FUZZY TIME SERIES METHODS FOR SHIPPING FREIGHT MARKETS

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ABSTRACT

This paper investigates predictive performance of fuzzy time series analysis methods for dry bulk freight market practice. Time series analysis is conventionally used for modelling univariate and multivariate data series. However, classical time series analysis has several limitations such stationarity, normality etc. Particularly for non linear dataset, difficulties exist in time series practice. Fuzzy time series analysis is first suggested by Song and Chissom (1993a, b) and it is a time-invariant method for modelling. Rather than classical methods, there are no prerequisites like stationarity and normality, and there is no necessity for treatment of missing data. Fuzzy time series methods are applied to dry bulk freight market and results are reported.

***Keywords*:** Fuzzy time series; freight market; dry bulk shipping.

INTRODUCTION

Developments of computer science disclosed several new research fields and new scientific methods. Fuzzy numbers are one of the huge step-ups of the uncertainty research. By the fuzzy numbers, automation and control studies gained crucial advances. Although, it is first presented 45 years ago (Zadeh, 1965), the importance and research boom rose in the last 20 years. Now, fuzzy studies are increasing day by day and application fields are various.

Use of fuzzy numbers in economic modelling is also one of the substantial implementing areas. Fuzzy set theory defines how a linguistic value is distributed between quantitative boundaries and how is the most certain point(s) in the range. This methodology is extended for the modelling of time series data by the studies of Song and Chissom (1993a,b). The method of Song and Chissom (1993a,b) which named Fuzzy Time Series (FTS), is improved by several scholars and the number of published papers on FTS is increasing very rapidly. The reason of the popularity of FTS mainly lies on lack of prerequisites and possibility of modelling by missing data too. FTS can be classified as a time series clustering method, pattern recognition method, in some versions it is a time-invariant method and it can be used to decrease dimensions of dataset by grouping.

Establishment of modelling, identification and control standards of FTS is still in progress. Necessity of stationarity is disputed, but it is also suggested to transform series in case of non-stationarity (Duru, 2010). However, it is clear that FTS can easily be used in limited datasets, linguistic series and series which have missing parts. For example, a researcher may collect judgmental description of the existing economic condition every day or every month by a linguistic scale (such as high liquidity, moderate liquidity etc.). Then it can be modelled by FTS for predictive purposes.

In the present research, four FTS algorithm are tested for a composite dry bulk freight index, Baltic Dry Index (BDI). BDI is a combined value including spot and period trading prices and currently it is converted to involve only period charters. Although it is composite representative of dry bulk freight market, many scholars disputed on content and the method used for fixing. In case of lack of declared fixtures, BDI is an estimate of market which is generated by panellist shipbrokers of Baltic Exchange. Veenstra and Dalen (2008) attempted to calculate various alternative indices including technical particulars of contract and ship. In short run, several disparities are found in comparative analysis. Because of convenience of collection of data, BDI is used in empirical work, but it is noted that BDI may differ from the short run cycles of a specific contract and ship particulars.

FUZZY TIME SERIES ANALYSIS

Fuzzy set theory is first presented by Zadeh (1965) for treatment of uncertain environment in several fields. Particularly fuzzy logic designs are well accepted and established for electronic devices and later fuzzy sets found a broad application potential on various study fields. According to Zadeh (1965), a fuzzy set A is defined by its universe of discourse U on x-axis and a membership grade $\mu_A(x)$ on y-axis.

In figure 1, a typical triangular fuzzy set is presented. 'a' and 'b' are lower and upper bounds respectively. 'm' is the midpoint of fuzzy set. An α-cut refers to grade of membership and the α-cut denoted by A_α of a fuzzy set A in X comprises all elements of X whose degrees of membership in A are all greater than or equal to α, where $0< \alpha \leq 1$.

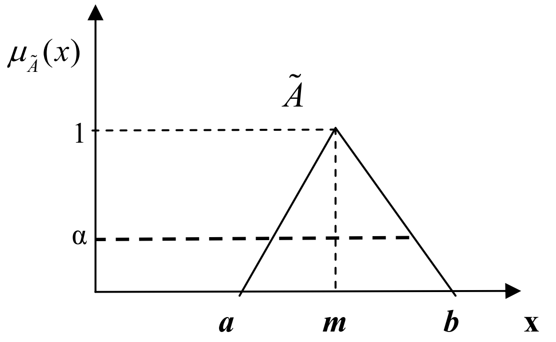

Figure 1 - Triangular fuzzy set.

