# The Cortisol Awakening Response Using Modified Method For Higher Order Logical Relationship

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***Abstract - A growing body of data suggests that a significantly enhanced salivary cortisol response to waking may indicate an enduring tendency to abnormal cortisol regulation. Based on the forecasting results, 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 high-order fuzzy logical relationships. First, the proposed method fuzzifies the historical data into fuzzy sets to form high-order fuzzy logical relationships. Then, it calculates the value of the variable between the subscripts of adjacent fuzzy sets appearing in the antecedents of high-order fuzzy logical relationships. Finally, it chooses a modified high-order fuzzy logical relationships group to forecast the free cortisol response to walking and the short day time profile.***

***Keywords: Fuzzy Time Series, Genetic Algorithms, Fuzzy Logical Relationship, Fuzzy Logical Relationship Groups, Mean Square Error, glucocorticoids, salivary cortisol, bipolar disorder, lithium, Dexamethasone Suppression Test, DST.***

## 1. INTRODUCTION

Forecasting plays an important role in day to day life. If there is an uncertainty about the future, then decision makes need to forecast. Forecasting is the process of predicting future outcomes, by which decision makers analyze the data and graphs to decide and take the best decisions for the future. For the past few decades, various approaches have been developed for forecasting[1] [2] [3].

A growing body of literature points to hypothalamo–pituitary–adrenocortical (HPA) axis dysregulation as a critical factor in the development of mood disorders. Long-term enhanced cortisol secretion may have important health ramifications in addition to its contribution to mood syndromes. 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[4].

We are interested in minimizing the error in the forecasting using regression models. In regression models, violation of assumptions regarding the behavior of stochastic variable contributions to error. Our attempts to minimize the error led us to search an alternative method which motivated us to work on fuzzy time series model based forecasting. Many researches are applying high-order fuzzy logical relationships to forecasting problems. However, the size of error still remains high. Hence we attempt to modify the algorithm in order to reduce the size of error in forecasting.

The aim this paper is to propose a method to attain better forecasting accuracy by using fuzzy time series. 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 high-order fuzzy logical relationships. First, the proposed method fuzzifies the historical data into fuzzy sets to form high-order fuzzy logical relationships. Then, it calculates the value of the variable between the subscripts of adjacent fuzzy sets appearing in the antecedents of high-order fuzzy logical relationships. Then, it lets the high-order fuzzy logical relationships with the same variable value form a high-order fuzzy logical relationship group. In section 2, the basic concept and definition of fuzzy time series are presented. In section 3, modified method [5] is given. In section 4, numerical example and the experimental results are presented. Finally conclusions are presented in section 5.

## 2. PRELIMINARIES

Recently, interest has turned to more refined testing and the probability that HPA dysregulation may even predate the onset of clinical illness [6]. Preliminary data suggest that this dysregulation may be concentrated within the families of individuals with mood disorders [7], 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.

The concepts of fuzzy time series are presented by Song and Chissom, where the values in a fuzzy time series are represented by fuzzy sets (Zadeh, 1965) [8]. 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:

$$A_i = \sum_{i=1}^{n} \frac{f_{A_i}(d_i)}{d_i}$$

, Where $f_{A_i}$ is the membership function of the fuzzy set $A_i$, $f_{A_i} : D \to [0,1]$, $f_{A_i}(d_j)$ is the degree of membership of $d_j$ in the fuzzy set $A_i$, $f_{A_i}(d_j) \in [0,1]$ and $1 \le j \le n$.

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 $f_i(t)\,(i = 1,2......)$, then $F(t)$ is called a fuzzy time series of $Y(t)\,(t = ....,0,1,2.....)$.

Assume that there is a fuzzy relationship $R(t-1,t)$, such that $F(t) = F(t-1)\, o\, R(t-1,t)$, where the symbol "$o$" represents the max-min composition operator, then $F(t)$ is called caused by $F(t-1)$.

Let $F(t-1) = A_i$ and let $F(t) = A_j$, where $A_i$ and $A_j$ are fuzzy sets, then the fuzzy logical relationship (FLR) between $F(t-1)$ and $F(t)$ can be denoted by $A_i \to A_j$, where $A_i$ and $A_j$ are called the left-hand side(LHS) and the right hand side (RHS) of the fuzzy logical relationship, respectively.

