NEUROFUZZY TECHNIQUES APPLIED TO MODEL AND PREDICT THE F2-LAYER CRITICAL FREQUENCY *fo*F2: FIRST RESULTS

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The aim of this poster is to present the application of neurofuzzy techniques to ionosphere modelling. Specifically, these techniques have been applied to model and predict the critical frequency of F2 layer, foF2. The method has been tested under quiet and moderately geomagnetic conditions using foF2 data from Slough ionosonde station, providing foF2 forecast (1-24 hours in advance) with relative mean deviation between 5-11%.

FUZZY MODELS

- Mamdani models: in the case of a one input/one output system, their rules have the form: $If\ (x\ is\ A)\ Then\ (y\ is\ B)$ (1) where A,B-fuzzy sets.

- Takagi-Sugeno models (TS) (also called Takagi-Sugeno- Kang – TSK Models): their rules are expressed as $If\ (x\ is\ A)\ Then\ (y = f(x))$ (2), where *f(x)* is a linear or non-linear function.

NEUROFUZZY MODELLING

➢ Let's consider the system established by:

$$y_1 = f_1(x_1, x_2, \ldots, x_n)$$
$$y_2 = f_2(x_1, x_2, \ldots, x_n) \quad (3)$$
$$y_m = f_m(x_1, x_2, \ldots, x_n)$$

or in the abbreviated form: $y = f(x)$ (4).

➢An equal Fuzzy model to this system can be represented by the following set of fuzzy rules

$$R^{(l)}: If\ x_1\ is\ A_1^l\ and\ x_2\ is\ A_2^l \ldots and\ x_n\ is\ A_n^l\ \ THEN\ y_i^l\ is\ g_i^l(x, \theta_i^l)$$

(5), where $l = 1 \ldots M$ is the number of rules of the fuzzy model, and the Fuzzy set A_k^l is defined in the universe of discourse of the input variable x_k, k=1,...n, and y the i-th equation of the process ($i = 1 \ldots m$).

➢If the consequent term in (5) is a TSK consequent with affine term, this can be written: $g_i^l(x, \theta_i^l) = a_{0i}^l + a_{1i}^l x_1 + \ldots + a_{ni}^l x_n$ (6), where a_{ki}^l represents the constant coefficient for the state variable x_k corresponding to the rule l of the i-th equation . Vector θ_i^l represents the set of adaptive parameters $\theta_i^l = (a_{0i}^l, a_{1i}^l, \ldots, a_{ni}^l)$ (7)

➢Considering a TSK Fuzzy system with a product inference operator and centre average defuzzifier, expression (3) can be written as:

$$\hat{y}_i = \frac{\sum_{l=1}^{M} w_i^l g_i^l(x, \theta_i^l)}{\sum_{l=1}^{M} w_i^l} \quad (8)$$

where $\hat{y}_i$ is the estimated output of the system and w_i^l is the firing degree (matching degree or fulfilment degree) of the rule l, that is: $w_i^l = \prod_{k=1}^{n} \mu_{A_k^l}(x_k, \sigma_i^l)$ (9), where σ_i^l are the characteristics parameters of the membership function $\mu_{A_k^l}(x_k, \sigma_i^l)$ that define the fuzzy set A_k^l. If the functions given in (3) are replaced by the equation (8), the appropriate adjustment of all rules group parameters , σ_i^l and θ_i^l , would permit that the final fuzzy system represents a model equivalent to the real system.

➢In order to minimise the error between the output of the fuzzy system and the output of the system defined by the equation (3), it is possible to apply the descending gradient method to adjust the parameters of the fuzzy model. Considering a one output system, an error function in the p-th iteration can be defined as: $J(p) = \frac{1}{2}\left[y(p) - \hat{y}(p)\right]^2$ (10), where y represents the output of the system that we want to model, $\hat{y}$ is the output of the fuzzy model to obtain, and $p=1 \ldots N$, N denoting the total number of input/output pairs in the training set. The descending gradient method minimises the cost function J adjusting the parameters σ_k^l and θ_i^l, with a value proportional to the derivate of the function respect to every parameter:

$$\sigma_k^l(p+1) = \sigma_k^l(p) - \eta \frac{\partial J(p)}{\partial \sigma_k^l(p)} \quad ; \quad \theta_i^l(p+1) = \theta_i^l(p) - \eta \frac{\partial J(p)}{\partial \theta_i^l(p)} \quad (11) \text{ and } (12).$$