A specific case of fuzzy logic design is based on time series clustering which named fuzzy time series (FTS) is modelling. Basic definitions of FTS are presented by Song and Chissom (1993a,b) and Chen (1996) as follows:

Definition 1. $Y(t)(t = ...,0,1,2,...)$, is a subset of real numbers. Let $Y(t)$ be the universe of discourse defined by the fuzzy set $\mu_i(t)$. If $F(t)$ consists of $\mu_i(t)(i = 1,2,...)$, $F(t)$ is called a fuzzy time series on $Y(t)$.

Definition 2. If there exists a fuzzy relationship $R(t\text{-}1, t)$, such that $F(t) = F(t\text{-}1) \circ R(t\text{-}1, t)$, where $\circ$ is an arithmetic operator, then $F(t)$ is said to be caused by $F(t\text{-}1)$. The relationship between $F(t)$ and $F(t\text{-}1)$ can be denoted by $F(t\text{-}1) \rightarrow F(t)$.

Definition 3. Suppose $F(t)$ is calculated by $F(t\text{-}1)$ only, and $F(t) = F(t\text{-}1) \circ R(t\text{-}1, t)$. For any t, if $R(t\text{-}1, t)$ is independent of t, then $F(t)$ is considered a time-invariant fuzzy time series. Otherwise, $F(t)$ is time-variant.

Definition 4. Suppose $F(t\text{-}1) = \tilde{A}_i$ and $F(t) = \tilde{A}_j$, the first order univariate fuzzy logical relationship can be defined as $\tilde{A}_i \rightarrow \tilde{A}_j$ where $\tilde{A}_i$ and $\tilde{A}_j$ are called the left-hand side (LHS) and right-hand side (RHS) of the FLR, respectively.

The FLRs are gathered into groups of same LHS fuzzy sets named the FLR Group (FLRG). LHSs of groups indicate input value (the point which prediction is performed) and RHS is variety of outputs that experienced in estimation period.
The forecasted value at time t, Fv_t, is determined by the following three IF-THEN rules.
Assume the fuzzy number of $Y(t\text{-}1)$ is $\tilde{A}_j$.

Rule 1. IF the FLRG of $\tilde{A}_j$ is not existing; $\tilde{A}_j \rightarrow \phi$, THEN the value of Fv_t is $\tilde{A}_j$, and calculate centroid of the fuzzy set $\tilde{A}_j$,which is located on midpoint, for inference point forecast.

Rule 2. IF the FLRG of $\tilde{A}_j$ is one-to-one; $\tilde{A}_j \rightarrow \tilde{A}_k$, THEN the value of Fv_t is $\tilde{A}_k$, and calculate centroid of the fuzzy set $\tilde{A}_k$,which is located on midpoint, for inference point forecast.

Rule 3. IF the FLRG of $\tilde{A}_j$ is one-to-many; $\tilde{A}_j \rightarrow \tilde{A}_{k1}$, $\tilde{A}_j \rightarrow \tilde{A}_{k2}$, $\tilde{A}_j \rightarrow \tilde{A}_{k3}, \ldots, \tilde{A}_j \rightarrow \tilde{A}_{kp}$, and THEN the value of Fv_t is calculated as follows:

$$Fv_t = \frac{\tilde{A}_{k1} + \tilde{A}_{k2} + \ldots + \tilde{A}_{kp}}{p} \qquad \text{(eq. 1)}$$

and calculate centroid of the resulting fuzzy set, which is the arithmetic average of m_{k1}, $m_{k2}, \ldots, m_{kp}$, the midpoints of u_{k1}, $u_{k2}, \ldots, u_{kp}$, respectively.

The high order univariate fuzzy logical relationship is defined as:

Definition 5. Suppose $F(t\text{-n}) = \tilde{A}_k$, $F(t\text{-(n-1)}) = \tilde{A}_l$, …, $F(t\text{-}1) = \tilde{A}_i$ and $F(t) = \tilde{A}_j$, the high order univariate fuzzy logical relationship can be defined as $\tilde{A}_k, \tilde{A}_l, \tilde{A}_i \rightarrow \tilde{A}_j$ where $\tilde{A}_k, \tilde{A}_l$ and $\tilde{A}_i$ are called the left-hand side (LHS) and $\tilde{A}_j$ is called right-hand side (RHS) of the FLR.

The first order multi-variate fuzzy logical relationship is defined as:

Definition 6. Let *F*, *G* and *H* be three fuzzy time series.

Suppose that $F(t\text{-}1)=A_i$, $G(t\text{-}1)=B_i$, and $F(t)=A_j$. A bivariate FLR is defined as A_i, $B_i \rightarrow A_j$, where A_i, B_i are referred to as the LHS and A_j as the RHS of the bivariate FLR.

