time is represented by the effect that has about the processing of sings in an implicit way and the explicit representation – where the time receives your own private representation. As recommendation found in the literature SILVA (2000) and FRANGU (2003), opted to work, especially with the implicit form (RNA without the variable time in the entrance layer).

WANG et al. (1998) showed a procedure for the use of tempory data using RNA essentially with topology static. That procedure consists of enlarging the entrance layer through the inclusion

Of the entrance variable and exit in passed instants. Is presents RWA similar to a model of the type NARX. The NARX discreet models are in time that explain the predicted value ŷ (him function of previous values of the exit signs and of entrance; SOURCES, 2001). This way it can be said that in the case of a temporary series, in the with the exit (foreseen value) is a function no linear of passed values of the own variable of entrances, the rede MPL can be sun as an extension of the classic auto-regressive models.

For the modeling of the temporary variables: direction of the wind, speed of the wind, temperature of the dew point, temperature of then bulb humid, temperature of the bulb shoal, and relative humidity, a "model unavailable" was evaluated, where only try to stammer each variable in one time t in function of the same in hours (previous time), forming a model Direction x Direction, Speed x Speed, and so on.

For the evaluation of the efficiency of the methodology used for neural net, they where used as indicative parameters of quality the correlation

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coefficient (R^2) and the square root of the medium (RMSE). The measure RMSE is the training stage and validation, so that the more high if it presents the value of RMSE, lager the will be the mistakes found in a simulate specific value, even if this presents a coefficient of reasonable correlation for the global result. That measure it is given for:

$$RMSE = \sqrt{\frac{\sum_{k=1}^{N} \left| \frac{a_k - y_k}{a_k} \right|^2}{N}} \qquad (3)$$

Where a_k represents the wanted exit or observed, y_k represents the calculated exit and N it represent the number of accomplished forecasts.

Pattern recognition requires the neural networks to match large amounts of input information and generate a categorical output with a reasonable response to noisy or incomplete data. Baughman and Liu (1995) present a standard neural network architecture for pattern classification. Beyond its feedforward feature, the output vector from the ANN is Boolean with zero indicating that the input pattern is not within the specific class, and one indicating that it is within the class. According to this procedure, the melting values, limited to interval, are classified in 11 output vectors.

The neural nets artificial “multi-layer perceptron” (MLP) can be used in the recognition of gauge through some modifications in the processing:

- Neural nets “feedforward” with 6 entrances and 1 neuron in the exit layer (illustration 2d);
- The intermediate layer with amount of neurons to be tested and with function of activation sigmóide (illustration 2a and 2d);
- Function of linear activation in the exit neurons (illustration 2c);
- Classification or standardization of the visibility values in exit values considering for these, “0” inferior visibility or same to 1000m and for 1 superior visibility to 1000m (illustration 2b);

Approximating the values obtained for the exit neurons. The highest value considering as the corresponding class (illustration 2).

In general way, it can be assumed that the preponderant factors in the determination of the visibility, they can be associates to the direction of the wind, speed of the wind, temperature of the dry bulb, temperature of the humid bulb, temperature of the dew point and relative humidity. The visibility for one given hour t, it is function of the variable in hour t and of the variable in the previous hours (t-1, t-2,…). Thus, the entrance layer can be composed for diverse combinations in order to verify the influence of the number of used last values for each one of the variable in terms in the forecast of the same ones through the neural nets.

Of this form the studied scene only relates the forecast of each variable one hour to the front having as base information the values of the last variable and current used as given of entrance and exit for neural net, as figure 2d, varying the number of used last data. The best models are presented in table 1.

Table 1 - Results gotten in the tested models for the phase of training and validation and in the model of the forecast of the a dimension.