If

$$F(t-n) = A_{in},$$
$$......., F(t-2) = A_{i2}, \quad ,$$
$$F(t-1) = A_{i1} \text{ and } F(t) = A_j$$

where $A_{in}, ....., A_{i2}, A_{i1}$ *and* $A_j$ are fuzzy sets, then the nth-order fuzzy logical relationship can be represented by $A_{in}, ....., A_{i2}, A_{i1} \to A_j$,

Where $A_{in}, ....., A_{i2}, andA_{i1}$ are called the antecedent fuzzy sets of the nth-order fuzzy logical relationship; "$A_{in}, ....., A_{i2}, A_{i1}$" and "$A_j$" are called the left hand-side and the right-hand side of the nth-order fuzzy logical relationship, respectively.

## 3. A NEW FORECASTING METHOD BASED ON HIGH-ORDER FUZZY LOGICAL RELATIONSHIPS

Following is the modified forecasting method based on higher order fuzzy logical relationships. In many of the exiting 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 $d_1, d_2, ....., d_n$ of equal length. Here we considered the universe of discourse using normal distribution range based definition, i.e., D = [$\mu$ - 3σ, $\mu$ + 3σ] where $\mu$ and σ are mean and standard deviation values of the data, respectively. Also, in the exiting method [9], 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. In this section, we present a modified forecasting method based on high-order fuzzy logical relationships as follows:

**Step1:** Define the universe of discourse $D$, D = [$\mu$ - 3σ, $\mu$ + 3σ] where $\mu$ and σ are mean and standard deviation values of the data, respectively and the universe of discourse $D$ divide into n intervals $d_1, d_2, ....., d_n$ of equal length.

**Step2:** Define the linguistic terms $A_i$ represented by fuzzy sets, shown as follows:

$$A_1 = \frac{1}{d_1} + \frac{0.5}{d_2} + \frac{0}{d_3} + \frac{0}{d_4} + \dots\dots\dots + \frac{0}{d_{n-2}} + \frac{0}{d_{n-1}} + \frac{0}{d_n},$$

$$A_2 = \frac{0.5}{d_1} + \frac{1}{d_2} + \frac{0.5}{d_3} + \frac{0}{d_4} + \dots\dots\dots + \frac{0}{d_{n-2}} + \frac{0}{d_{n-1}} + \frac{0}{d_n},$$

$$A_3 = \frac{0}{d_1} + \frac{0.5}{d_2} + \frac{1}{d_3} + \frac{0.5}{d_4} + \dots\dots\dots + \frac{0}{d_{n-2}} + \frac{0}{d_{n-1}} + \frac{0}{d_n},$$

$$A_{n-1} = \frac{0}{d_1} + \frac{0}{d_2} + \frac{0}{d_3} + \frac{0}{d_4} + \dots\dots\dots + \frac{0.5}{d_{n-2}} + \frac{1}{d_{n-1}} + \frac{0.5}{d_n},$$

$$A_n = \frac{0}{d_1} + \frac{0}{d_2} + \frac{0}{d_3} + \frac{0}{d_4} + \dots\dots\dots + \frac{0}{d_{n-2}} + \frac{0.5}{d_{n-1}} + \frac{1}{d_n},$$

Where $A_1, A_2, \dots\dots, and A_n$ are linguistic terms represented by fuzzy sets.

**Step3:**Fuzzify each historical datum into a fuzzy set defined in **Step2.** If the historical datum belongs to $d_i$ and the maximum membership value of $A_i$ occurs at $d_i$, then the historical datum is fuzzified into $A_i$, where $1 \le i \le n$.

**Step4:** Construct the nth-order fuzzy logical relationships from the fuzzified historical datum of the training data set.

