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The Cortisol Awakening Response for Modified Method for Higher Order Logical Relationship Using Different Mean Techniques

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ABSTRACT
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 using various mean techniques like, Arithmetic Mean, Geometric Mean, Heronian Mean, Root Mean Square and Harmonic Mean.

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

I. Introduction

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[1].

In 1996, chen [2] presented a method to forecast the enrollments of the university of Alabama by using a simple fuzzy time series forecasting model. Chen along with chung [3] and chen with chen [4] applied higher order fuzzy logical relationship for forecasting problems. 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[5] [6] [7].

II. Preliminaries

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

Recently, interest has turned to more refined testing and the probability that HPA dysregulation may even predate the onset of clinical illness [9].

Preliminary data suggest that this dysregulation may be concentrated within the families of individuals with mood disorders [10], 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.

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

$$F(t-n) = A_{in},$$

If $\ldots\ldots, F(t-2) = A_{i2},$,

$$F(t-1) = A_{i1}\ and\ F(t) = A_j$$

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

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

III. 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 $d_1, d_2,\ldots\ldots, d_n$ of equal length. Here we considered the universe of discourse using normal distribution range based definition, i.e., D = [μ - 3σ, μ + 3σ] where μ and σ are mean and standard deviation values of the data, respectively. Also, in the exiting method [11], 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 proposed method is minimum composed to the existing method.

In this section, we present a modified forecasting method based on high-order fuzzy logical relationships. The proposed method is now presented as follows:

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

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

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

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

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

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

$$A_n = {}^{0}\!/_{d_1} + {}^{0}\!/_{d_2} + {}^{0}\!/_{d_3} + {}^{0}\!/_{d_4} + \ldots\ldots + {}^{0}\!/_{d_{n-2}} + {}^{0.5}\!/_{d_{n-1}} + {}^{1}\!/_{d_n},$$

Where $A_1, A_2, \ldots\ldots and A_n$ 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 $"A_{X_1}, A_{X2}, A_{X3}, \ldots\ldots, A_{Xj}, \ldots\ldots, A_{X_n} \to A_{Xr}"$ into the following form:

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

where $V(X_1), V(X_2), \ldots, and V(X_n)$ 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:

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

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

.

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

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

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

where $X = a_1, b_1, \ldots\ldots k_1$, $V(Y_1) = V(a_1) = V(b_1) = \ldots\ldots = V(k_1)$ and $V(Y_2) = V(a_2) = V(b_2) = \ldots\ldots = V(k_2)$.

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 $\ldots\ldots F(t-2) = A_{i2}, and\ F(t-1) = A_{i1}$ assume that we want to predict $F(t)$, where $A_{i1}, A_{i2}, \ldots\ldots, and\ A_{in}$ 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:

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

where $A_{in} = A_X, A_{i(n-1)} = A_{X+V(Y_1)}, \ldots\ldots, A_{i1} = A_{X+V(Y_1)+V(Y_2)+\ldots+V(Y_{n-1})}$, then replace X by the subscript in of the fuzzy set A_{in} to get the derived fuzzy sets $A_{in+V(Y_1)+\ldots+V(Y_{(n-1)})+V(a_n)}, A_{in+V(Y_1)+\ldots+V(Y_{(n-1)})+V(b_n)}, \ldots\ldots, and A_{in+V(Y_1)+\ldots+V(Y_{(n-1)})+V(k_n)}$ for prediction. Let $A_{j1} = A_{in+V(Y_1)+\ldots+V(Y_{n-1})+V(a_n)}$,

let $A_{j2} = A_{in+V(Y_1)+\ldots+V(Y_{n-1})+V(b_n)}, \ldots\ldots,$ and let $A_{jk} = A_{in+V(Y_1)+\ldots+V(Y_{n-1})+V(k_n)}$. Then, the modified forecasted variable $FVar$ is calculated as follows:

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

Where the maximum membership values of $A_{i1}, A_{j1}, A_{j2}, \ldots\ldots, and A_{jk}$ occur at the intervals $d_{i1}, d_{j1}, d_{j2}, \ldots\ldots, and\ d_{jk}$, respectively, and