Model	Nº of returns	Normalization	R^2 Validation	R^2 Training	RMSE Validation	RMSE Training
Direction of the Wind	5	Max/Min	0,8709	0,7240	60,3774	75,9377
	10	Max/Min	0,9396	0,7270	60,1890	75,8237
	15	Max/Min	1,0000	0,8967	62,5143	77,0285
Speed of the Wind	5	Max/Min	0,9883	0,8236	2,0708	2,2058
	10	Max/Min	0,9933	0,8933	1,9648	2,1575
	15	Max/Min	0,9994	0,9605	1,9196	2,1247
Temperature of the dry Bulb	5	Max/Min	0,9971	0,9960	0,6064	0,7630
	10	Max/Min	0,9994	0,9625	0,5829	0,7411

	15	Max/Min	0,9950	0,9922	0,5405	0,7118
Temperature of the humid Bulb	**5**	Max/Min	0,4326	0,9309	0,4116	0,4949
	10	Max/Min	0,9114	0,9304	0,4174	0,4958
	15	Max/Min	0,9777	1,0000	0,4281	0,4798
Temperature of the dew point	**5**	Max/Min	0,9996	0,5534	0,7836	0,6411
	10	Max/Min	0,9354	0,8393	0,6922	0,6047
	15	Max/Min	0,9505	0,9993	0,6849	0,5900
Relative Humidity	**5**	Max/Min	0,9995	0,9926	4,2410	4,6211
	10	Max/Min	0,9944	0,9594	4,1639	4,4694
	15	Max/Min	0,9978	0,9590	3,6806	4,4640

In the presented configuration above, for data period of training and verification, the number of us in the intermediate layer received the values 8, 12, and 16. In this analysis, the corresponding variable of entrance had been: the direction of the wind, speed of the wind, temperature of the dry bulb, temperature of the humid bulb, temperature of the dew point and relative humidity in n previous Hours in V_{t-n} , V_{t-2}, $V_{t-1.}$ For the period of training and chosen validation, that it corresponded the eleven months for training and one month for verification, we on the basis of analyze the performance of each model value RMSE and also for the R^2 coefficient. Independent of the model it can be said that the number of neurons in the intermediate layer did not show to be a compromised parameter a time that had been gotten resulted similar for the RMSE and also for the R^2 coefficient.

Of this form, if it will be followed to the recommendation of literature in always using in the intermediate layer a bigger number of neurons that of the layers of entrance and the exit, they will be able to be gotten resulted satisfactory. It must be observed, however, that the fact of if using a great number neurons in the intermediate layer it will cause the increase of the number of parameters to be determined such as the weights and bias binding, causing one high computational demand for the calculations. Still with relation to the number of us in the intermediate layer, no functional relation was not observed between this number and the peculiarities of the layer of entrance and exit.

A bad performance in the validation phase, with low values for the RMSE and the R^2 coefficient, it can have to the learning of the net, that in a first period, it does not obtain "to learn" the relation enter – exit, or either, to assimilate the established standards, recording all its peculiarities and noises, what it leads to a reduction in the capacity to generalize, as it affirms FURTADO (1998). The best ones resulted observed in the models had been: Direction (15 returns), Speed (15 returns), Temperature of the Dry Bulb (10 returns), Temperature of the Humid Bulb (15 returns), Temperature of the Dew Point (5 returns) and Relative Humidity (5 returns) in the phase of training and validation.

Of one it forms generality it can be said that some models had presented resulted without significant differences for all the tested configurations. Of this form to visualize the results better gotten the hourly graphs foreseen in the training phases and validation are presented (figure 3) for the entrance variable. These presented models are of better would consistency the ones that better esteem the variable in the AIZP in the training phase and validation.