**Step5:** Transform each nth-order fuzzy logical relationship "$A_{X_1}, A_{X2}, A_{X3}, \dots\dots, A_{Xj}, \dots\dots, A_{X_n} \rightarrow A_{Xr}$" into the following form:

$$A_{X_1}, A_{X_{1+V(X_1)}}, A_{X_{1+V(X_1)+V(X_2)}}, \dots\dots\dots A_{X_{1+V(X_1)+V(X_2)+\dots\dots+V(X_i)+\dots\dots}}, A_{X_{1+V(X_1)+V(X_2)+\dots\dots+V(X_i)+\dots\dots+V(X_m)}}$$
$$\rightarrow A_{X_{1+V(X_1)+V(X_2)+\dots\dots+V(X_i)+\dots\dots+V(X_m)+V(X_n)}},$$

where $V(X_1), V(X_2), \dots\dots, and V(X_n)$ are integers.

**Step6:** Let the transformed nth-order fuzzy logical relationships obtained in **Step5** having the same left-hand side form a nth-order fuzzy logical relationship group. For example, let us consider the following transformed third-order fuzzy logical relationships:

$$A_{a_1}, A_{a_{1+V(a_1)}}, A_{a_{1+V(a_1)+V(a_2)}} \rightarrow A_{a_{1+V(a_1)+V(a_2)+V(a_3)}},$$

$$A_{b_1}, A_{b_{1+V(b_1)}}, A_{b_{1+V(b_1)+V(b_2)}} \rightarrow A_{b_{1+V(b_1)+V(b_2)+V(b_3)}},$$

.

$$A_{k_1}, A_{k_{1+V(k_1)}}, A_{k_{1+V(k_1)+V(k_2)}} \rightarrow A_{k_{1+V(k_1)+V(k_2)+V(k_3)}},$$

Where $V(a_1) = V(b_1) = \dots\dots\dots = V(k_1)$ and $V(a_2) = V(b_2) = \dots\dots\dots = V(k_2)$, then these third- order fuzzy logical relationships can be grouped into a transformed third-order fuzzy logical relationships group, shown as follows:

$$A_X, A_{X_{+V(Y_1)}}, A_{X_{1+V(Y_1)+V(Y_2)}} \rightarrow A_{X_{+V(Y_1)+V(Y_2)+V(a_3)}}, A_{X_{+V(Y_1)+V(Y_2)+V(b_3)}}, , \dots\dots\dots, A_{X_{+V(Y_1)+V(Y_2)+V(k_3)}}$$

where

$X = a_1, b_1, \dots\dots k_1$,

$V(Y_1) = V(a_1) = V(b_1) = \dots\dots\dots = V(k_1)$ and

$V(Y_2) = V(a_2) = V(b_2) = \dots\dots\dots = V(k_2)$.

**Step7:** Choose a transformed nth-order fuzzy logical relationship group for prediction. Assume that $F(t-n) = A_{in}$, $F(t-(n-1)) = A_{i(n-1)}$, and assume that $\dots\dots F(t-2) = A_{i2}, and\ F(t-1) = A_{i1}$ we want to predict $F(t)$, where $A_{i1}, A_{i2}, \dots\dots, and\ A_{in}$ are fuzzy sets. Based on the transformed nth-order fuzzy logical relationship groups obtained in **Step6**, choose the corresponding transformed nth-order fuzzy logical relationship group for prediction. If the chosen transformed nth-order fuzzy logical relationship group is:

$A_X, A_{X_{+V(Y_1)}}, \ldots\ldots\ldots\ldots, A_{X_{1+V(Y_1)+V(Y_2)+\ldots\ldots\ldots+V(Y_{n-1})}}$

$\rightarrow A_{X_{+V(Y_1)+\ldots\ldots\ldots+V(Y_{n-1})+V(a_n)}}, A_{X_{+V(Y_1)+\ldots\ldots\ldots+V(Y_{n-1})+V(b_n)}},$ where

$\ldots\ldots\ldots, A_{X_{+V(Y_1)+V(Y_2)+\ldots\ldots+V(Y_{n-1})+V(k_n)}}$

$A_{in} = A_X, A_{i(n-1)} = A_{X+V(Y_1)}, \ldots\ldots, A_{i1} = A_{X+V(Y_1)+V(Y_2)+\ldots\ldots+V(Y_{n-1})}$, then replace $X$ by the subscript in of the fuzzy set $A_{in}$ to get the derived fuzzy sets $A_{in+V(Y_1)+\ldots\ldots+V(Y_{(n-1)})+V(a_n)}$, $A_{in+V(Y_1)+\ldots\ldots+V(Y_{(n-1)})+V(b_n)}, \ldots\ldots,$ $andA_{in+V(Y_1)+\ldots\ldots+V(Y_{(n-1)})+V(k_n)}$ for prediction. Let

