THE DEVELOPMENT OF A NEURAL NETWORK BASED BOTTOMSIDE PROFILE MODEL FOR THE IONOSPHERE OVER GRAHAMSTOWN, SOUTH AFRICA

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ABSTRACT

This paper discusses the development of a single station ionospheric model for the bottomside electron density profile. Archived data from the Grahamstown (33.3°S, 26.5°E) South Africa station have been used to train neural networks (NNs) to predict the parameters required to determine the entire bottomside electron density profile. The inputs to this NN based model are day number (DN), hour (HR), a measure of solar activity (R) and a measure of magnetic activity (A). Results show that this new model is more successful at predicting Grahamstown electron density profiles for a particular set of inputs than the IRI. Future plans include expanding the model by including data from other South African ionospheric stations and producing a NN based South African ionospheric model that provides more accurate predictions for the electron density profile than current global models.

INTRODUCTION

This paper discusses the development of a South African bottomside ionospheric model. There are twenty-eight years of hourly vertical incidence ionospheric parameters and five years of electron density profile measurements archived for our Grahamstown (33.3°S, 26.5°E), South Africa ionospheric station. This large ionospheric database means that Grahamstown is the ideal station with which to begin developments towards a South African ionospheric model.
Recently there has been a move towards using neural networks (NNs) to predict ionospheric parameters. In particular, we have shown, [1] [2], that NNs can be used to successfully predict the peak ionospheric electron density (foF2) for Grahamstown. Various other groups, [3] [4], have also made use of NNs for predicting ionospheric parameters.
In this paper, we have employed NNs for the task of predicting the parameters required for constructing the bottomside ionospheric electron density profile. The inputs to this NN based model are day number (DN), hour (HR), a measure of solar activity (R) and a measure of magnetic activity (A). Different combinations of these inputs are used to predict each parameter required. For the solar activity input a running mean of the daily sunspot number is used and for the magnetic activity input a running mean of the 3-hourly magnetic a_k index is used. The optimum time length of these running means is dependent on the required output parameter. Since, due to a paucity of data in other areas, this South African model has been restricted to a single station, Grahamstown, the latitude and longitude information has, at this stage, been excluded from the input space.

DETERMINING THE PROFILE

For the purposes of developing this model, the electron density profile was split into two layers (E and F). The electron density profile data that is used for training the NNs is provided by measurements taken at Grahamstown with a University of Massachusetts Lowell Center for Atmospheric Research (UMLCAR) digisonde (DPS) and scaled with the UMLCAR automatic scaling software, Artist. As part of the output from Artist a description of the electron density profile is provided as sets of Chebyshev coefficients for each layer. These coefficients describe the shape of the profile for that layer. The peak parameters of each layer, and the E-F Valley width are also provided. Only five years of Artist scaled data with electron density profile descriptions were available, although twenty-eight years of critical frequency data, measured by a chirp sounder and manually scaled, were also available.
NNs were trained to predict the peak of each layer, both real height and critical frequency parameters. For the E layer, a NN, “E Limits NN”, was trained to determine the hours, for a given DN and R, between which an E layer is measurable by a ground based ionospheric sounder. This was necessary in order to avoid interrogating the NN with data for which it had not been trained. At hours outside of those determined by this NN, the Titheridge [5] and UMLCAR [6] models

were used. An E layer profile NN was then trained to predict the Chebyshev coefficients required for describing the shape of the profile.
For the F layer, a mechanism was required for determining the existence of a F1 layer. This was accomplished by training a NN, "F1 Probability NN", to predict the probability of (i) no F1 layer present, (ii) F1 layer definitely present and (iii) F1 layer in L condition state. L condition state is where a F1 layer is present but it is not possible to scale any F1 parameters. Two NNs were trained to predict the F layer parameters required for each of these situations. In the event of no F1 layer, only a F2 layer is present and a NN (F2NN) was trained to predict the required parameters in this case. For a definite F1 layer, the NN (F1F2NN) was trained to predict all the parameters required to determine the shape of the profile from the F layer start to the peak at foF2. When a L condition state is reported as probable, an algorithm that combines results from both F1F2NN and F2NN is implemented. The output from both F1F2NN and F2NN is in the form of five Chebyshev coefficients for each layer (F1, when present, and F2).
For each layer, the predicted coefficients are used in conjunction with the predicted peak parameters in an analytical expression [6] to determine the real height at any given frequency. We have adopted the valley region used by the UMLCAR model [6] to provide the E-F boundary and a smoothing technique has been developed for modifying the F1-F2 boundary in order to provide a smooth and continuous profile. We have named this new NN based model the "LAM model" and a block diagram illustrating the process that this model follows in predicting the electron density profile is shown in fig.1.

