The Asian Journal of Shipping and Logistics ● Volume 26 Number 2 December 2010 pp. 205-223 ●

Bivariate Long Term Fuzzy Time Series Forecasting of Dry Cargo Freight Rates

Okan DURU* · Emrah Bulut** · Shigeru YOSHIDA***

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Abstract

This paper proposes a bivariate long term fuzzy inference system for time series forecasting task in the field of freight market. Fuzzy time series methods are applied by many scholars and it is broadly accepted pattern recognition and forecasting tool. Previous studies mainly establish algorithms for high frequency time series data such as daily and monthly intervals. The proposed model performs similar techniques for long term annual base data and also extends the conventional method with multi-variate heuristic algorithm.

Empirical work is accomplished on shipping freight rate data and life expectancy is used as a leading indicator in the bivariate fuzzy time series model.

Key words : Fuzzy Time Series, Multi-variate Modelling, Forecasting, Freight Rate

* PhD candidate in Kobe University, Japan and Research Fellow in Istanbul Technical University, Turkey, Email: duruokan@yahoo.com.

** PhD candidate in Kobe University, Japan, Email: bltemrah@gmail.com.

*** Professor of Maritime Logistics Science in Kobe University, Japan, Email: syoshida@maritime.kobe-u.ac.jp.

I. Introduction

Importance of forecasting is unavoidable in business administration and also in shipping business. Planning and strategy developing tasks are directly depended on a prediction of future events. The traditional forecasting science provided various methods including both extrapolation and causal reasoning approaches. Many scholars suggest improvements of prediction accuracy by moving average, auto regression, smoothing methods etc..[1) One of the critical drawbacks of statistical technique is arisen from several diagnostic preconditions such as normality, stationarity etc. In practical business life, most of the data is non-stationary and these data should be transformed anyhow. Non-stationary forecasting studies deal with such problems.

Computer sciences improved prediction task by various approaches.

Artificial neural networks (ANNs) and fuzzy integrated studies are typical computer pattern recognition techniques. After the development of the fuzzy set theory (FST), a new generation of time series methodology is implemented by fuzzy time series (FTS) approach.[2) FTS method does not require a large sample data (but if it is available, recognition will be more accurate), stationarity, normality, or a pure quantitative data. FTS can execute linguistic variables, and the traditional fuzzification of time series is a transformation of quantitative data to linguistic terms. It is generally based on the data consolidation in intervals by a procedure.[3)

FTS method fundamentally combines two conventional tools; time series clustering and rule-based forecasting. Time series clustering is used for grouping large datasets and decreasing uncertainty. Rule-based forecasting (RBF) is well suggested and applied by Collopy and Armstrong.[4) RBF is designed as an expert system which is based on IF-THEN rules. In the FTS method, dataset is transformed to fuzzy numbers which are connected to a linguistic term and patterns of historical data is defined by rules of tracing.

If a fuzzy number, say *A*, is followed by another fuzzy number, say *B*; it is a

1) Holt (1957); Winters (1960); Box and Jenkins (1970); Bowerman and O'Connell (1979); Harvey (1990) among others.
2) Zadeh (1965); Song and Chissom (1993a,b).
3) Palit and Popovic (2005).
4) Collopy and Armstrong (1992).

simple rule that there is a forecasting rule between A and B which is $B \rightarrow A$.

However, practical use consists of many fuzzy numbers and several rules.

FTS is developed and implemented by various studies[5]. Song and Chissom first show the availability of the FST for analysis and forecasting of time series[6]. Later, Chen developed the initial study, and improved arithmetic operations rather than the logic max-min composition methodology of Song and Chissom[7]. This method also provides robust predictions when the historical data are not accurate for forecasting task. Huarng consolidated the study of Chen with his heuristic rule structure.[8] Yu suggested a weighting algorithm for fuzzy logical relationships (FLRs).[9] This study improves that the highly probable movements have the higher effect on FLRs. That process can be performed by an expert judgment, the latest FLR weighting approach, or it can be calculated from the existence density of FLRs. Liu extended the literature by trapezoidal design of FTS[10]. Chu et al developed a model to implement causality of various time-series by fuzzy dual time series algorithm.[11] This paper introduced a dual-factor approach to TAIEX (Taiwan stock exchange capitalization weighted stock index) and NASDAQ (National association of securities dealers automated quotations) index forecasting task, and used dynamics of stock markets based on price-volume relationships.