$m_{i1}, m_{j1}, m_{j2}, \ldots\ldots, and\, m_{jk}$ are the midpoints of the intervals $d_{i1}, d_{j1}, d_{j2}, \ldots\ldots., and\, d_{jk}$, respectively (only take distinct value). Here the midpoints $m_{i1}, m_{j1}, m_{j2}, \ldots\ldots, and\, m_{jk}$ of the intervals $d_{i1}, d_{j1}, d_{j2}, \ldots\ldots., and\, d_{jk}$ are calculated using various averages like Arithmetic Mean, Geometric Mean, Heronian Mean, Root Mean Square and Harmonic Mean.modified forecasted value FV is calculated as follows:

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

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

IV. Example

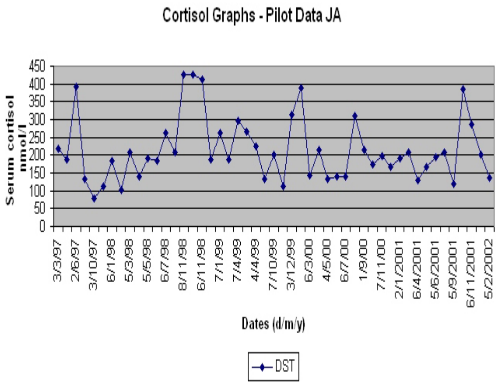

Figure 1: The Longitudinal Dexamethasone Suppression Test (DST) data on a fully remitted lithium responder for past 5 years who was asymptomatic and treated with lithium throughout

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

- Here μ = 216.61, σ = 89.03, μ - 3σ = -50.48 and μ + 3σ = 483.7, the universe of discourse D = [-50.48, 483.7] ≃ [-50, 480]. But $A_1, A_2, \ldots\ldots and A_8$ 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]

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	$A_X, A_{X+5} \rightarrow A_{X+5-2}$

V. 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:

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

Modified Error of each value$_i$ (M.E) = RMSE / forecasted value$_i$

Where n denotes the number of dates needed to be forecasted, $\text{forecasted value}_i$ denotes the forecasted value on trading day i, $acutualvalue_i$ 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: Forecasted value of Different Means and Modified Error of given data