- ALGORITHM USED TO IMPLEMENT THE DESCENDING GRADIENT METHOD -

```
γ, β,y',e = bp (η, m, n, γ, β, x, y, r, ε)
for each epoch
    for each training point
        y'(p) = Compute_Fx
        e(p) = y(p)-y'(p)
        γ = Update_Centres
        β = Update_Widths
        y'= Update_Consequents
    endfor
error(epoch) = MSE (e)
if (error (epoch) < ε) Or (Stable(error(epoch)))
        return (γ, β,y',error)
endif
if (error (epoch) < error (epoch-1)
        Inc(η,r)
endif
if (error (epoch) > error (epoch-1)
        Dec(η,r)
endif
endfor
return (γ, β,y',error)
end
```

where:
- "m": number of rules.
- "n": number of inputs.
- "γ", "β": centres and widths of the Gaussian membership functions.
- "MSE": medium square error calculated from total number of errors e(p) in the training set.
- "η": learning rate
- "x": inputs
- "y": output
- " y' ": consequent
- "r": tolerance margin
- "ε" : error limit.
- "Fx": function implementing the consequent part TSK with affine term

➢The adaptation of the learning rate parameter is made in the functions "Inc(η,r)" and "Dec(η,r)" according to the expression:

$$\eta(epoch+1) = \begin{cases} inc\_\eta \times \eta(epoch) & error(epoch) \le error(epoch-1) \\ dec\_\eta \times \eta(epoch) & error(epoch) \ge r \times error(epoch-1) \\ \eta(epoch) & error(epoch-1) \le error(epoch) < r \times error(epoch-1) \end{cases} \quad (13)$$

➢The described method to adjust the parameters and the algorithm that implements it, are based on one of the more important neural networks learning algorithms: ***Backpropagation (BP),*** so this modelling technique is named ***neurofuzzy***.

DATA AND METODOLOGY

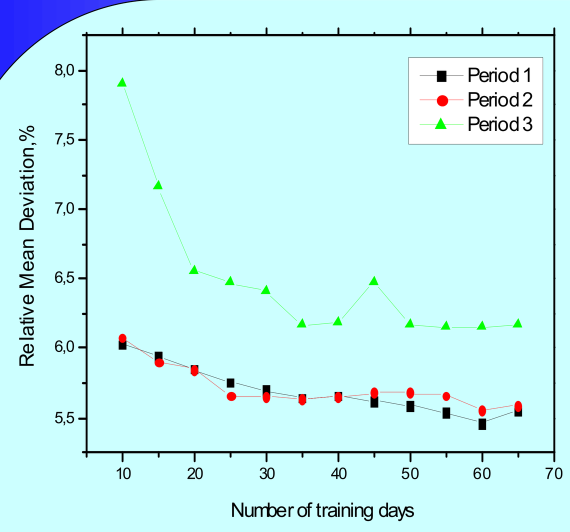


Figure 1.- Relative mean deviation (in %) of 1-hour lead time foF2 predictions

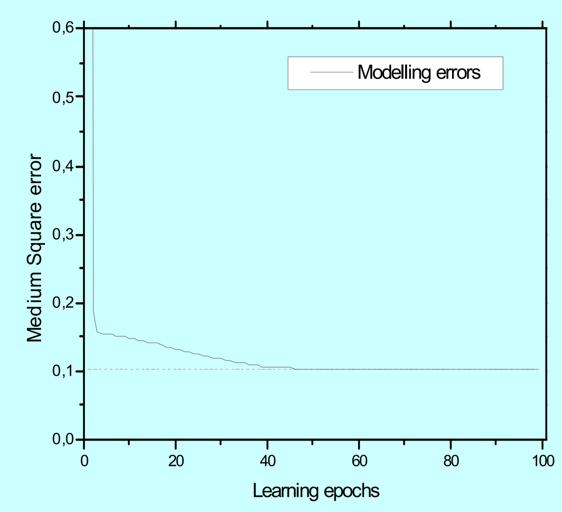


Figure 4.- Modelling Error vs number of learning epoch during the training time of the model

Data and periods: In this study, hourly *fo*F2 observations on Slough Station are used to propose a method for *fo*F2 short-term (1-24 hours in advance) prediction. Special quiet and moderate geomagnetic activity time periods (Ap<30) have been analysed to test the method. Shown periods in this poster are listed on table 1.