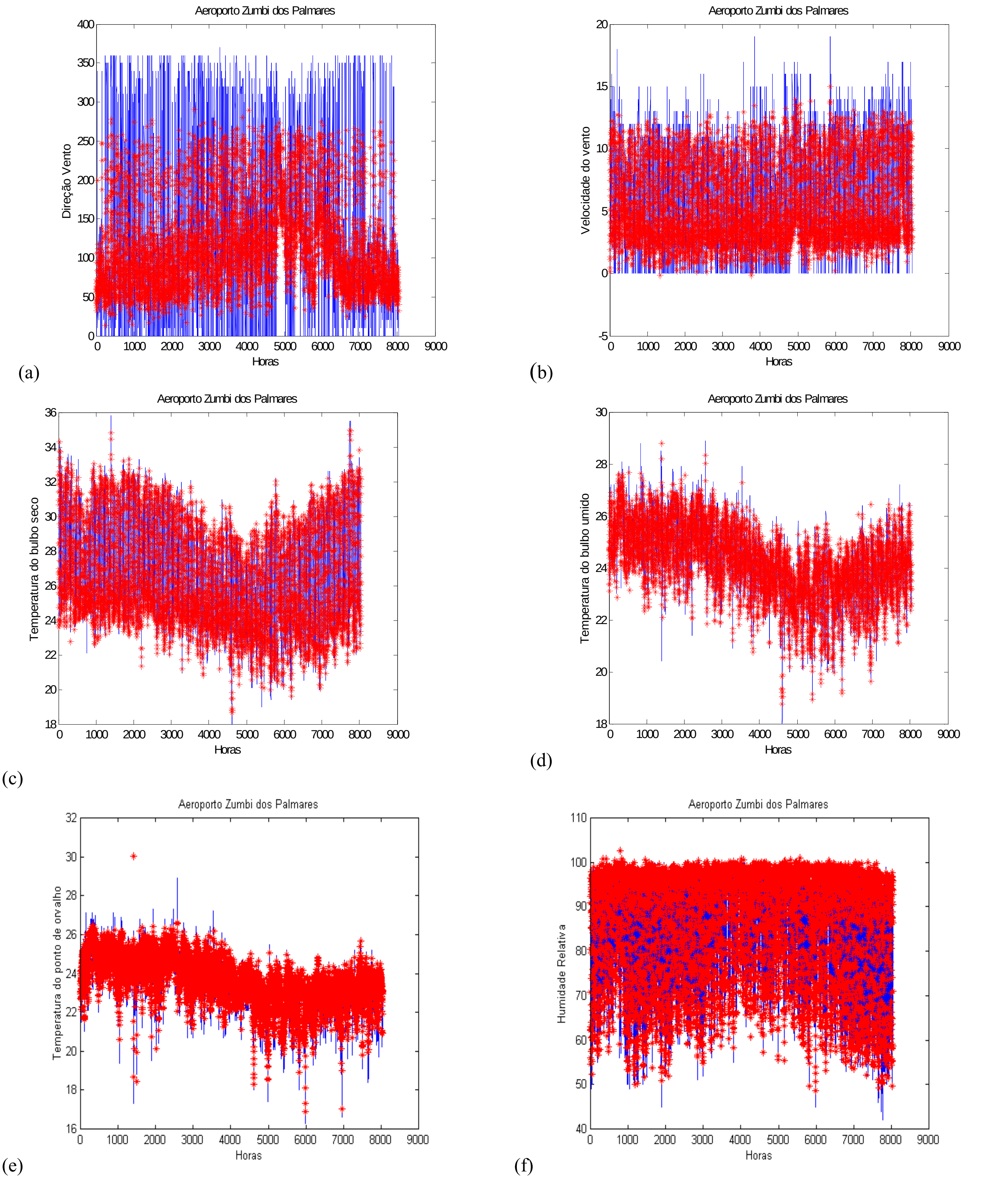