$A_{j1} = A_{in+V(Y_1)+\ldots\ldots+V(Y_{n-1})+V(a_n)}$, let

$A_{j2} = A_{in+V(Y_1)+\ldots\ldots+V(Y_{n-1})+V(b_n)}, \ldots\ldots,$ and let

$A_{jk} = A_{in+V(Y_1)+\ldots\ldots+V(Y_{n-1})+V(k_n)}$. Then, the modified forecasted variable $FVar$ is calculated as follows:

$$MFVar = \frac{\sum_{i=1}^{k} m_{ji}}{k} - m_{i1.} \qquad (1)$$

Where the maximum membership values of $A_{i1}, A_{j1}, A_{j2}, \ldots\ldots, andA_{jk}$ occur at the intervals $d_{i1}, d_{j1}, d_{j2}, \ldots\ldots, and\ d_{jk}$, respectively, and $m_{i1}, m_{j1}, m_{j2}, \ldots\ldots, andm_{jk}$ are the midpoints of the intervals $d_{i1}, d_{j1}, d_{j2}, \ldots\ldots, and\ d_{jk}$, respectively (only take distinct value). The modified forecasted value $FV$ is calculated as follows:

$$MFV = RV(t-1) + FVar, \qquad (2)$$

Where $RV(t-1)$ is the real value on trading day t-1.

## 4. EXAMPLE

We apply the proposed method to forecast 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 high order fuzzy logical relationships. D = [$\mu$ - 3σ, $\mu$ + 3σ] where $\mu$ and σ are mean and standard deviation values of the data, respectively and the universe of discourse $D$ divide into n intervals $d_1, d_2, \ldots.., d_n$ of equal length. Here $\mu$ = 216.61, σ = 89.03, $\mu$ - 3σ = -50.48 and $\mu$ + 3σ = 483.7, the universe of discourse $D$ = [-50.48, 483.7] ≃ [-50, 480]. But $A_1, A_2, \ldots..andA_8$ are linguistic terms represented by fuzzy sets. $A_1$ = [50, 100], $A_2$ = [100, 150], $A_3$ = [150, 200], $A_4$ = [200, 250], $A_5$ = [250, 300], $A_6$ = [300, 350], $A_7$ = [350, 400], $A_8$ = [400, 450]

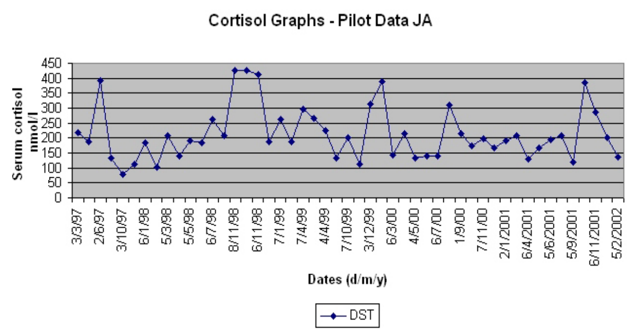


Figure 1: The Longitudinal Dexamethasone Suppression Test (DST) data on a fully remitted lithium responder for past 5 years who was asymptomatic and treated with lithium throughout