Duru suggested fuzzy integrated logical forecasting model (FILF) and its extended version (E-FILF) by error correction algorithm.[12] FILF and E-FILF algorithms are based on the first order, univariate FTS and its improvements are derived from differencing, last value adjustment and error correction. Both FILF and E-FILF applied to the case of forecasting Baltic Dry Index (BDI) on monthly frequency and its superiority is presented among Chen and Yu approaches.[13] The present study applies percentage change transformation and the first order bivariate solution. Tercentenary series of LFI is an

5) Song and Chissom (1993a, 1993b, 1994); Sullivan and Woodall (1994); Chen (1996); Hwang et. al. (1998); Chen and Hwang (2000); Huarng (2001); Yu (2005); Huarng and Yu (2005, 2006); Liu (2007); Cheng et. al. (2008); Duru (2010).

6) Song and Chissom (1993a,b).

7) Chen (1996).

8) Huarng (2001).

9) Yu (2005).

10) Liu (2007).

11) Chu et. al. (2008).

12) Duru (2010).

13) Chen (1996); Yu (2005).

annual frequency data and it should be preferred for long term strategically extrapolations rather than short term monthly inferences of the FILF family FTS. Duru and Yoshida improved econometric models of previous scholars for freight rates and seaborne trade. The present paper applies fuzzy inference to bivariate relations of LFI and life expectancy.[14)]

Long term freight rate index (LFI) and Life expectancy

The long term freight index (here after LFI) is first presented by Duru and Yoshida.[15)] The origin of LFI is based on combinations of 15 different series of dry cargo freight rate and indices and also deflators are used for extracting price inflation effects. Both input data and deflators are introduced in table 1. The series is calculated by available data which is collected from various shipping periodicals and scholarly journal papers. Calculation method is basically performed by using ratio-to-change deviations year by year and initial year is assumed to be 100 points (See appendix A).

LFI series is calculated for annual frequency since most of the available data is organised for yearly periods. Before building LFI, sequential series of data are tested to be correlated and continuity is confirmed. Correlation matrix of sequential series indicated over coefficient of 0.90 except a few number of samples (minimum 0.70). An additional test is performed to investigate whether the freight indices have ability to reflect real prices of shipping service. An extensive discussion on this issue is presented by Veenstra and Dalen.[16)] By using technical particulars of fleet and hedonic model design, they tested some freight indices about the representative capability.

Results pointed out disparities among the short run analysis while long term fluctuations are found broadly identical. The empirical results of Duru and Yoshida indicated that Baltic Dry Index which is included in the LFI and market prices of several routes and sizes are absolutely same (correlation coefficient is over 0.98). Therefore, input data is used for LFI while possible drawbacks of missing data on construction of input data itself or quality of data remain since adjustment of the intended dataset is broadly unfeasible.

14) Duru and Yoshida (2009).
15) Supra note 15.
16) Veenstra and Dalen (2008).

<Table 1> Description of data which is used for building the LFI.

Term	Description	Code	Source
	Freight rates & indices		
1741-1872	Tyne - London Coal route freight rate series.	TLCH	Harley (1988)
1741-1872	U.S. - British Grain route freight rate series.	USGH	Harley (1988)
1790-1815	British Import Freight Rate Index series.	BIFRI	North (1958)
1814-1910	American Export Freight Rate Index series.	AEFRI	North (1958)
1869-1936	Isserlis Composite Index series.	ISSCI	Isserlis (1938)
1869-1913	New UK Index series.	NUKFI	Klovland (2002)
1898-1913	Economist's Freight Index series.	ECONI	Yoshimura (1942)
1921-1939	Economist's Freight Index series.	ECONI	Yoshimura (1942)
1920-1969	UK Chamber of Shipping Index series.	UKCSV	Isserlis (1938), Hummels (1999
1948-1997	Norwegian Shipping News Voyage Freight Index series.	NSNVI	Hummels (1999)
1948-1990	Norwegian Shipping News Time Charter Index series.	NSNTI	Hummels (1999)
1952-1989	UK Chamber of Shipping Time Charter Index series.	UKCST	Hummels (1999)
1986-2008	Baltic Freight Index / Baltic Dry Index series.	BFI/ BDI	Baltic Exchange Co., London;
			Hummels (1999).
1988-1996	German Ministry of Transport Time Charter Index series.	GMTTI	Hummels (1999)
1991-2007	Lloyd's Shipping Economist (LSE) Tramp Index series.	LSEFI	LSE Magazine various issues.
	Deflator series		
1741-1954	Price of Composite Unit of Consumables.	PUCON	Brown & Hopkins (1956)
1954-2008	RPI: Retail Price Index of U.K.	RPIUK	Office for national statistics, U.K.