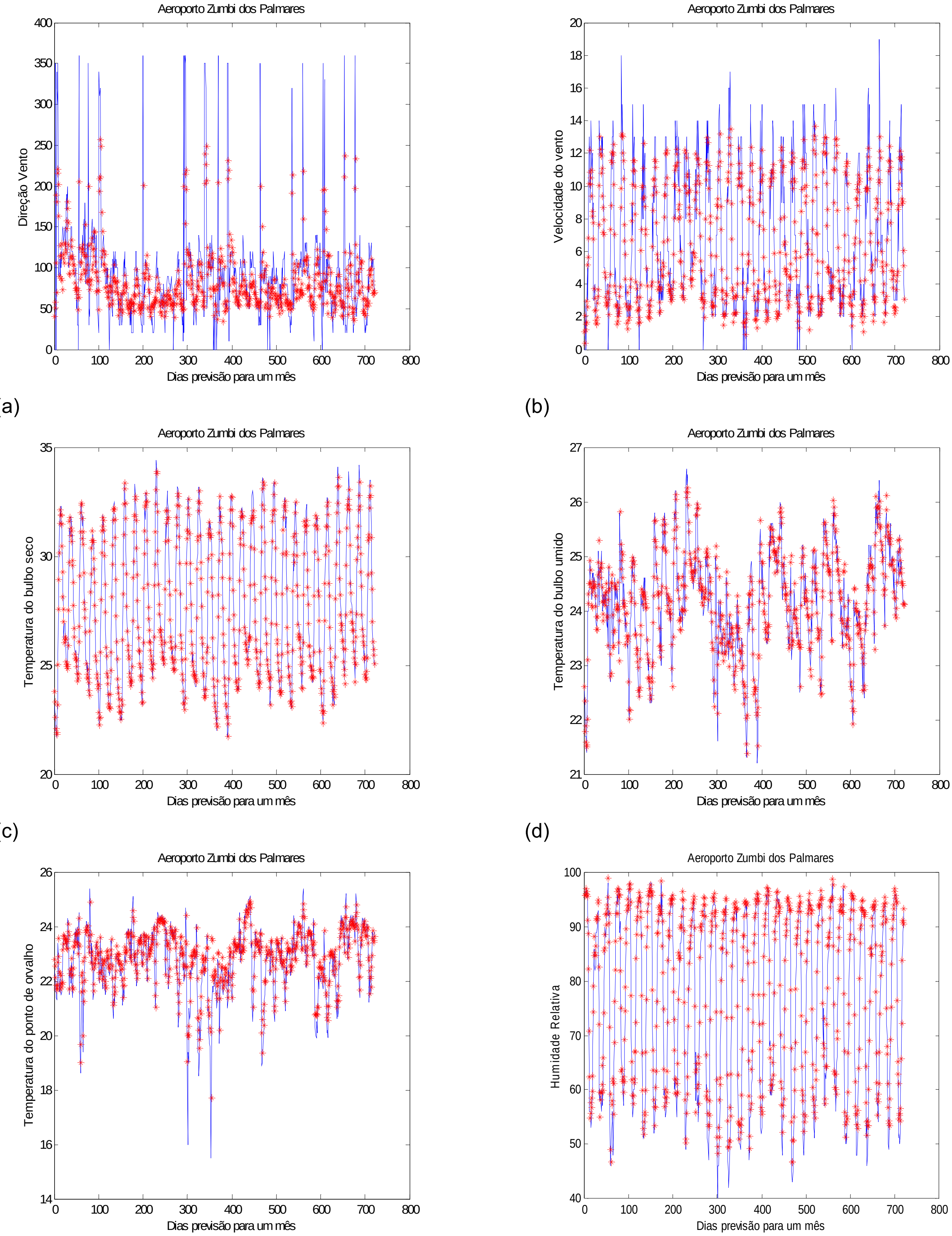


