The Cortisol Awakening Response Using Modified Computational Method of Forecasting Based on Fuzzy Time Series

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Abstract- In this paper, our objective was to apply the response test to a population already known to have long-term hypothalamo–pituitary–adrenocortical (HPA) axis dysregulation. We hypothesized that the free cortisol response to waking, believed to be genetically influenced, would be elevated in a significant percent age of cases, regard less of the afternoon Dexamethasone Suppression Test (DST) value based on fuzzy time series and genetic algorithms. The modified computational method adjusts the length of each interval in the universe of discourse for forecasting the Longitudinal Dexamethasone Suppression Test (DST) data on a fully remitted lithium responder for past 5 years who was asymptomatic and treated with lithium throughout the experimental results show that the modified computational method gets good forecasting results.

Index Terms- Fuzzy Time Series, Fuzzy Logical Relationship, Mean Square Error, glucocorticoids, salivary cortisol, bipolar disorder, lithium, Dexamethasone Suppression Test, DST.

I. INTRODUCTION

Forecasting has always been a crucial challenge for managers and scientists to arrive accurate decisions. Time-series analysis is an important tool for forecasting the future in terms of past history. Time-series methods are generally used when there is not much information about the generation process of the underlying variable and when other variables provide no clear explanation of the studied variable. A recent review of the literature on time series forecasting is considered by Gooijer and Hyndman[1]. Many techniques for time-series analysis have been developed assuming linear relationships among the series variables[2]. On the other hand, in many manufacturing and services industries, because of lacking sufficient historical data, traditional time series forecasting methods do not usually make reasonable judgments, so that there are large margins of errors between the predictive and actual values [3]. To solve this problem, Song and Chissom[4] first proposed the concept of fuzzy time series. The main property of the fuzzy time series is that the values of the demand variables are linguistic values.

The free cortisol response to waking is a promising series of salivary tests that may provide a useful and non-invasive measure of HPA functioning in high-risk studies. The small sample size limits generalizability of our findings. Because interrupted sleep may interfere with the waking cortisol rise, we may have underestimated the proportion of our population with enhanced cortisol secretion. Highly cooperative participants are required [5].

II. FUZZY TIME SERIES

In this session, we brief review the concept of fuzzy time series from [6], [7], [8]. The main difference of fuzzy time series and traditional time series is that the values of fuzzy time series are represented by fuzzy sets [9] rather than real values.

Let \( D \) be the universe of discourse, where \( D = \{d_i\}_{i=1}^n \). A fuzzy set \( A_i \) in the universe of discourse \( D \) is defined as follows:

\[
A_i = \sum_{i=1}^{n} f_{A_i}(d_i) \quad \text{d}_i, \quad \text{Where } f_{A_i} \text{ is the membership function of the fuzzy set } A_i, \quad f_{A_i}(d_j) \quad \text{is the degree of membership of } d_j \text{ in the fuzzy set } A_i, \quad f_{A_i}(d_j) \in [0,1] \quad \text{and } 1 \leq j \leq n.
\]

Recently, interest has turned to more refined testing and the probability that HPA dysregulation may even predate the onset of clinical illness [10]. Preliminary data suggest that this dysregulation may be concentrated within the families of individuals with mood disorders [11], suggesting the hypothesis that early abnormalities in cortisol regulation may confer a risk for the future development of mood disorders. To understand the temporal relation between HPA dysregulation and the onset of bipolar disorder (BD), it is essential to have a reliable and non-invasive test that can be repeatedly administered prospectively and is acceptable to high-risk populations. Promising candidates for such a test include the salivary free cortisol response to waking and the short day time profile, a test that adds afternoon and evening measurements to the waking values[10].

Let \( Y(t) (t = ..., 0, 1, 2, ...) \) be the universe of discourse in which fuzzy sets \( f_i(t) (i = 1, 2, ...) \) are defined in the universe
of discourse $Y(t)$. Assume that $F(t)$ is a collection of $f_i(t) \ (i = 1, 2, \ldots)$, then $F(t)$ is called a fuzzy time series of $Y(t) \ (t = \ldots, 0, 1, 2, \ldots)$.

Assume that there is a fuzzy relationship $R(t - 1, t)$, such that $F(t) = F(t - 1) \circ R(t - 1, t)$, where the symbol “$\circ$” represents the max-min composition operator, then $F(t)$ is called caused by $F(t - 1)$. The relation $R$ is called first order fuzzy time series and genetic algorithms.