**Table 1: Fuzzy logical relationships of first order and second order**

| S. No | Actual Value | Fuzzy set | Fuzzy logical relationships of first order | Fuzzy logical relationships of second order |
|---|---|---|---|---|
| 1 | 225 | $A_4$ | - | - |
| 2 | 190 | $A_3$ | $A_4 \rightarrow A_3$ | - |
| 3 | 395 | $A_7$ | $A_3 \rightarrow A_7$ | $A_4, A_3 \rightarrow A_7$ |
| 4 | 140 | $A_2$ | $A_7 \rightarrow A_2$ | $A_3, A_7 \rightarrow A_2$ |
| 5 | 90 | $A_1$ | $A_2 \rightarrow A_1$ | $A_7, A_2 \rightarrow A_1$ |
| 6 | 120 | $A_2$ | $A_1 \rightarrow A_2$ | $A_2, A_1 \rightarrow A_2$ |
| 7 | 180 | $A_3$ | $A_2 \rightarrow A_3$ | $A_1, A_2 \rightarrow A_3$ |
| 8 | 110 | $A_2$ | $A_3 \rightarrow A_2$ | $A_2, A_3 \rightarrow A_2$ |
| 9 | 210 | $A_4$ | $A_2 \rightarrow A_4$ | $A_3, A_2 \rightarrow A_4$ |
| 10 | 145 | $A_2$ | $A_4 \rightarrow A_2$ | $A_2, A_4 \rightarrow A_2$ |
| 11 | 190 | $A_3$ | $A_2 \rightarrow A_3$ | $A_4, A_2 \rightarrow A_3$ |
| 12 | 185 | $A_3$ | $A_3 \rightarrow A_3$ | $A_2, A_3 \rightarrow A_3$ |
| 13 | 260 | $A_5$ | $A_3 \rightarrow A_5$ | $A_3, A_3 \rightarrow A_5$ |
| 14 | 210 | $A_4$ | $A_5 \rightarrow A_4$ | $A_3, A_5 \rightarrow A_4$ |

| | | | | |
|---|---|---|---|---|
| 15 | 430 | $A_8$ | $A_4 \rightarrow A_8$ | $A_5, A_4 \rightarrow A_8$ |
| 16 | 430 | $A_8$ | $A_8 \rightarrow A_8$ | $A_4, A_8 \rightarrow A_8$ |
| 17 | 420 | $A_8$ | $A_8 \rightarrow A_8$ | $A_8, A_8 \rightarrow A_8$ |
| 18 | 190 | $A_3$ | $A_8 \rightarrow A_3$ | $A_8, A_8 \rightarrow A_3$ |
| 19 | 260 | $A_5$ | $A_3 \rightarrow A_5$ | $A_8, A_3 \rightarrow A_3$ |
| 20 | 190 | $A_3$ | $A_5 \rightarrow A_3$ | $A_3, A_5 \rightarrow A_3$ |
| 21 | 295 | $A_5$ | $A_3 \rightarrow A_5$ | $A_5, A_3 \rightarrow A_5$ |
| 22 | 270 | $A_5$ | $A_5 \rightarrow A_5$ | $A_3, A_5 \rightarrow A_5$ |
| 23 | 230 | $A_4$ | $A_5 \rightarrow A_4$ | $A_5, A_5 \rightarrow A_4$ |
| 24 | 140 | $A_2$ | $A_4 \rightarrow A_2$ | $A_5, A_4 \rightarrow A_2$ |
| 25 | 199 | $A_2$ | $A_2 \rightarrow A_2$ | $A_4, A_2 \rightarrow A_2$ |
| 26 | 120 | $A_2$ | $A_2 \rightarrow A_2$ | $A_2, A_2 \rightarrow A_2$ |
| 27 | 315 | $A_6$ | $A_2 \rightarrow A_6$ | $A_2, A_2 \rightarrow A_6$ |
| 28 | 390 | $A_7$ | $A_6 \rightarrow A_7$ | $A_2, A_6 \rightarrow A_7$ |
| 29 | 145 | $A_2$ | $A_7 \rightarrow A_2$ | $A_6, A_7 \rightarrow A_2$ |
| 30 | 210 | $A_4$ | $A_2 \rightarrow A_4$ | $A_7, A_2 \rightarrow A_4$ |
| 31 | 135 | $A_2$ | $A_4 \rightarrow A_2$ | $A_2, A_4 \rightarrow A_2$ |
| 32 | 140 | $A_2$ | $A_2 \rightarrow A_2$ | $A_4, A_2 \rightarrow A_2$ |
| 33 | 140 | $A_2$ | $A_2 \rightarrow A_2$ | $A_2, A_2 \rightarrow A_2$ |
| 34 | 310 | $A_6$ | $A_2 \rightarrow A_6$ | $A_2, A_2 \rightarrow A_6$ |
| 35 | 210 | $A_4$ | $A_6 \rightarrow A_4$ | $A_2, A_6 \rightarrow A_4$ |
| 36 | 180 | $A_3$ | $A_4 \rightarrow A_3$ | $A_6, A_4 \rightarrow A_3$ |
| 37 | 195 | $A_3$ | $A_3 \rightarrow A_3$ | $A_4, A_3 \rightarrow A_3$ |
| 38 | 175 | $A_3$ | $A_3 \rightarrow A_3$ | $A_3, A_3 \rightarrow A_3$ |
| 39 | 190 | $A_3$ | $A_3 \rightarrow A_3$ | $A_3, A_3 \rightarrow A_3$ |
| 40 | 210 | $A_4$ | $A_3 \rightarrow A_4$ | $A_3, A_3 \rightarrow A_4$ |
| 41 | 135 | $A_2$ | $A_4 \rightarrow A_2$ | $A_3, A_4 \rightarrow A_2$ |
| 42 | 175 | $A_3$ | $A_2 \rightarrow A_3$ | $A_4, A_2 \rightarrow A_3$ |
| 43 | 195 | $A_3$ | $A_3 \rightarrow A_3$ | $A_2, A_3 \rightarrow A_3$ |
| 44 | 210 | $A_4$ | $A_3 \rightarrow A_4$ | $A_3, A_3 \rightarrow A_4$ |
| 45 | 120 | $A_2$ | $A_4 \rightarrow A_2$ | $A_3, A_4 \rightarrow A_2$ |
| 46 | 385 | $A_7$ | $A_2 \rightarrow A_7$ | $A_4, A_2 \rightarrow A_7$ |
| 47 | 290 | $A_5$ | $A_7 \rightarrow A_5$ | $A_2, A_7 \rightarrow A_5$ |
| 48 | 195 | $A_3$ | $A_5 \rightarrow A_3$ | $A_7, A_5 \rightarrow A_3$ |
| 49 | 140 | $A_2$ | $A_3 \rightarrow A_2$ | $A_5, A_3 \rightarrow A_2$ |