Testing method: In order to test the *fo*F2 neurofuzzy models, short-term predictions (1-24 hour lead times) are obtained over these selected periods and compared with the real observations to calculate the relative mean deviation (RMD) (14), where y_i and $\hat{y}_i$ are the hourly observed and predicted values respectively and N is the number of analysed samples.

$$RMD(\%) = \frac{\sum_{i=1}^{N} \left|\frac{y_i - \hat{y}_i}{y_i}\right|}{N} x100$$

Length of training period: A 30-days time period has been selected to train the model. Dependence of RMD on the number of training days over quiet geomagnetic periods is shown on figure 1 as an example.

Input parameters: Relative *fo*F2 deviations from running median over the training period, *ΔfoF2*=(*fo*F2- *fo*F2$_{med}$)/ *fo*F2$_{me\ d}$ are considered. To predict the *fo*F2 value with *n* hours in advance, *Δfo*F2[*t*+n], the model takes into account the following inputs (see figures 2 and 3):

- Last three known hourly *fo*F2 values: *Δfo*F2[*t*-2], *Δfo*F2[*t*-1], *Δfo*F2[*t*], where a current instant of time *t* is supposed.
- *Ap:* index used to include the dependence on magnetic activity.
- Error between the observed and estimated values, $e = y(t) - \hat{y}(t)$, and the velocity of the error between successive steps $\Delta e = e(t) - e(t-1)$

Learning epochs: This number is determined from the medium square error *MSE* defined for each epoch in algorithm 1. As it can be observed from figure 4, *MSE* decreases in an approximated exponential form with the number of epochs until the model goes in a saturation state. In order to avoid the model overfitting, the number of learning epoch has been selected to 50.

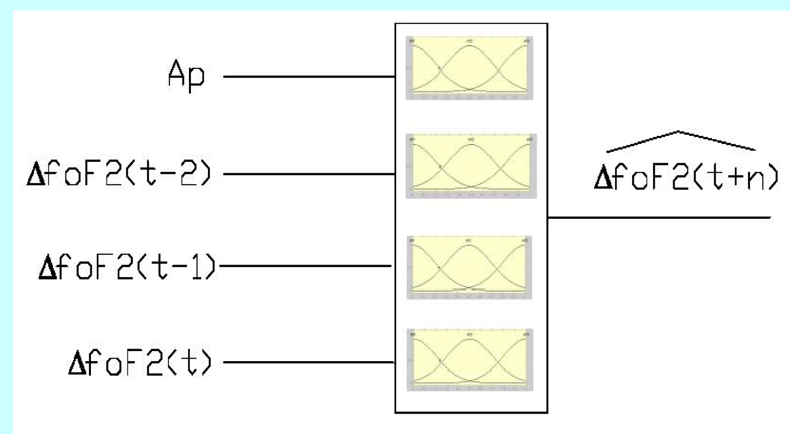


Figure 2.- Initial model used *Δfo*F2[*t*+n] =*f*(A$_p$, *Δfo*F2[*t*-2], *Δfo*F2[*t*-1], *Δfo*F2[*t*]). This model did not allow to capture the dynamic of the system appropiately.