RESULTS

The LAM model provides a realistic electron density profile that is representative of the average behaviour of the ionosphere over Grahamstown for a particular set of inputs. Profiles from this model have been compared with real DPS data and with profiles obtained from the International Reference Ionosphere (IRI).
Six examples of actual profiles obtained by the DPS are shown in fig.2. The input variables from these actual profiles were used as inputs to the LAM model and the IRI 2001. Comparison between the actual profiles and those predicted by the LAM model and IRI 2001 are illustrated in fig.2.
These results show that the NN based LAM model is more successful at predicting the electron density profile for a particular set of inputs than the IRI, for Grahamstown.

CONCLUSION

Twenty-eight years of data were available for the NNs trained to predict the critical frequencies but only five years of data were available for training all the other NNs. In order to have a NN based model that is truly representative of the behaviour of the bottomside ionosphere at least one solar cycle of data is ideally required. However, in spite of the current limitations imposed by the dataset, the LAM model appears to be extremely successful at predicting the electron density profile for Grahamstown.
The LAM model will be continuously updated as more data becomes available. For the past year ionospheric data from two other South African ionospheric stations have been archived. Future plans are to expand this model to include data from these other stations with the aim of providing a South African ionospheric model that gives more accurate predictions than current global models.

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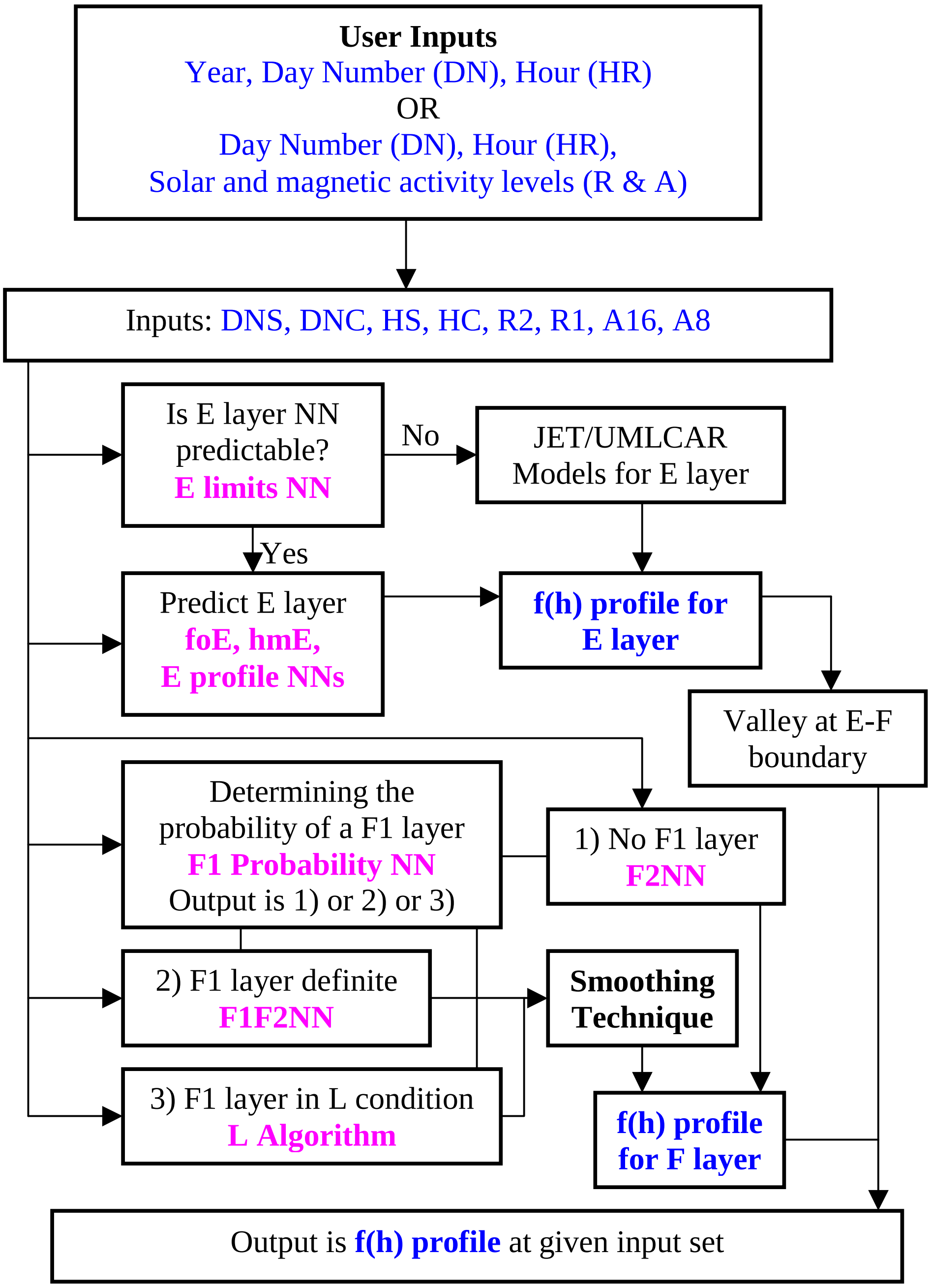

Fig. 1: A block diagram depicting the process that the LAM model follows when predicting a profile for a particular set of inputs.