Suppose that $F(t\text{-}1)=A_i$, $G(t\text{-}1)=B_i$, $H(t\text{-}1)=C_i$, and $F(t)=A_j$. A multi-variate FLR is defined as A_i, B_i ,$C_i \rightarrow A_j$, where A_i, B_i ,C_i are referred to as the LHS and A_j as the RHS of the multi-variate FLR.

Outline of Chen (1996)'s time-invariant methodology has four steps as follows:

Step 1. Partition of the universe of discourse *U* into equal-length intervals.

Step 2. Define the fuzzy sets on *U*, fuzzify the historical data, and derive the FLRs.

Step 3. Allocate the derived fuzzy logical relationships into groups.

Step 4. Calculate the forecasted values under the three defuzzification rules.

Yu (2005) suggested weighted FTS method which is based on magnification of the most recent experiences by a weighting coefficient.

Definition 7: Suppose the RHS of FLRG of $F(t)$ is $A_{j1}, A_{j2}, \ldots, A_{jk}$. Calculation of prediction is based on individual weights, *w*, of the RHS components rather than simple average. The corresponding weights of $A_{j1}, A_{j2}, \ldots, A_{jk}$ are $w_1, w_2, \ldots, w_k$.

According to Yu (2005)'s time-variant algorithm, weights are assigned by the order of existence.

For example, four FLR are recorded and weights are assigned as follows:

If t=1 and $A_1 \rightarrow A_2$ then w_1=1;
If t=2 and $A_1 \rightarrow A_1$ then w_2=2;
If t=3 and $A_1 \rightarrow A_1$ then w_3=3;
If t=4 and $A_1 \rightarrow A_2$ then w_4=4.

Therefore, the weight of the most recent FLR is increased and the final result has higher proportion of short run records. The weight matrix, $W(t)$, is composed by standardised weights, w_1', w_2',…, w_k', which are calculated by normalising raw values by

$$W(t) = \left[w_1', w_2', ..., w_k'\right] = \left[\frac{w_1}{\sum_{h=1}^{k} w_h}, \frac{w_2}{\sum_{h=1}^{k} w_h}, ..., \frac{w_k}{\sum_{h=1}^{k} w_h}\right] \quad \text{(eq. 2)}$$

where

$$\sum_{h=1}^{k} w_h = w_1 + w_2 + ... + w_k \quad \text{(eq. 3)}$$

It is clear that

$$\sum_{h=1}^{k} w_h' = 1 \quad \text{(eq. 4)}$$

The forecast of the weighted FTS is

$$Fv_t = M(t) \times W(t)^T = \left[m_1, m_2, ..., m_k\right] \times \left[w_1', w_2', ..., w_k'\right]^T \quad \text{(eq. 5)}$$

where m_1, m_2,…, m_k are midpoints of the RHS fuzzy sets. Same algorithm can be easily extended with rate of occurrence weighting rather than order of occurrence. Hereafter it is named density weighted FTS.

Duru (2010) proposed that the conventional FTS methods have drawbacks due to lack of data transformation. Although it is frequently used in econometrics, FTS methods attempt to develop a pattern recognition model even on the trended dataset. It is obviously noted that data transformation can increase generality and accuracy of the classical FTS approach.

Duru (2010)'s lemma indicated that sporadic and large-scale fluctuations may cause unnecessary deviations on final results. Therefore last value correction is suggested in fuzzy integrated logical forecasting (FILF) model. Particulars of FILF and its error correction version E-FILF are defined as follows:

Definition 8. The lag, or a backward linear function for raw data that defines the first order differences of the original series, is as follows:

$$\Delta Y(t) = Y(t) - Y(t\text{-}1) \quad \text{(eq. 6)}$$

Definition 9. β is an adjustment coefficient that defines the combination function of the last actual value of the fuzzified data set and the forecasted value for t +1. The fuzzified data can be the raw time series data, the first differenced data or the second differenced set as well.

$$F_R(t+1) = Y(t)^* \beta + F(t+1)(1-\beta) \quad \text{(eq. 7)}$$

$\beta \rightarrow [0, 1]$

β is the coefficient which minimises error rates according to reference of sum of squared errors, mean absolute percentage error or root mean squared error metrics.

Definition 10. A FILF algorithm is described by its order:

FILF (i, d, β)

i: number of fuzzy sets.
d: order of differencing operator ($\Delta^d Y(t)$).
β: value of adjustment coefficient.

For example, if the FILF algorithm is specified with 20 fuzzy numbers ($\tilde{A}_i$, i =1,2,...,20), the first order differenced series (d=1) and the adjustment coefficient is 0.6 (β=0.6), then the specification is FILF (20,1,0.6).

