© September 2018 | IJIRT | Volume 5 Issue 4 | ISSN: 2349-6002

Universal Forecasting Scheme (Version 2)

Ramesh Chandra Bagadi

Associate Professor & Head, Department of Civil Engineering, Sanketika Vidya Parishad Engineering College, Visakhapatnam-41, India

***Abstract*- In this research investigation, the author has detailed a novel method of forecasting.**

INTRODUCTION

The best known methodology of Forecasting is that of Time Series Forecasting. A lot of literature is available in this domain.

THEORY

Firstly, we define the definitions of Similarity and Dissimilarity as follows:
Given any two real numbers a and b, their Similarity is given by

$$Similarity(a,b) = \begin{matrix} a^2 \ if \ a<b \\ b^2 \ if \ b<a \end{matrix}$$

and their Dissimilarity is given by

$$Dissimilarity(a,b) = \begin{matrix} ab-a^2 \ if \ a<b \\ ab-b^2 \ if \ b<a \end{matrix}$$

Given any time series or non-time series sequence of the kind

$$S = \{y_1, y_2, y_3, ..., y_{n-1}, y_n\}$$

We can now write y_{n+1} as

$$y_{(n+1)} = y_{(n+1)S} + y_{(n+1)DS}$$ where

$$y_{(n+1)S} = \sum_{i=1}^{n} y_i \left\{ \frac{\displaystyle\sum_{\substack{j=1\\ j\neq i}}^{n} \left(\frac{Total\ Exhaustive\ Similarity(y_i, y_j)}{Total\ Exhaustive\ Similarity(y_i, y_j) + Total\ Exhaustive\ Dissimilarity(y_i, y_j)} \right)}{\displaystyle\sum_{r=1}^{n} \sum_{\substack{j=1\\ j\neq r}}^{n} \left(\frac{Total\ Exhaustive\ Similarity(y_r, y_j)}{Total\ Exhaustive\ Similarity(y_r, y_j) + Total\ Exhaustive\ Dissimilarity(y_r, y_j)} \right)} \right\}$$

and

$$y_{(n+1)DS} = \sum_{i=1}^{n} y_i \left\{ \frac{\displaystyle\sum_{\substack{j=1\\ j\neq i}}^{n} \left(\frac{Total\ Exhaustive\ Dissimilarity(y_i, y_j)}{Total\ Exhaustive\ Similarity(y_i, y_j) + Total\ Exhaustive\ Dissimilarity(y_i, y_j)} \right)}{\displaystyle\sum_{r=1}^{n} \sum_{\substack{j=1\\ j\neq r}}^{n} \left(\frac{Total\ Exhaustive\ Dissimilarity(y_r, y_j)}{Total\ Exhaustive\ Similarity(y_r, y_j) + Total\ Exhaustive\ Dissimilarity(y_r, y_j)} \right)} \right\}$$

The definitions of Total Exhaustive Similarity and Total Exhaustive Dissimilarity are detailed as follows:

$$Total\ Exhaustive\ Similarity(y_i, y_j) = Similarity(y_i, y_j) + Similarity(S_1, S_2) + Similarity(S_3, S_4) + Similarity(S_4, S_5) + \ldots\ldots + Similarity(S_k, S_{k+1})\ till\ S_k = S_{k+1}$$

$$for\ some\ k$$

$$where\ S_1 = \{Smaller(y_i, y_j)\}\ and$$

$$S_2 = \{Larger(y_i, y_j) - Smaller(y_i, y_j)\}$$

$$where\ S_3 = \{Smaller(S_1, S_2)\}\ and$$

$$S_4 = \{Larger(S_1, S_2) - Smaller(S_1, S_2)\}$$

$$where\ S_4 = \{Smaller(S_3, S_4)\}\ and$$

$$S_5 = \{Larger(S_3, S_4) - Smaller(S_3, S_4)\}$$

$$and\ so\ on\ so\ forth$$

$$where\ S_k = \{Smaller(S_{k-1}, S_k)\}\ and$$

$$S_{k+1} = \{Larger(S_{k-1}, S_k) - Smaller(S_{k-1}, S_k)\}$$

Similarly, we write

$$Total\ Exhaustive\ Dissimilarity(y_i, y_j) =$$
$$Dissimilarity(y_i, y_j) + Dissimilarity(S_1, S_2) +$$
$$Dissimilarity(S_3, S_4) + Dissimilarity(S_4, S_5) +$$
$$....... + Dissimilarity(S_k, S_{k+1})\ till\ S_l = S_{l+1}$$
$$for\ some\ l$$
$$where\ S_1 = \{Smaller(y_i, y_j)\}\ and$$
$$S_2 = \{Larger(y_i, y_j) - Smaller(y_i, y_j)\}$$
$$where\ S_3 = \{Smaller(S_1, S_2)\}\ and$$
$$S_4 = \{Larger(S_1, S_2) - Smaller(S_1, S_2)\}$$
$$where\ S_4 = \{Smaller(S_3, S_4)\}\ and$$
$$S_5 = \{Larger(S_3, S_4) - Smaller(S_3, S_4)\}$$

$$and\ so\ on\ so\ forth$$
$$where\ S_l = \{Smaller(S_{l-1}, S_l)\}\ and$$
$$S_{l+1} = \{Larger(S_{l-1}, S_l) - Smaller(S_{l-1}, S_l)\}$$

Similarly, we can write the Total Exhaustive Similarity and Total Exhaustive Dissimilarity for

REFERENCES

[1] Ramesh Chandra Bagadi, Universal Forecasting Scheme http://vixra.org/abs/1803.0069

[2] Ramesh Chandra Bagadi, Universal Forecasting Scheme, International Journal Of Innovative Research & Technology, Vol 4, Issue 11, April 2018, Pages 43-43, ISSN 2349-6002 http://ijirt.org/Article?manuscript=145722