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HF Frequency Short-Term Forecast Method Research in the Asia Oceania Region

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***Abstract*—With analysis on ionosphere propagation features, and on the basis of ionospheric data in Sanya, Hainan, the self-correlation coefficient analysis method is applied to the ionospheric parameter prediction, then the method is compared with the artificial neural network prediction method. The prediction of the autocorrelation coefficients method is more close to the actual value, and more accurate scientific basis is provided for the HF frequency prediction.**

Keywords—autocorrelation coefficient; artificial neural network; foF2

I. INTRODUCTION

HF communication is one of the main means of remote communication, and play a strong role in communication distance and maneuverability. Because propagation of sky waves mainly depends on ionosphere reflection, and propagation parameters have the characteristics of time-varying dispersive, so the frequency is unpredictable and communication performance declines. Ionospheric variability is very acute and abnormal in the Asia Oceania region, especially for the South China Sea with "ionospheric gradients" and "double hump" phenomenon, so how to predict HF frequency accurately is always one of the research hotspot.

The prediction of ionospheric parameters is the critical point of HF frequency prediction. ITU-RP.1239 method is adopted in the REC533 model recommended by ITU to predict ionospheric parameters, and the digital map data in the Chinese region is deduced from the ionospheric data of few observation station, the predicted value compared with the actual value is still a gap. The Asia-Oceania method is a calculation model to predict ionospheric parameters in Asia Oceania region, and the method proves that the correlation in between ionospheric parameters and forecast index(Ic) are better than in between ionospheric parameters and sunspot number(R12); but ionospheric acute movements in the South China Sea has been concentrated less, and the method is mainly used to mid-and-long term forecasting. At present, short-term forecast methods of ionospheric parameters at home and abroad include autocorrelation analysis[1], multiple source linear regression[2-4], artificial neural network[5-7] and similar day method[8-9], and so on. Various predicted methods produce different predicted results, and each has merits and defects.

With analysis on ionosphere propagation features in Sanya, Hainan, the autocorrelation coefficient analysis method is applied to the critical frequency's (foF2) Short-Term prediction, then the predicted value is compared with the artificial neural network prediction method's. The conclusion could be drowned, that more accurate predicted value will be acquired by the autocorrelation coefficients method.

II. AUTOCORRELATION COEFFICIENTS UNSTABLE PREDICTED METHOD

For a random process x(t), which statistical characteristics can usually be described by mathematic expectation, variance and autocorrelation coefficients in probability theory. When second order stationarity is meet, the x(t)' s regularities of distribution will not change over time. Its definity is

$$m = E[x(t)] \tag{1}$$

$$\sigma = \sqrt{E[(x(t) - m)^2]} \tag{2}$$

$$\rho(\tau) = \frac{E[x(t_1)x(t_2)] - m^2}{\sigma^2} \tag{3}$$

The mathematic expectation m is described as the average of x(t), and the variance σ is expressed as the change intension of x(t) around the average value, and the ρ(t) is defined as the x(t)'s autocorrelation coefficient with the value range from -1 to +1. The ρ(t) is described as linear dependence relation between two random variables x(t) and x(t+τ) in time t and t+τ, and the greater the correlation index the greater will be the linear relation.

In practice, the number of the sample is limited, then suppose that x(t_p)is measured value of x(t) in time t_p (p=0,1,2,…,N-1). So practical design formulas could be acquired:

$$E[x(t)] = \frac{1}{N}\sum_{p=0}^{N-1} x(t_p) \tag{4}$$

$$\sigma = \sqrt{\frac{1}{N}\sum_{p=0}^{N-1}\left(x(t_p) - \overline{x(t)}\right)^2} \tag{5}$$

$$\rho(\tau) = \frac{E[x(t_p)x(t_p+\tau)] - E[x(t_p)]E[x(t_p+\tau)]}{\sigma_{t_p}\sigma_{t_p+\tau}} = \frac{NS_{12} - S_1S_2}{\sqrt{[NS_{11} - S_1^2][NS_{22} - S_2^2]}} \quad (6)$$

Where:

$$S_1 = \sum_{P=0}^{N-1} x\,(t_p) \qquad S_2 = \sum_{P=0}^{N-1} x\,(t_p+\tau)$$

$$S_{11} = \sum_{P=0}^{N-1} x^2\,(t_p) \qquad S_{22} = \sum_{P=0}^{N-1} x^2\,(t_p+\tau)$$

$$S_{12} = \sum_{P=0}^{N-1} [x(t_p)x(t_p+\tau)]$$

First, the hour values of ionosphere characteristic parameters z are arranged to a function of stationarity time series, then linear filter is adapted, and the z (predicted value) at one point is expressed as weighted average of n measured values.

$$Z(t) = \sum_{j=0}^{n-1} \lambda_j\, Z(t_j) \quad (7)$$

Under the optimal and unbiased conditions, Z(t) is considered as a stationary stochastic process, where weighted coefficient λ_j can be obtained by the autocorrelation coefficient ρ(t) of Z(t). Then λ_j and ρ(t) meet the following linear formulas:

$$\sum_{j=0}^{n-1} \lambda_j\, \rho(t_i - t_j) + \mu = \rho(t - t_i), i = 0,1,2,\ldots,n-1 \quad (8)$$

$$\sum_{j=0}^{n-1} \lambda_j = 1 \quad (9)$$

Where $\boldsymbol{\mu}$ is the Lagrange multiplication factor, and $\boldsymbol{\rho}(\tau)$ is the autocorrelation coefficient of the function Z(t).

$$\rho(\tau) = \frac{MZ(t)Z(t+\tau) - (MZ)^2}{MZ^2 - (MZ)^2} \quad (10)$$

If the autocorrelation coefficient ρ of Z(t) is known, then these n+1 linear formulas can be worked out. Those answers λ_j and μ will be plugged into equation (3-8), then the observed value in t time can be obtained.