Definition 11. A percentage error (PE, ε) is defined by

$$PE = (Dv_t - Fv_t) / Dv_t \qquad \text{(eq. 8)}$$

Dv_t : Actual value of time t.
Fv_t : Forecasted value of time t.

Definition 12. An error correction function is defined as follows:
A simple moving average (SMA) is the unweighted mean (simple average) of the previous q data points. For error correction, an SMA of PEs of the model is calculated as

$$SMA_\varepsilon = \left(\varepsilon_t + \varepsilon_{t-1} + ... + \varepsilon_{t-q}\right) / q \qquad \text{(eq. 9)}$$

q is an integer number that denotes the SMA_ε horizon for previous errors. The corrected forecast, $F_C(t+1)$, is

$$F_C(t+1) = F_R(t+1) + F_R(t+1) * SMA_\varepsilon \qquad \text{(eq. 10)}$$

Definition 13. An error correction modified FILF is defined as an E-FILF model that has specification

E-FILF (i, d, β, q)

i: number of fuzzy sets.
d: order of differencing operator.
β: value of adjustment coefficient.
q: the SMA_ε horizon for previous errors.

For example, if the E-FILF algorithm is specified with 20 fuzzy numbers ($\tilde{A}_i$, i =1,2,...,20), the first order differenced series (d=1), the adjustment coefficient is 0.6 (β=0.6), and the SMA_ε horizon is 6 period backward, then the specification is E-FILF (20,1,0.6,6).
The present research compares results of the Chen (1996)'s traditional time-invariant FTS, Yu (2005)'s weighted time-variant model and its density weighted version, and Duru (2010)'s time-variant FILF models.

APPLICATION AND EMPIRICAL RESULTS

The FTS modelling of BDI is performed in four components. The first is application of conventional FTS method (cFTS), Chen (1996)'s algorithm. Later, it is extended to Yu (2005)'s weighted FTS method (wFTS) and its density weighted version (dwFTS). Finally, the FILF algorithm is applied to BDI prediction problem.

Assume there are m intervals, which are $u_1 = [d_1,d_2]$, $u_2 = [d_2,d_3]$, $u_3 = [d_3,d_4]$, $u_4 = [d_4,d_5]$,..., $u_{m-3} = [d_{m-3},d_{m-2}]$, $u_{m-2} = [d_{m-2},d_{m-1}]$, $u_{m-1} = [d_{m-1},d_m]$, and $u_m = [d_m,d_{m+1}]$.
Define fuzzy sets $\tilde{A}_1, \tilde{A}_2, ..., \tilde{A}_k$ on the universe of discourse U as follows:

$$\tilde{A}_1 = a_{11}/u_1+a_{12}/u_2+a_{13}/u_3+...+a_{1m}/u_m,$$
$$\tilde{A}_2 = a_{21}/u_1+a_{22}/u_2+a_{23}/u_3+...+a_{2m}/u_m,$$
$$... \qquad ...$$
$$\tilde{A}_k = a_{k1}/u_1+a_{k2}/u_2+a_{k3}/u_3+...+a_{km}/u_m,$$

where $a_{ij} \in [0,1]$, $1 \le i \le k$, and $1 \le i \le m$. The value of a_{ij} indicates the grade of membership of u_j in the fuzzy set $\tilde{A}_i$. The degree of each data is found out according to their membership grade to fuzzy sets. When the maximum membership grade is existed in $\tilde{A}_k$, the fuzzified data is treated as $\tilde{A}_k$. The fuzzy sets $\tilde{A}_1, \tilde{A}_2, ..., \tilde{A}_k$ are defined by

$$\tilde{A}_1 = 1/u_1+0.5/u_2+0/u_3+0/u_4+...+0/u_m,$$
$$\tilde{A}_2 = 0.5/u_1+1/u_2+0.5/u_3+0/u_4+...+0/u_m,$$
$$\tilde{A}_3 = 0/u_1+0.5/u_2+1/u_3+0.5/u_4+...+0/u_m,$$
$$... \qquad ...$$
$$\tilde{A}_{k-1} = 0/u_1+0/u_2+...+0/u_{m-3}+0.5/u_{m-2}+1/u_{m-1}+0.5/u_m,$$
$$\tilde{A}_k = 0/u_1+0/u_2+...+0/u_{m-3}+0/u_{m-2}+0.5/u_{m-1}+1/u_m,$$

The detailed application steps of the cFTS, wFTS and dwFTS are as follows:

Step 1. Collect and arrange the historical data Dv_t.
Define the universe of discourse U. Find the maximum D_{max} and the minimum D_{min} among all Dv_t. For easy partitioning of U, two small numbers D_1 and D_2 are assigned. The universe of discourse U is then defined by:

$$U = [D_{min} - D_1 , D_{max} + D_2] \qquad \text{(eq. 11)}$$

Descriptive statistics of raw BDI data and its 1st order differenced version are displayed on table 2. The universe of discourse U is defined as:

$$U = [663 – 63, 11793 + 307] = [600, 12100]$$

D_1 and D_2 are 63 and 307 respectively.