**Table 2: Transformed second order fuzzy logical relationship groups**

| Groups | Transformed second order fuzzy logical relationship |
|---|---|
| Group 1 | $A_X, A_{X-5} \rightarrow A_{X-5-1}, A_{X-5+2}, A_{X-5+2}$ |
| Group 2 | $A_X, A_{X-2} \rightarrow A_{X-2+1}, A_{X-2+2}, A_{X-2+0}, A_{X-2+0}, A_{X-2-1}, A_{X-2+1}, A_{X-2+5}, A_{X-2-2}, A_{X-2-1}$ |
| Group 3 | $A_X, A_{X-1} \rightarrow A_{X-1+4}, A_{X-1+1}, A_{X-1+2}, A_{X-1+4}, A_{X-1-2}, A_{X-1+0}$ |
| Group 4 | $A_X, A_{X+0} \rightarrow A_{X+0+2}, A_{X+0+0}, A_{X+0-5}, A_{X+0-1}, A_{X+0+0}, A_{X+0+4}, A_{X+0+0}, A_{X+0+4}, A_{X+0+0}, A_{X+0+0}, A_{X+0+1}, A_{X+0+1}$ |
| Group 5 | $A_X, A_{X+1} \rightarrow A_{X+1+1}, A_{X+1-1}, A_{X+1+1}, A_{X+1-5}, A_{X+1+0}, A_{X+1+2}$ |
| Group 6 | $A_X, A_{X+2} \rightarrow A_{X+2-2}, A_{X+2-1}, A_{X+2-2}, A_{X+2+0}, A_{X+2-2}$ |
| Group 7 | $A_X, A_{X+4} \rightarrow A_{X+4+0}, A_{X+4+1}, A_{X+4-2}$ |
| Group 8 | $A_X, A_{X+5} \rightarrow A_{X+5-2}$ |