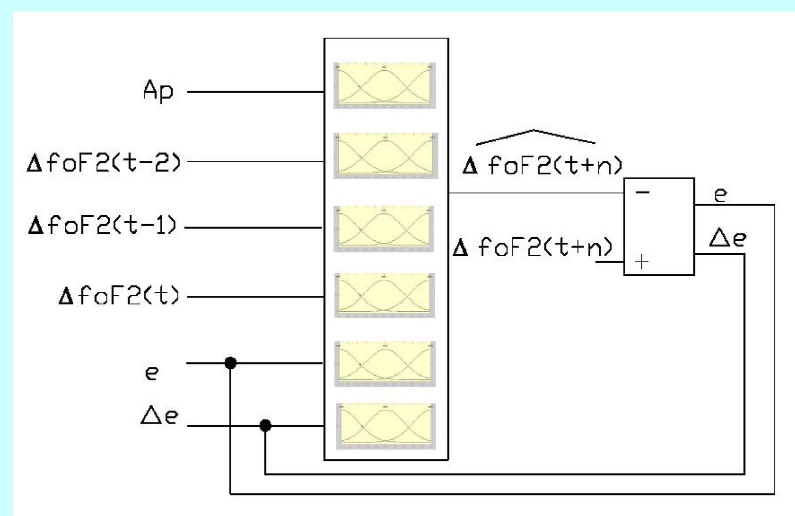
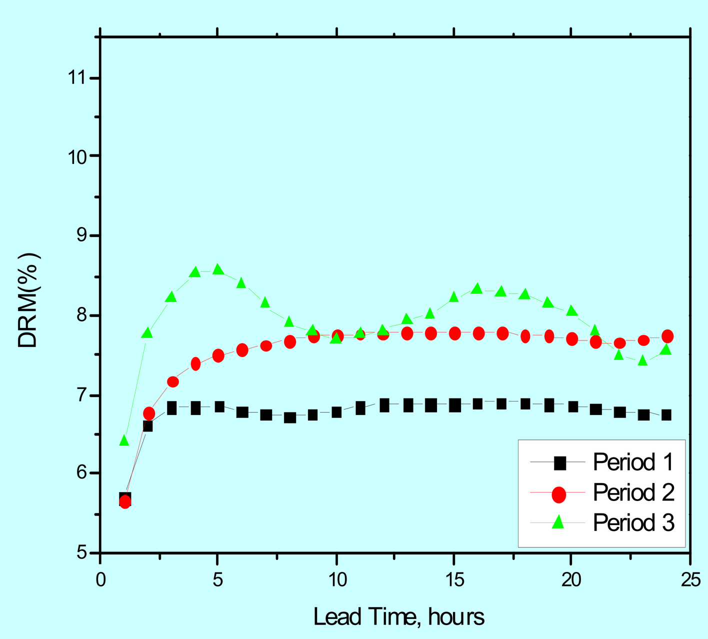
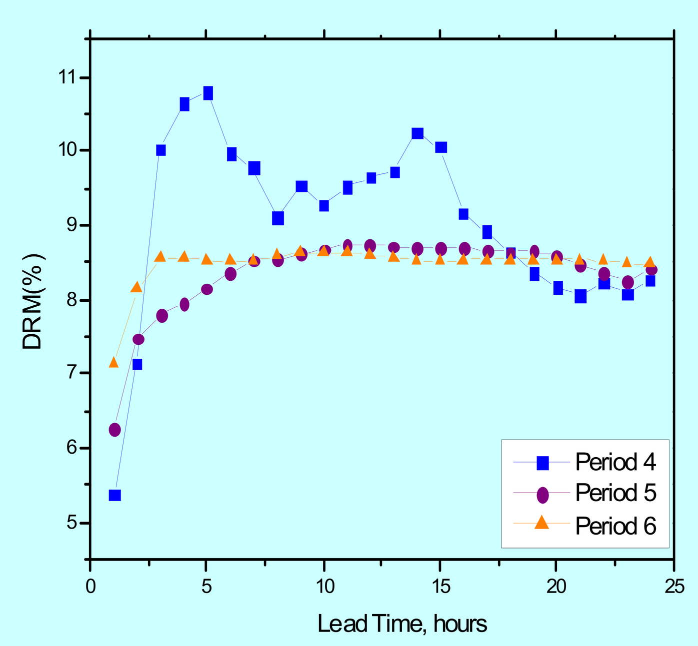


Figure 3.- Final model: *fo*F2[*t*+n] =*f*(Ap, *Δfo*F2[*t*-2], *Δfo*F2[*t*-1], *Δfo*F2[*t*], e, *Δe*).