Table I - Descriptive statistics of BDI raw dataset (January 2, 2007- January 19, 2010) and the 1st order differences.

Descriptive statistics of BDI dataset		
	Raw data	the 1st diff.
Minimum value	663	-963
Maximum value	11793	425
Standard deviation	3075	120
No. of data	761	760
Mean	5328	-2

Step 2. In analysis of cFTS, wFTS and dwFTS, universe of discourse U is between 600 and 12100 (including sample period range) and 23 fuzzy sets are defined in equal length intervals (Fig. 2). The length of fuzzy sets is based on average weekly returns on BDI which is 415 in sample period. For an easy calculation it is defined 500-point steps in U.

There are twenty three intervals which are u_1 = [600, 1100], u_2 = [1100, 1600], u_3 = [1600, 2100], u_4 = [2100, 2600], u_5 = [2600, 3100], u_6 = [3100, 3600], u_7 = [3600, 4100], u_8 = [4100, 4600], u_9 = [4600, 5100], u_{10} = [5100, 5600], u_{11} = [5600, 6100], u_{12} = [6100, 6600], u_{13} = [6600, 7100], u_{14} = [7100, 7600], u_{15} = [7600, 8100], u_{16} = [8100, 8600], u_{17} = [8600, 9100], u_{18} = [9100, 9600], u_{19} = [9600, 10100], u_{20} = [10100, 10600], u_{21} = [10600, 11100], u_{22} = [11100, 11600], u_{22} = [11600, 12100].

Step 3. The raw BDI data is transformed to fuzzy time series according to previous fuzzy interval dimensions.

Step 4. The FLRs are recorded based on definition 4.

$$...; \tilde{A}_8 \rightarrow \tilde{A}_8;\ \tilde{A}_8 \rightarrow \tilde{A}_9;\ \tilde{A}_9 \rightarrow \tilde{A}_9;...$$

Step 5. The FLRs are combined into the FLR group (FLRG). LHSs of groups indicate input value for the FTS inference and RHS is variety of outputs that recorded in sample period.

Step 6. Calculate the forecasted outputs. The forecasted value at time t, Fv_t, is determined by the following three IF-THEN rules. Assume the fuzzy number of Dv_{t-1} at time t-1 is $\tilde{A}_j$.

Rule 1. IF the FLRG of $\tilde{A}_j$ is not existing; $\tilde{A}_j \rightarrow \phi$, THEN the value of Fv_t is $\tilde{A}_j$, and calculate centroid of the fuzzy set $\tilde{A}_j$,which is located on midpoint, for inference point forecast.

Rule 2. IF the FLRG of $\tilde{A}_j$ is one-to-one; $\tilde{A}_j \rightarrow \tilde{A}_k$, THEN the value of Fv_t is $\tilde{A}_k$, and calculate centroid of the fuzzy set $\tilde{A}_k$,which is located on midpoint, for inference point forecast.

Rule 3. IF the FLRG of $\tilde{A}_j$ is one-to-many; $\tilde{A}_j \rightarrow \tilde{A}_{k1}$, $\tilde{A}_j \rightarrow \tilde{A}_{k2}$, $\tilde{A}_j \rightarrow \tilde{A}_{k3}, \ldots, \tilde{A}_j \rightarrow \tilde{A}_{kp}$, and THEN the value of Fv_t is calculated as follows:

For cFTS,

$$Fv_t = \frac{\tilde{A}_{k1} + \tilde{A}_{k2} + \ldots + \tilde{A}_{kp}}{p} \quad \text{(eq. 12)}$$

and calculate centroid of the resulting fuzzy set, which is the arithmetic average of m_{k1}, $m_{k2}, \ldots, m_{kp}$, the midpoints of u_{k1}, $u_{k2}, \ldots, u_{kp}$, respectively.
For wFTS, it is described before in definition 5 (Yu (2005)'s algorithm).
For dwFTS,

$$Fv_t = \frac{\tilde{A}_{k1}\theta_{k1} + \tilde{A}_{k2}\theta_{k2} + \ldots + \tilde{A}_{kp}\theta_{kp}}{\theta_{k1} + \theta_{k2} + \ldots + \theta_{kp}} \quad \text{(eq. 13)}$$

where θ is number of occurrence in sample period. The crisp result of the final fuzzy set can be calculated directly by

$$Fv_t = \frac{m_{k1}\theta_{k1} + m_{k2}\theta_{k2} + \ldots + m_{kp}\theta_{kp}}{\theta_{k1} + \theta_{k2} + \ldots + \theta_{kp}} \quad \text{(eq. 14)}$$