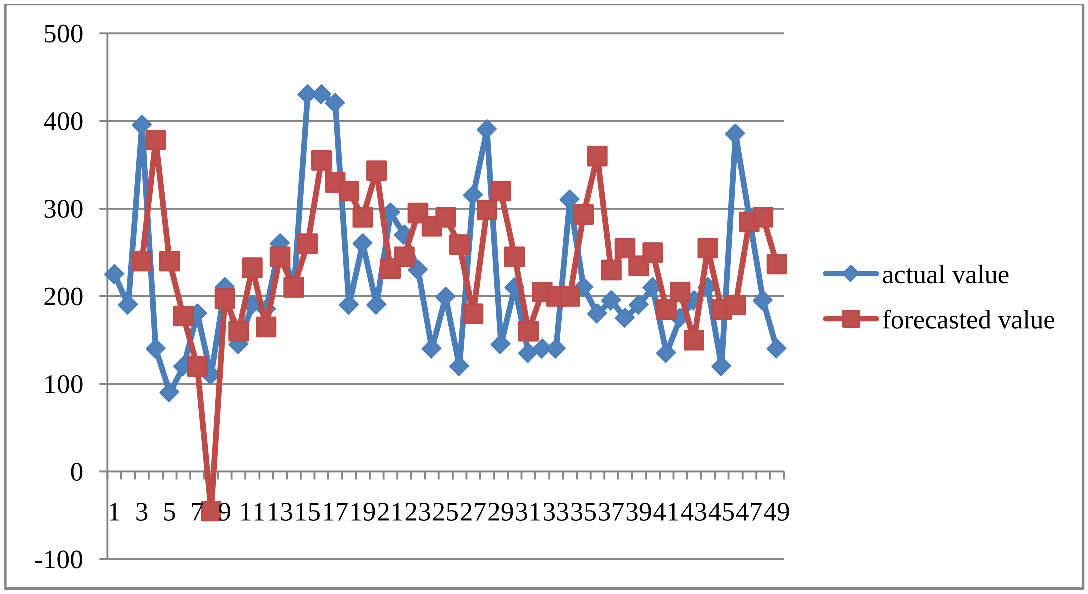


Figure 2: Comparison of actual and forecasted values of given data, The Longitudinal Dexamethasone Suppression Test (DST) data on a fully remitted lithium responder for past 5 years who was asymptomatic and treated with lithium throughout

**Experimental results**

There was a significant difference between BD patients and our control subjects in the maximum percentage rise of salivary cortisol response to awakening. Those showing a waking response also had significantly higher mean cortisol values at 30 minutes after waking, compared with 509 normal subjects described in Wust's and others study. Base line values at time zero, immediately upon waking, did not differ significantly between our sample and Wust's control subjects. Patients and our 5 control subjects did not differ significantly in the percent age decline from the peak morning value to the evening values.

In this section we apply the proposed 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. We evaluate the performance of the proposed method using the root mean square error (RMSE), which is defined as follows:

$$\text{RMSE} = \sqrt{\frac{|\text{forecasted value}_i - acutual\ value_i|^2}{n}}$$

Modified Error of each value$_i$ (M.E)

= |forecasted value$_i$ – actual value$_i$| / forecasted value$_i$

Where $n$ denotes the number of dates needed to be forecasted, forecasted value$_i$ denotes the forecasted value on trading day$_i$, actual value$_i$ denotes the actual value on trading day$_i$ and $1 \le i \le n$. It means that the proposed 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 proposed method get the smallest RMSE than Huarng's method and Huarng's and Yu's method for forecasting the enrollments of the University of Alabama.

**Table 3: Actual value and Forecasted value of given data**

| S. No | Actual Value | Forecasted Value | M.E |
|---|---|---|---|
| 1 | 225 | - | - |
| 2 | 190 | - | - |
| 3 | 395 | 240 | 0.645833 |
| 4 | 140 | 378.33 | 0.629953 |
| 5 | 90 | 240 | 0.625 |
| 6 | 120 | 177.5 | 0.323944 |
| 7 | 180 | 120 | 0.5 |
| 8 | 110 | -45 | 3.444444 |
| 9 | 210 | 197.5 | 0.063291 |
| 10 | 145 | 160 | 0.09375 |
| 11 | 190 | 232.5 | 0.182796 |
| 12 | 185 | 165 | 0.121212 |
| 13 | 260 | 245 | 0.061224 |
| 14 | 210 | 210 | 0 |
| 15 | 430 | 260 | 0.653846 |
| 16 | 430 | 355 | 0.211268 |
| 17 | 420 | 330 | 0.272727 |