*fo*F2 PREDICTION ACCURACY UNDER NOT DISTURBED GEOMAGNETIC ACTIVITY PERIODS

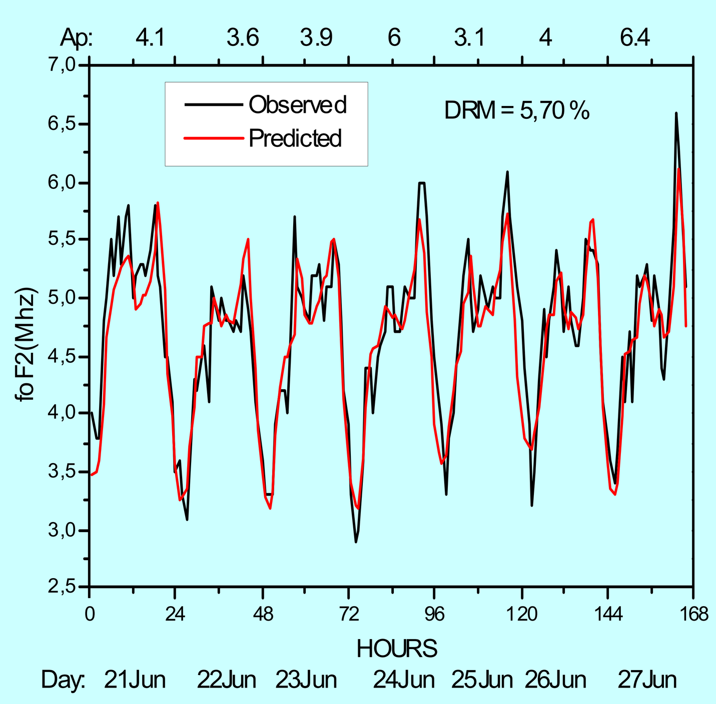
➢ A quiet acceptable *fo*F2 prediction accuracy with RMD around 5-6% is provided for 1-2 hour lead times. For larger lead times, the method provides prediction accuracy with RMD varying between 6-11%.

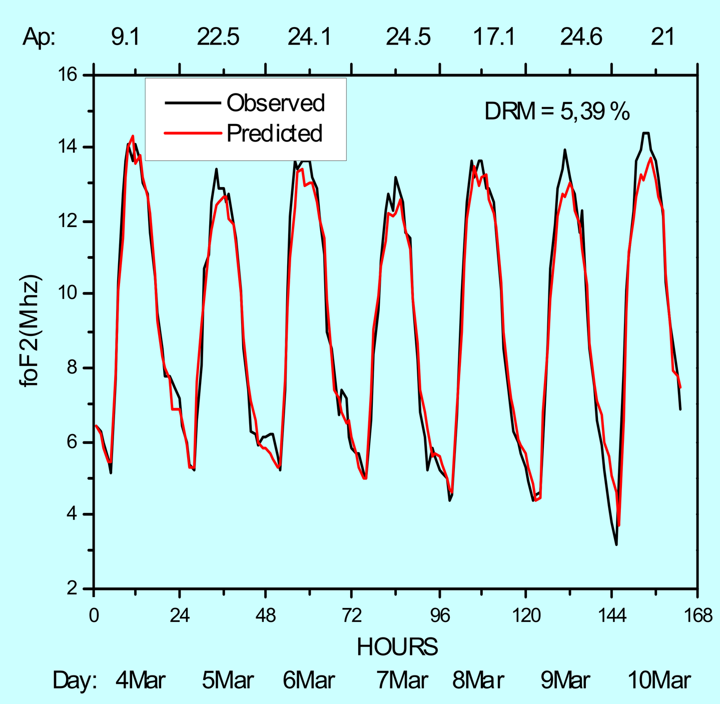




Figures 5 and 6: An example of *fo*F2 prediction accuracy in dependence on the lead time for three quiet (left figure) and three moderately disturbed periods (right figure)

Table 1	Period	Ap av
1	21-27 Jun 96	4,44
2	10-16 Ago 97	7,94
3	25-31 Oct 85	5,94
4	4-10 Mar 91	20,41
5	20-26 Mar 86	16,27
6	5-11 Jan 86	13,74





Figures 7 and 8.- An example of *fo*F2 prediction (1 hour in advance) over a quiet (left figure) and a moderately disturbed period (right figure). Both observed and predicted *fo*F2 variations are very close, which indicates the great efficiency of the neurofuzzy *fo*F2 model under these conditions.

FUTURE WORKS

The main following step will be to check the efficiency of neurofuzzy modelling to predict *fo*F2 during disturbed geomagnetic activity periods. It is well known by scientific community the natural capability that neurofuzzy systems show to model highly non-lineal systems and/or about uncertainty where other techniques do not work properly. Therefore, its application to predict *fo*F2 under these geomagnetic conditions may be considered as promising for obtaining prediction accuracy acceptable from practical point of view.

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