In case of the FILF, the FTS process is somewhat different than the previous methods. First of all, dataset is transformed to the first difference series and subsequent calculations are based on daily returns of the BDI. U is defined as follows:

U = [-963 – 37, 425 + 75] = [-1000, 500]

D_1 and D_2 are -37 and 75 respectively.

The length of fuzzy sets is defined around standard deviation of series (120). For an easy partitioning it is defined 100-point steps in U.

There are fifteen intervals which are u_1 = [-1000, -900], u_2 = [-900, -800], u_3 = [-800, -700], u_4 = [-700, -600], u_5 = [-600, -500], u_6 = [-500, -400], u_7 = [-400, -300], u_8 = [-300, -200], u_9 = [-200, -100], u_{10} = [-100, 0], u_{11} = [0, 100], u_{12} = [100, 200], u_{13} = [200, 300], u_{14} = [300, 400], u_{15} = [400, 500] (See Figure 3).

The daily returns of BDI data is transformed to fuzzy time series, and FLRs and FLRGs are assigned according to previous FTS rules.
β coefficient is defined as 0.32 by minimising root mean squared errors (RMSE) (Fig. 4). Finally, FILF (15,1,0.32) algorithm is selected.
Results of the four method are presented in table 3.

Table 2 - Results of error metrics for cFTS, wFTS, dwFTS and FILF (15,1,0.32).

	MAE	MAPE	RMSE
Chen (1996), cFTS	162.46	0.06	200.55
Yu (2005), wFTS	159.57	0.04	210.05
dwFTS	159.00	0.04	209.91
FILF (15,1,0.32)	49.63	0.01	72.42

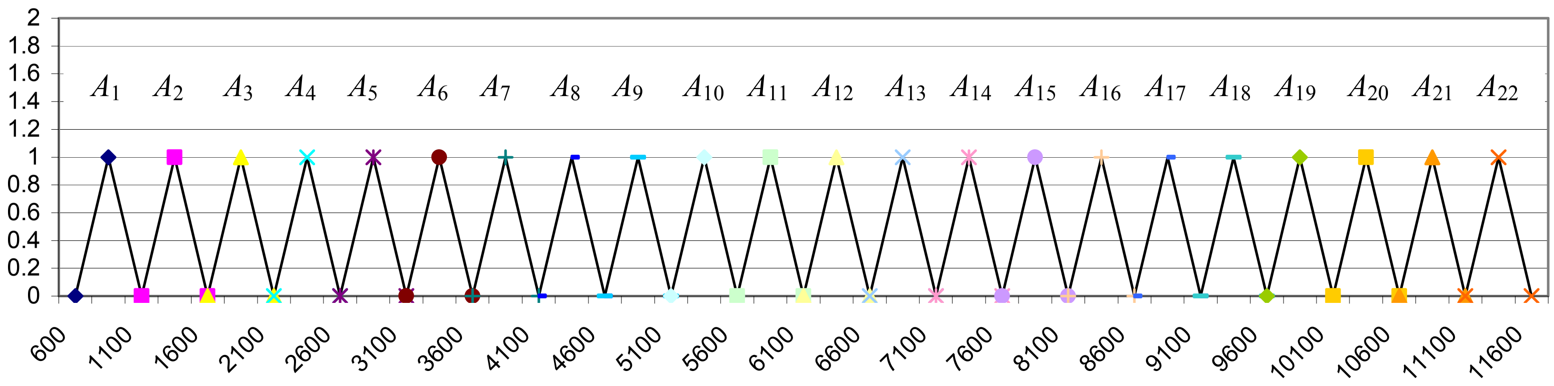

Figure 2 - Fuzzy sets for cFTS, wFTS and dwFTS algorithms.