III. PREDICTED RESULT ANALYSIS

Ionospheric data in Sanya, Hainan in 2014 is adopted to predict, and different seasons are selected in one year, that is June (the Sun activity is stronger) and December (the sun activity is weaker). Seven days' ionospheric data which are known are selected to predict the eighth day's, then the predicted value is compared to the known value, and analyzed.

Ionospheric data in June and December are adopted to predict and analyze respectively, then seven days' data are randomly selected as the forecast object, and these seven days' data, autocorrelation predicted value and practical value are drawed out, compared and analyzed.

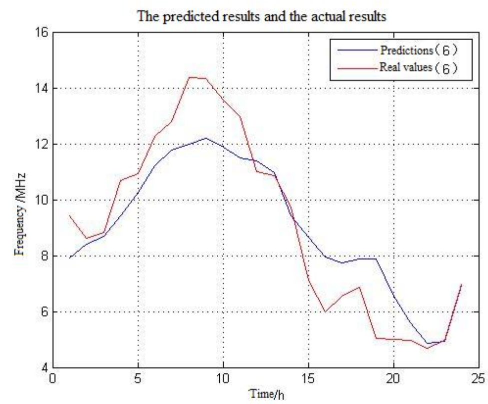

FIGURE I. PREDICTED VALUE AND ACTUAL VALUE IN JUNE

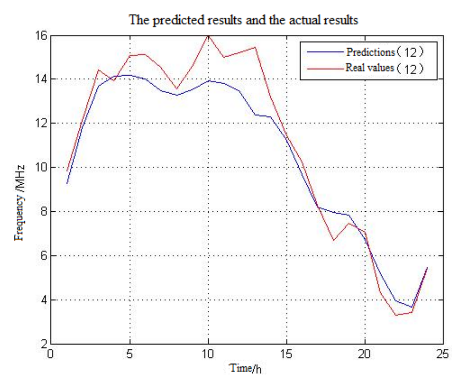

FIGURE II. PREDICTED VALUE AND ACTUAL VALUE IN DECEMBER

Comparison of these two pictures in June and December reveals that predicted value and practical value of different seasons are nearly consistent, and achieve ideal results.

To test the advantage of autocorrelation coefficient prediction method further, autocorrelation coefficient predicted foF2, artificial neural network predicted foF2 and practical foF2 are compared and analyzed, then the MUF of these foF2 in June and December are worked out to compared too.

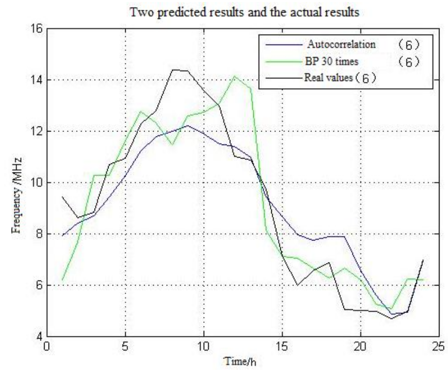

FIGURE III. PREDICTED RESULTS ANALYSIS IN JUNE

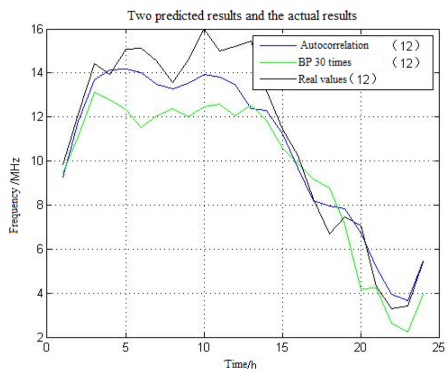

FIGURE IV. PREDICTED RESULTS ANALYSIS IN DECEMBER

FIGURE III is the compared results: the foF2 on the 12 noon of autocorrelation coefficient prediction method is 10.9643MHz, and the corresponding MUF is 11.5143MHz; the foF2 on the 12 noon of artificial neural network prediction method(30 times) is 13.6441MHz, and the corresponding MUF is 14.1914MHz; the practical foF2 on the 12 noon is 10.8500MHz, and the corresponding MUF is 12.4500MHz.

Results can also be worked out from Fig.4, the MUF on the 12 noon of autocorrelation coefficient prediction method is 15.3314MHz, and the MUF on the 12 noon of artificial neural network prediction method is 14.3149MHz, and the practical MUF on the 12 noon is 16.2761MHz.

Finally, we arrive at the conclusion by calculation and analysis, the predicted data with autocorrelation coefficient method is close to the practical frequency than artificial neural network method.

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