S.No	FV	FV(AM)	FV(GM)	FV(HRM)	FV(RMS)	FV(HM)	ME(AM)	ME(GM)	ME(HRM)	ME(RMS)	ME(HM)
1	225	-	-	-	-	-	-	-	-	-	-
2	190	-	-	-	-	-	-	-	-	-	-
3	395	240	198.03	220.5	246.22	167.81	0.6458	0.994647	0.791383	0.604256	1.353853
4	140	378.33	352.57	356.89	363.72	346.58	0.6299	0.602916	0.607722	0.615089	0.596053
5	90	240	184.97	214.99	256.17	146.74	0.625	0.513435	0.581376	0.648671	0.38667
6	120	177.5	145.74	159.15	178.54	130.36	0.323944	0.176616	0.245994	0.327882	0.079472
7	180	120	117.94	123.34	131.5	110.91	0.5	0.5262	0.459381	0.368821	0.622938
8	110	-45	138.61	147.72	160.08	127.02	-3.44444	0.206406	0.255348	0.312844	0.133995
9	210	197.5	199.99	209.99	225	188.36	0.063291	0.050053	4.76E-05	0.066667	0.114886
10	145	160	170.1	173.77	179.7	165.21	0.09375	0.14756	0.165564	0.1931	0.122329
11	190	232.5	182.42	206.48	238.48	152.91	0.182796	0.041552	0.079814	0.203287	0.242561
12	185	165	138.61	147.72	160.08	127.02	0.121212	0.33468	0.252369	0.155672	0.456464
13	260	245	219.33	232.39	250.25	204.4	0.061224	0.185428	0.118809	0.038961	0.272016
14	210	210	221.23	224.06	228.67	217.46	0	0.050762	0.062751	0.081646	0.034305
15	430	260	254.53	271.59	292.62	232.44	0.653846	0.689388	0.583269	0.469483	0.84994
16	430	355	349.11	349.7	350.89	348.21	0.211268	0.231703	0.229625	0.225455	0.234887
17	420	330	303.26	319.57	342.47	279.49	0.272727	0.38495	0.314266	0.226385	0.502737
18	190	320	303.26	319.57	342.47	279.49	0.40625	0.373475	0.405451	0.445207	0.32019
19	260	290	244.46	267.37	301.04	214.45	0.103448	0.063569	0.027565	0.136327	0.212404
20	190	343.33	352.57	356.89	363.72	346.58	0.446597	0.4611	0.467623	0.47762	0.451786
21	295	231.66	187.28	212.47	244.52	160.08	0.273418	0.575182	0.388431	0.206445	0.842829
22	270	245	221.23	224.06	228.67	217.46	0.102041	0.220449	0.205034	0.180741	0.241608
23	230	295	294.68	298.94	305.16	289.34	0.220339	0.219492	0.230615	0.246297	0.205087
24	140	280	254.53	271.59	292.62	232.44	0.5	0.449967	0.484517	0.521564	0.397694
25	199	290	271.94	274.23	278.01	268.87	0.313793	0.268221	0.274332	0.284198	0.259865
26	120	259	164.37	181.56	204.02	144.64	0.53668	0.26994	0.339061	0.411822	0.170354
27	315	180	164.37	181.56	204.02	144.64	0.75	0.916408	0.734964	0.543966	1.177821
28	390	298.33	301.55	306.64	314.58	294.46	0.307277	0.293318	0.27185	0.239748	0.324458
29	145	320	281.91	301.15	321.91	253.38	0.546875	0.485651	0.518512	0.549564	0.427737
30	210	245	184.97	214.99	256.17	146.74	0.142857	0.135319	0.02321	0.180232	0.431103
31	135	160	170.1	173.78	179.7	253.38	0.15625	0.206349	0.223156	0.248748	0.467203
32	140	205	169.14	190.69	220.51	146.38	0.317073	0.172283	0.265824	0.365108	0.043585
33	140	200	164.37	181.56	204.02	144.67	0.3	0.148263	0.228905	0.313793	0.03228
34	310	200	164.37	181.56	204.02	144.67	0.55	0.885989	0.707425	0.519459	1.142808
35	210	293.33	301.55	306.64	314.58	294.46	0.284083	0.303598	0.315158	0.332443	0.28683
36	180	360	372.76	374.44	377.22	370.53	0.5	0.517116	0.519282	0.522825	0.514209
37	195	230	198.03	220.5	246.22	167.81	0.152174	0.015301	0.115646	0.208025	0.162028
38	175	255	219.33	232.39	250.25	204.4	0.313725	0.202116	0.246956	0.300699	0.143836
39	190	235	219.33	232.39	250.25	204.4	0.191489	0.133725	0.182409	0.240759	0.07045
40	210	250	219.33	232.39	250.25	204.4	0.16	0.042539	0.096347	0.160839	0.027397
41	135	185	191.81	198.36	207.67	183.53	0.27027	0.296179	0.319419	0.34993	0.264425
42	175	205	169.14	190.69	220.51	146.38	0.146341	0.034646	0.08228	0.206385	0.195519
43	195	150	138.61	147.72	160.08	127.02	0.3	0.406825	0.320065	0.218141	0.535191
44	210	255	219.33	232.39	250.25	204.4	0.176471	0.042539	0.096347	0.160839	0.027397

45	120	185	191.81	198.36	207.67	183.53	0.351351	0.374381	0.395039	0.42216	0.346156
46	385	190	169.14	190.69	220.51	146.38	1.026316	1.276221	1.018984	0.745953	1.630141
47	290	285	275	275	275	275	0.017544	0.054545	0.054545	0.054545	0.054545
48	195	290	265.52	273.42	283.95	255.9	0.327586	0.265592	0.286811	0.313259	0.237984
49	140	236.66	187.28	212.47	244.52	160.08	0.408434	0.252456	0.341083	0.42745	0.125437