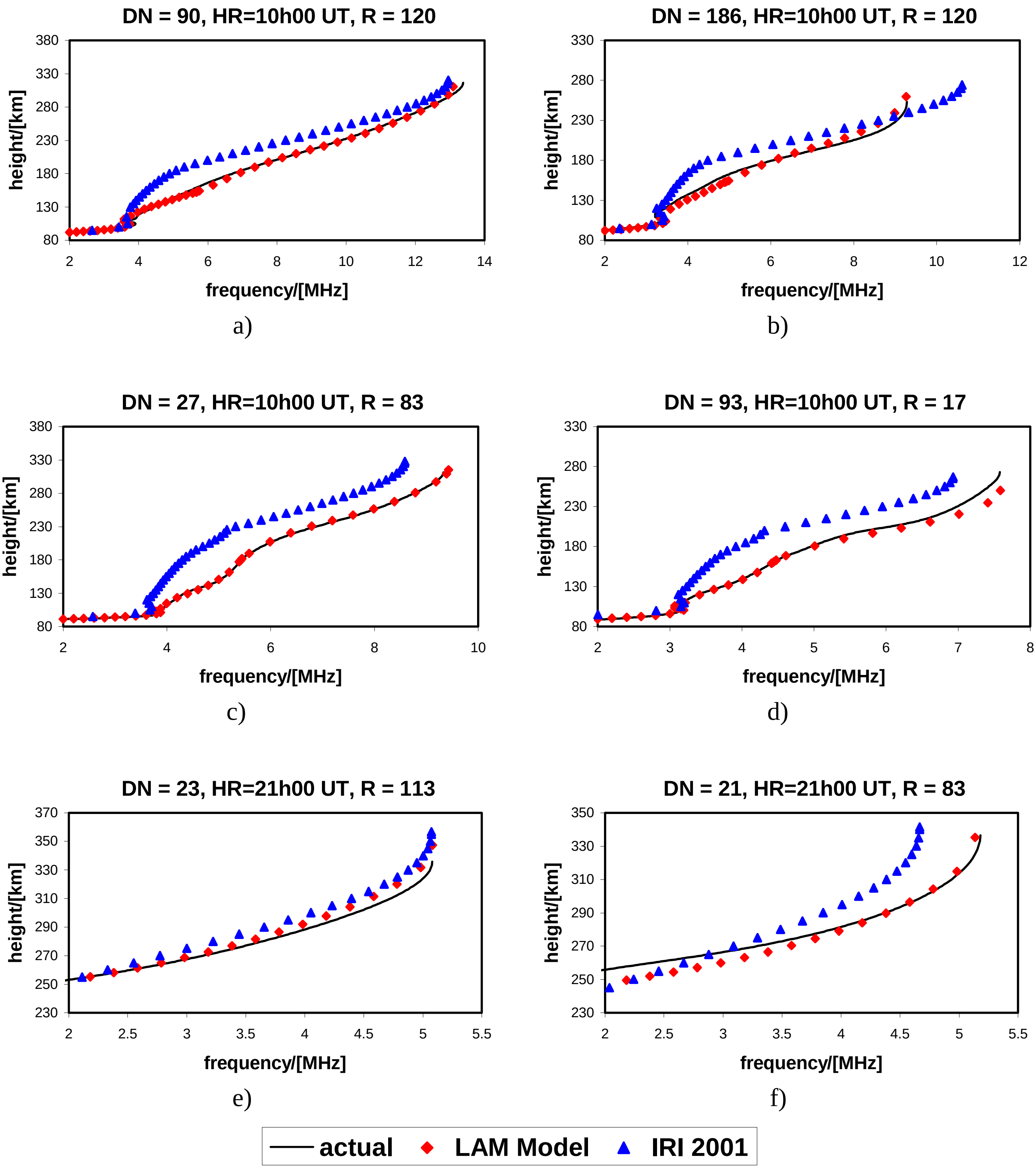

Fig. 2: Comparisons of actual DPS profiles with predicted LAM model and IRI 2001 profiles. The first four graphs correspond to midday local time while the last two correspond to midnight local time.