Figure 3 – Results for the phase of training of the visibility model, where the blue line (-)it represents the measured values and the asterisks (*)they represent the esteem values. SOURCE: AIZP.

For the model of neural nets as it recognizes of standards they had been used as entered the data foreseen for one hour of all the variable related in n Hours, correspondents to one month. As the exit data had been used the values for the visibility had been related to standards 0 and 1. They had been used given hourly, testing the same parameters of the neural nets used previously in the model of standard recognition, being also used given of 11 months for the training and data of one month for validation. The used scenes had followed the standard represented in the figure 2d.



(a) (b) (c) (d) (e) (f)

Figure 4 – Results for the phase of validation of the visibility model, where the blue line (-)it represents the measured values and the asterisks (*)they represent the esteem values. SOURCE: AIZP.

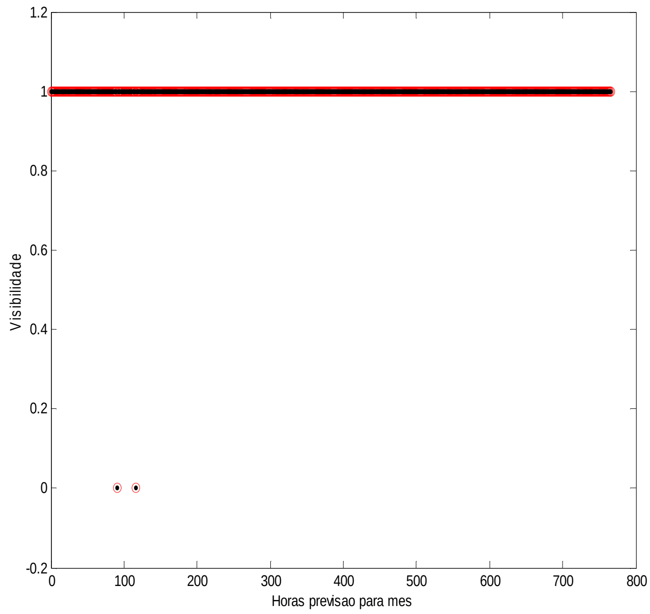


Figure 5 - Results for the phase of validation of the visibility model.

In the inquiry of the development of strategies for use of the neural nets in the modeling of the process of visibility forecast diverse simulations had been carried through with the objective to test different configurations of models of neural nets as much for the secular forecast how much for the variable as the forecast of the visibility. Some parameters they had been taken as defining by the tested models: scenes of entrance and exit, or either, number and characteristics of we in the input/output layer, number of us in the intermediate layer, functions of activation and algorithm of training.

In general the characteristics of we of entrance influence significantly in the results. The best statisticians in the secular forecast for the models they had been: direction of the wind (15 returns), Speed of the wind (15 returns), Temperature of the Dry Bulb (10 returns), Temperature of the Humid Bulb (15 returns), correspondents to the periods t, t-1,…, t-n, in set with the visibility. It is evident that the performance of the models it is related to the period of training and used validation. Periods many short ones, they tend to harm the learning of the net, while long periods of training and short periods of validation they can cause *overfiting*. In both the cases, the capacity of generalization of the net drastically is reduced.

The results can be considered entertainers, despite the limited data base of available meteorological information. The use of neural nets and its success they are associates to the set of events used in the calibration. How much bigger this set and more heterogeneous these events, better they will be the gotten results. The use of a bigger number of calibration events is given credit that and a perfectioning of bigger details of the method it will be able to reduce the average error the levels lowest.

More specifically we can affirm established in the gotten results, that the RNA demonstrated to be adjusted in the learning of the processes of transformation of the variable, being necessary only previous knowledge of the data. The shown results for the forecast with RNA they had been gotten for a step the front. An inquiry was not carried through for some steps to the front because this would burden the time of accomplishment of the work, however this analysis is indicated as a suggestion for posterior works. In relation the visibility forecast we can affirm that the considered model one revealed efficient with an excellent index of rightness for the samples of training and test using in average 9 neurons in the intermediate layer.

Continuity of the evaluation of the performance of the neural nets sends regards to it using other architectures and processes of activation. Also it is interesting to verify better methodologies and alternative for initial estimate of the weights and bias binding, a time that this procedure is of vital importance to the process of training of the nets, fact this observed in the number of times that was necessary to restart the training program. Different algorithms of learning they must be investigated for models used in this work and the comparative results to gotten here.

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