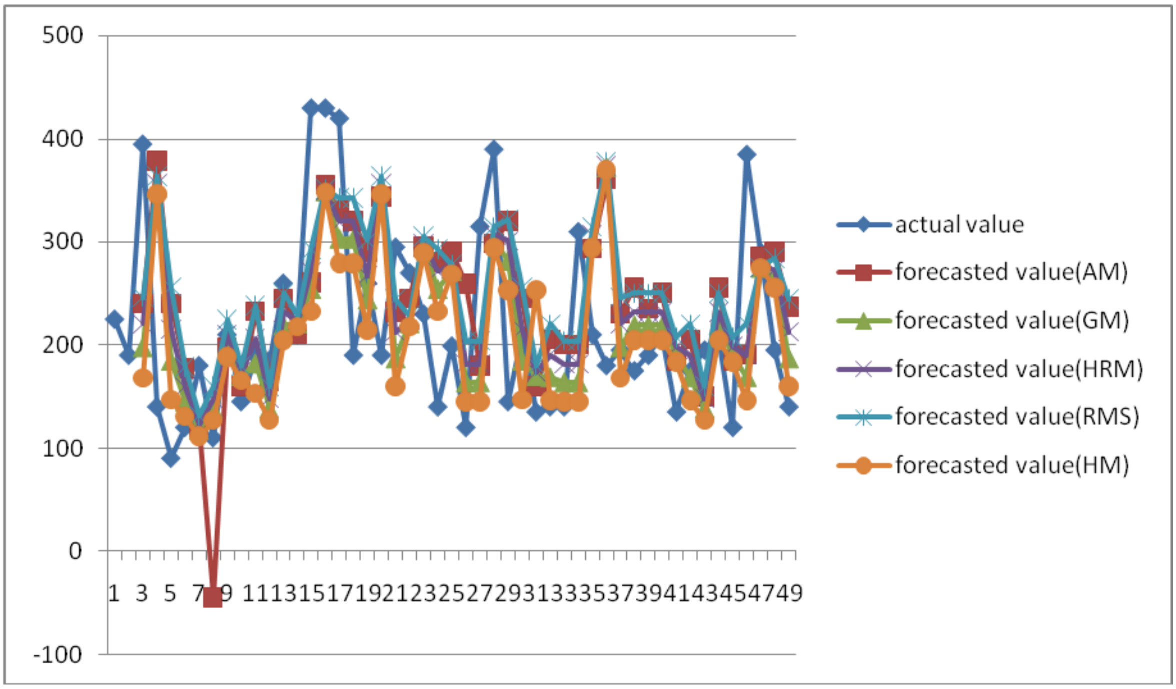

Figure 1: Comparison of actual and forecasted values of given data for various mean like Arithmetic Mean, Geometric Mean, Heronian Mean, Root Mean Square and Harmonic Mean.

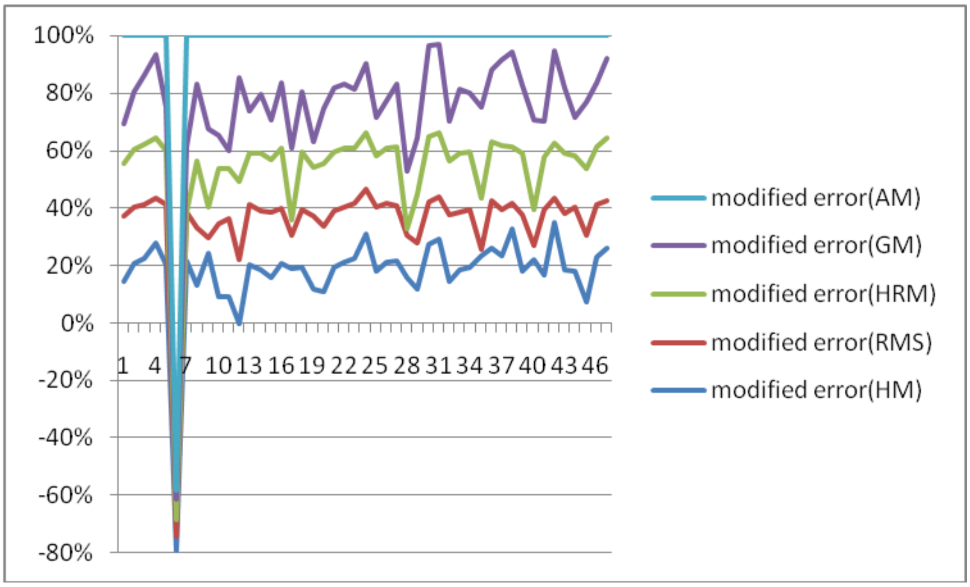

FIGURE 2: MODIFIED ERROR COMPARISON OF ACTUAL AND FORECASTED VALUES OF GIVEN DATA FOR VARIOUS MEAN LIKE ARITHMETIC MEAN, GEOMETRIC MEAN, HERONIAN MEAN, ROOT MEAN SQUARE AND HARMONIC MEAN.

VI. 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. Modified high-order fuzzy logical relationships group to forecast the free cortisol response to walking and the short day time profile using various mean techniques like, Arithmetic Mean, Geometric Mean, Heronian Mean, Root Mean Square and Harmonic Mean. Modified error of Harmonic mean gets a higher forecasting rate than the existing methods.

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