Step 1: In many of the existing algorithms, the universe of discourse is considered as $D = [B_{\min} - B_1, B_{\max} + B_2]$ into intervals of equal length, where $B_{\min}$ and $B_{\max}$ are the minimum value and the maximum value of the historical data, respectively, and $B_1$ and $B_2$ are two proper positive real values to divide the universe of discourse $D$ into $n$ intervals $d_1, d_2, \ldots, d_n$ of equal length. Here we considered the universe of discourse using normal distribution range based definition, i.e., $D = [\mu - 3\sigma, \mu + 3\sigma]$ where $\mu$ and $\sigma$ are mean and standard deviation values of the data, respectively. Also, in the existing method[12], the forecasted variable is calculated by taking into account all the values including the repeated values are considered as single value. We call the forecasted value is modified forecasted variable, because of these modifications, the root mean square error of the modified method is minimum composed to the existing method [13],[14].

Step 2: Here $\mu = 216.61, \sigma = 89.03, \mu - 3\sigma = -50.48$ and $3\sigma = 483.7$
the universe of discourse $D = [-50.48, 483.7] \simeq [-50, 480]$.
But $A_1, A_2, \ldots, A_8$ are linguistic terms represented by fuzzy sets. Therefore, the universe of the discourse $D = [50, 450]$. Firstly, divide the universe of discourse $D$ into Eight intervals $d_1, d_2, d_3, d_4, d_5, d_6, d_7$ and $d_8$, where $d_1 = [50, x_1]$, $d_2 = [x_1, x_2]$, $d_3 = [x_2, x_3]$, $d_4 = [x_1, x_4]$, $d_5 = [x_4, x_5]$, $d_6 = [x_5, x_6]$, $d_7 = [x_6, x_7]$ and $d_8 = [x_7, 450]$; $x_1, x_2, x_3, x_4, x_5, x_6$ and $x_7$ are integer variables and $x_1 < x_2 < x_3 < x_4 < x_5 < x_6 < x_7$. We can see that the universe discourse $D = [50, 450]$ into Eight intervals $d_1, d_2, d_3, d_4, d_5, d_6, d_7$ and $u_8$, where $d_1 = [50, 100]$, $d_2 = [100, 150]$, $d_3 = [150, 200]$, $d_4 = [200, 250]$, $d_5 = [250, 300]$, $d_6 = [300, 350]$, $d_7 = [350, 400]$ and $d_8 = [400, 450]$;

Step 3: Define the linguistic terms $A_i$ represented by fuzzy sets, shown as follows:

III. A MODIFIED COMPUTATIONAL METHOD FOR FUZZY TIME SERIES FORECASTING

In this session, we present a new method to forecast the Longitudinal Dexamethasone Suppression Test (DST) [11] data on a fully remitted lithium responder for past 5 years who was asymptomatic and treated with lithium throughout, based on fuzzy time series and genetic algorithms.

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Where $A_1, A_2, .......A_8$ are linguistic terms represented by fuzzy sets. Then, we can fuzzify the Longitudinal Dexamethasone Suppression Test (DST) data on a fully remitted lithium responder for past 5 years who was asymptomatic and treated with lithium throughout, shown in Table 1, as shown in Table 3. Furthermore, we can get the fuzzy logical relationship groups as shown in Table 4, where the ith fuzzy logical relationship group contains fuzzy logical relationships whose current state is $A_i$, where $1 \leq i \leq 8$. Then, apply the following forecasting method to forecast the data [15], [16]:

**Step 4:** Assume that the fuzzified data of the ith year is $A_j$ and assume that there is only one fuzzy logical relationship in the fuzzy logical relationship groups in which the current state of the fuzzy logical relationship is $A_i$, shown as follows:

\[ A_j \rightarrow A_k \]

where $A_j$ and $A_k$ are fuzzy sets and the maximum membership value of $A_k$ occurs at interval $d_k$, then the forecasted data of the i + 1th year is the midpoint $m_k$ of the interval $d_k$.

**Step 5: Rules for forecasting**
- LV$_j$ – lower value of the interval $d_j$
- UV$_j$ – upper value of the interval $d_j$
- $L_j$ – length of the interval $d_j$
- The midpoint $m_k$ of the interval $d_k$

The fuzzified data of the jth year is $A_j$ in which the current state of the fuzzy logical relationship is $A_k$, shown as follows:

\[ A_j \rightarrow A_k \]

G$_n$ – Given value of state ‘n’
G$_{n-1}$ – Given value of state ‘n-1’
G$_{n-2}$ – Given value of state ‘n-2’
F$_j$ – forecasted value of the current state ‘j’

**Computational Algorithms**
For $i = 3, 4, 5, .......(end of time series data)$
Obtained fuzzy logical relation for “$A_j \rightarrow A_k$”

\[ V = 0 \text{ and } x = 0 \]
\[ 1.D_n = |(G_n - 2G_{n-1} + G_{n-2})| \]