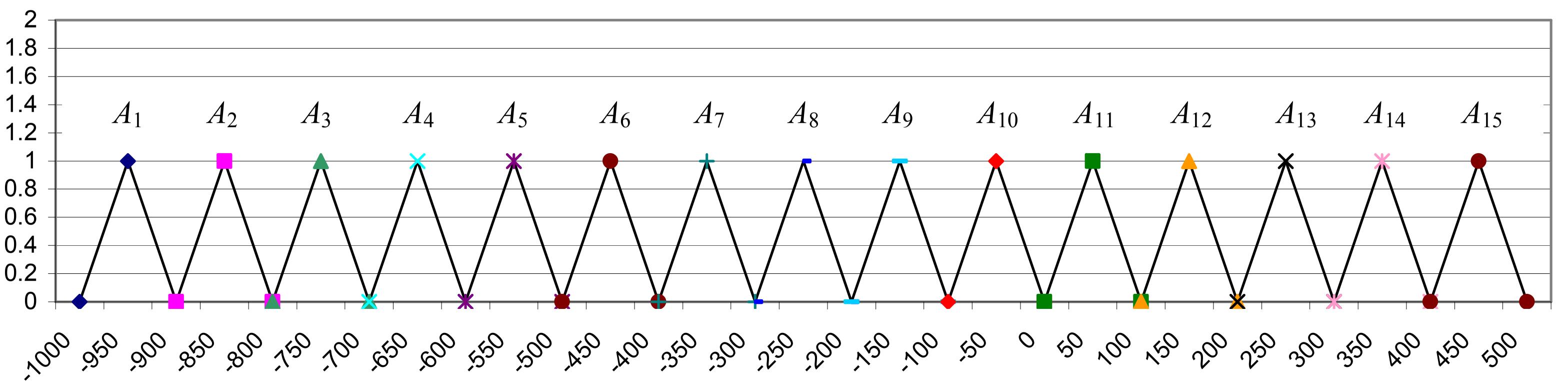

Figure 3 - Fuzzy sets for FILF (15,1, β) algorithm.

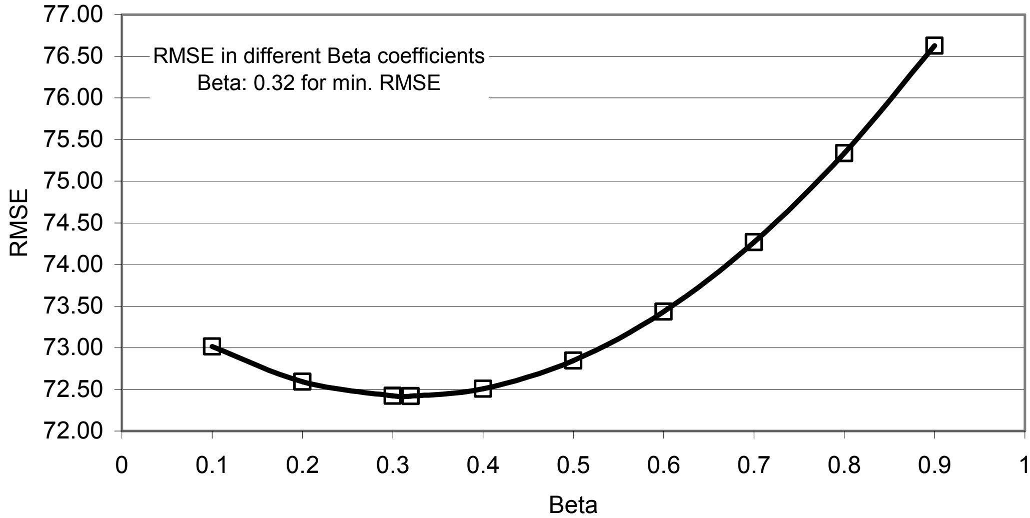

Figure 4 - RMSE results for several β values.

According to results, FILF (15,1,0.32) algorithm indicates the best accuracy output. Time-invariant cFTS method provided better RMSE results than wFTS and dwFTS algorithm. Since wFTS and dwFTS are based on order of occurrence or rate of occurrence, every single new data requires a number of revisions on calculations. However, the gain of these methods is not so superior to former one. FILF (15,1,0.32) improves all error metrics and rate of error reduction is around 70%. Figure 5 shows graphical presentation of actual BDI and FILF (15,1,0.32).