| | | | |
|---|---|---|---|
| 18 | 190 | 320 | 0.40625 |
| 19 | 260 | 290 | 0.103448 |
| 20 | 190 | 343.33 | 0.446597 |
| 21 | 295 | 231.66 | 0.273418 |
| 22 | 270 | 245 | 0.102041 |
| 23 | 230 | 295 | 0.220339 |
| 24 | 140 | 280 | 0.5 |
| 25 | 199 | 290 | 0.313793 |
| 26 | 120 | 259 | 0.53668 |
| 27 | 315 | 180 | 0.75 |
| 28 | 390 | 298.33 | 0.307277 |
| 29 | 145 | 320 | 0.546875 |
| 30 | 210 | 245 | 0.142857 |
| 31 | 135 | 160 | 0.15625 |
| 32 | 140 | 205 | 0.317073 |
| 33 | 140 | 200 | 0.3 |
| 34 | 310 | 200 | 0.55 |
| 35 | 210 | 293.33 | 0.284083 |
| 36 | 180 | 360 | 0.5 |
| 37 | 195 | 230 | 0.152174 |
| 38 | 175 | 255 | 0.313725 |
| 39 | 190 | 235 | 0.191489 |
| 40 | 210 | 250 | 0.16 |
| 41 | 135 | 185 | 0.27027 |
| 42 | 175 | 205 | 0.146341 |
| 43 | 195 | 150 | 0.3 |
| 44 | 210 | 255 | 0.176471 |
| 45 | 120 | 185 | 0.351351 |
| 46 | 385 | 190 | 1.026316 |
| 47 | 290 | 285 | 0.017544 |
| 48 | 195 | 290 | 0.327586 |
| 49 | 140 | 236.66 | 0.408434 |

## 5. CONCLUSION

In this paper, Our dysregulation, even when lithium-responsive BD patients are clinically well and their DSTs are observations support the hypothesis that the free cortisol response to waking can reflect relatively enduring HPA normal. Because the test is easy to administer, the free cortisol response to waking 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 high-order fuzzy logical relationships. The Modified method gets a higher forecasting rate than the existing methods.

## REFERENCES

[1] Chen, S.M. “Forecasting enrollments based on fuzzy time series”, Fuzzy sets and systemd, 81(3), 311-319. (1996).

[2] Huarng,K., & Yu, H. K. “Ratio-based lengths of intervals to improve fuzzy time series forecasting”, IEEE Transactions on Systems, Man, and Cybernetics-PartB: Cybernetics, 36(2), 328-340. (2006).

[3] Song, Q,& Chissom, B.S. “Fuzzy time series and its model”, Fuzzy sets and systems, 54(3), 269-277. (1993a).

[4] Kirschbaum C, Hellhammer DH. “Salivary cortisol in psychoneuroendocrine research”, recent developments and applications. Psychoneuroendocrinology;19:313–33. (1994)

[5] Ismail Mohideen, S. and Abuthahir, U. “A modified method for Forecasting problems based on higher order logical relationship”. Advances in Fuzzy sets and system, 81(3), 311-319.(2014)

[6] Goodyer IM, Park RJ, Netherton CM, Herbert J. “Possible role of cortisol and dehydroepiandrosterone in human development and psychopathology”, Br J Psychiatry;179:243–9. (2001)

[7] Guazzo EP, Kirkpatrick PJ, Goodyer IM, Shiers HM, Her bert J. “Cortisol dehydroepiandrosterone (DHEA), and DHEA sulfatein the cerebrospinal fluid of man: relation to blood levels and the effects of age”, J Clin Endocrinol Metab;81:3951–60.(1996)

[8] Zadeh, L.A “Fuzzy sets”, Information and control, 8, 338-353.(1965).

[9] Chen, S.M. and Hsu, C.C. “A new method to forecast enrolments using fuzzy time series”, International Journal of Applied Science and Engineering 2(3), 234-244. (2004)