2. a) if $m_j + D_n/6 \geq LV_k$ & $m_j + D_n/6 \leq UV_k$ then $V = V + m_j + D_n/6, x = x + 1$
b) if $m_j - D_n/6 \geq LV_k$ & $m_j - D_n/6 \leq UV_k$ then $V = V + m_j - D_n/6, x = x + 1$
c) if $m_j + D_n/4 \geq LV_k$ & $m_j + D_n/4 \leq UV_k$ then $V = V + m_j + D_n/4, x = x + 1$
d) if $m_j - D_n/4 \geq LV_k$ & $m_j - D_n/4 \leq UV_k$ then $V = V + m_j - D_n/4, x = x + 1$
e) if $m_j + D_n/2 \geq LV_k$ & $m_j + D_n/2 \leq UV_k$ then $V = V + m_j + D_n/2, x = x + 1$
f) if $m_j - D_n/2 \geq LV_k$ & $m_j - D_n/2 \leq UV_k$ then $V = V + m_j - D_n/2, x = x + 1$
g) if $m_j + D_n \geq LV_k$ & $m_j + D_n \leq UV_k$ then $V = V + m_j + D_n, x = x + 1$
h) if $m_j - D_n \geq LV_k$ & $m_j - D_n \leq UV_k$ then $V = V + m_j - D_n, x = x + 1$
i) if $m_j - 2D_n \geq LV_k$ & $m_j - 2D_n \leq UV_k$ then $V = V + m_j - 2D_n, x = x + 1$
j) if $m_j + 2D_n \geq LV_k$ & $m_j + 2D_n \leq UV_k$ then $V = V + m_j + 2D_n, x = x + 1$
k) if $m_j - 3D_n \geq LV_k$ & $m_j - 3D_n \leq UV_k$ then $V = V + m_j - 3D_n, x = x + 1$
l) if $m_j + 3D_n \geq LV_k$ & $m_j + 3D_n \leq UV_k$ then $V = V + m_j + 3D_n, x = x + 1$

3. $F_k = (V + m_k) / (x + 1)$

**Next i**

**IV. EXAMPLE**

**Figure 1:** The Longitudinal Dexamethasone Suppression Test (DST) data on a fully remitted lithium responder for past 5 years who was asymptomatic and treated with lithium throughout.

**TABLE 1: FUZZIFIED VALUE AND FUZZY LOGICAL RELATIONSHIPS FOR MEDICAL DATA**

<table>
<thead>
<tr>
<th>S. No</th>
<th>Actual Value</th>
<th>Fuzzy set</th>
<th>Fuzzy logical relationships</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>225</td>
<td>$A_4$</td>
<td>$A_4 \rightarrow A_3$</td>
</tr>
<tr>
<td>2</td>
<td>190</td>
<td>$A_3$</td>
<td>$A_4 \rightarrow A_3$</td>
</tr>
<tr>
<td>3</td>
<td>395</td>
<td>$A_7$</td>
<td>$A_3 \rightarrow A_7$</td>
</tr>
<tr>
<td>4</td>
<td>140</td>
<td>$A_2$</td>
<td>$A_7 \rightarrow A_2$</td>
</tr>
<tr>
<td>5</td>
<td>90</td>
<td>$A_1$</td>
<td>$A_2 \rightarrow A_1$</td>
</tr>
</tbody>
</table>
Forecasted Error = |Forecasted value – Actual value|/Actual

Mean square error = \[ \frac{\sum_{i=1}^{n} |\text{forecasted value}_i - \text{actual value}_i|^2}{n} \]

Forecasted Error = |Forecasted value – Actual value|/Actual value

Average Forecasting Error = sum of forecasting error / number of errors

Mean square error = 1103.02
Average forecasted error = 8.9%
EXP. RESULTS

V. EXPERIMENTAL RESULTS

It means that the modified computational method gets a higher average forecasting accuracy rate than other existing methods to forecast the maximum percentage rise of salivary cortisol response to awakening. We can see that the modified computational method get the smallest Mean square error.

CONCLUSION

VI. CONCLUSION

In this paper, the test is easy to administer, the free cortisol response to awakening may hold promise as a marker in studies of high-risk families predisposed to, or at risk for, mood disorders, we have presented a new method for forecasting the Longitudinal Dexamethasone Suppression Test (DST) data on a fully remitted lithium responder for past 5 years who was asymptomatic and treated with lithium throughout based on fuzzy time series. We also make a comparison of the MSE of the forecasted medical data for different methods. In this paper, we use the MSE to compare the performance of prediction of medical data. Therefore, in the future, we will develop a new method to deal with a more accurate prediction by narrowing the maximum deviation of predicted value from the actual one.

REFERENCES


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