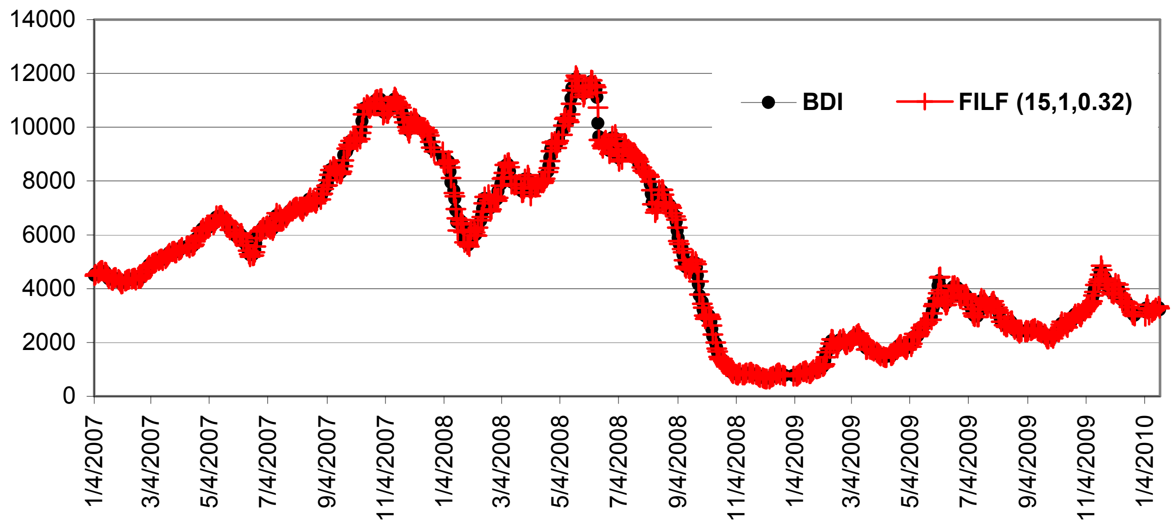

Figure 5 - The BDI and FILF (15,1,0.32) in sample period (January 2, 2007-January 19, 2010).

In figure 6, errors of FILF (15,1,0.32) indicate random walk pattern. According to histogram of error rates, 85% of errors are in the range of -100 - +100.

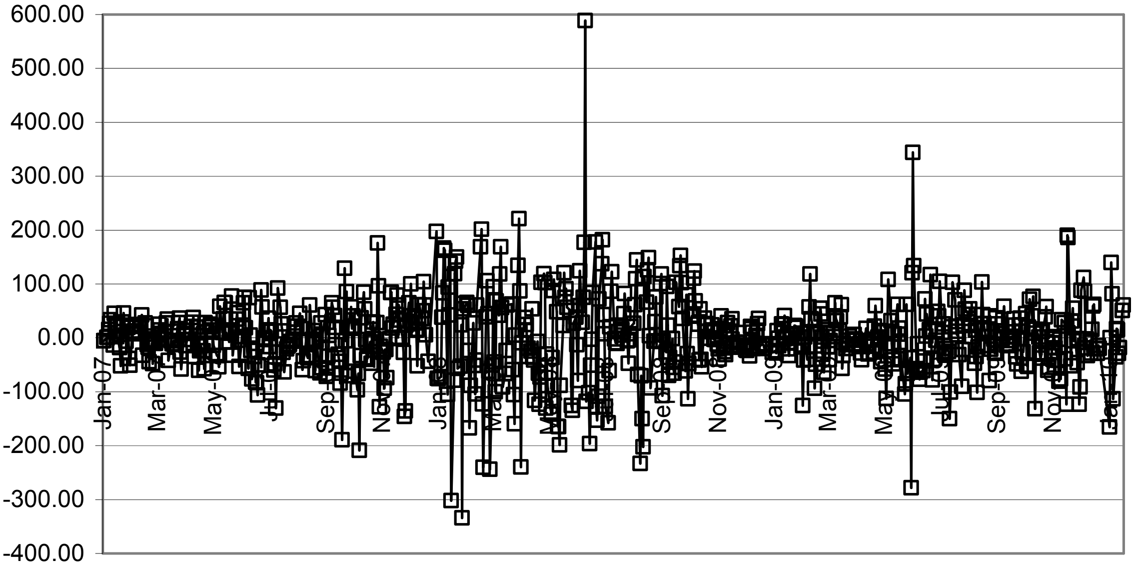

Figure 6 - Errors of FILF (15,1,0.32).

CONCLUSIONS AND FURTHER RESEARCH

The present research compared various FTS algorithms for the sample period of the BDI. After the first development of FTS method, it is developed by various revisions and today it is available to estimate high order multivariate case too. The advantages of FTS are indicated that lack of need for several diagnostic tests for such as normality, stationarity among others. Although, they are stated as unnecessary, Duru (2010)'s lemma pointed out that modelling with non-stationary data has crucial drawbacks under the trended and high volatile cases. Use of levels of data may cause impossibility to predict series. Therefore, transformations are strictly suggested even in FTS algorithms.

Empirical results indicate superiority of FILF (15,1,0.32) algorithm among the tested models and it improves previous algorithms more than 50%. Due to percentage error metrics, wFTS and dwFTS improve base method cFTS.

The present research does not deal with multivariate case and high order modelling. Further research can be based on establishment of multivariate causal-FTS and series can be modelled in long run by high order inference.

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