Source: Duru and Yoshida.[17)]

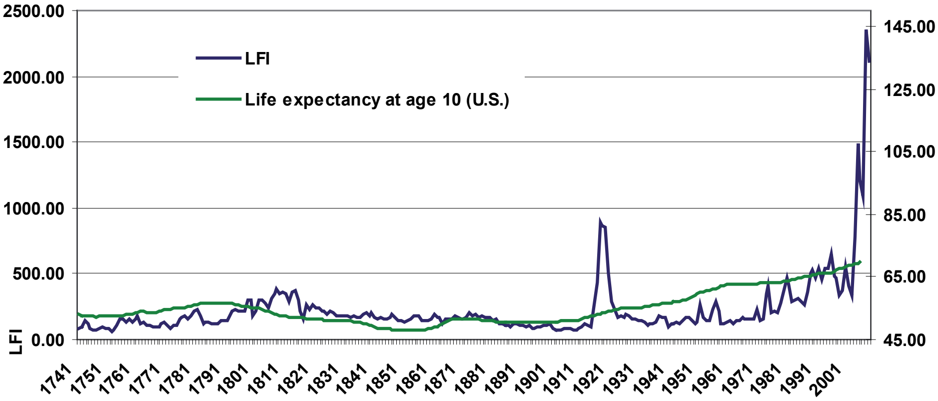
In the bivariate model of the present paper, the long term freight index (LFI) is proposed to be predicted and life expectancy is used as a leading indicator. LFI is first presented by Duru and Yoshida and it is a combined freight index for dry cargo shipments. Duru and Yoshida also denoted long term relationship between LFI and life expectancy at age 10 (U.S. data is used because of availability). Fogel indicates that life expectancy and physical size of humankind affect various issues in economics.[18)] Fig. 1 shows LFI series

17) Supra note 15.

18) Fogel (1986).

together with life expectancy data at age 10 in period of 1741 and 2002 for U.S. population (life expectancy data is available till 2005).

<Figure 1> LFI and Life expectancy (at age 10, U.S.) between 1741 and 2008



II. Methodology

1. Fuzzy Time Series

Song and Chissom proposed FTS to model fuzzy logical relationships (FLRs) among the data.[19] A fuzzy set is a group of data which has a grade of membership through the mentioned fuzzy set. Let U be the universe of discourse with $U = (u_1, u_2, \ldots, u_m)$ where ui are linguistic variables. The basic definitions of FTS are as follows:

Definition 1. $Y(t)(t = \ldots,0,1,2,\ldots)$, 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 $\mu_i(t)(i = 1,2,\ldots)$, $F(t)$ 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 $F(t\text{-}1) \rightarrow F(t)$.

19) Song and Chissom (1993a,b).

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 $F(t) = \tilde{A}_j$, a 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.

Chen developed the method of Song and Chissom, and ensured more accurate results.[20] As a benchmark of the proposed model, the procedure of Chen's methodology is 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.

An additional definition indicates difference of Chen (1996)'s method as follows:

Definition 5. The forecasted value at time t, Fv_t, is determined by the following three IF-THEN rules.

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

Rule 2. IF the FLRG of A_i is $A_i \rightarrow \tilde{A}_k$, 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 A_i is $A_i \rightarrow \tilde{A}_{k1}$, $A_i \rightarrow \tilde{A}_{k2}$, $A_i \rightarrow \tilde{A}_{k3}$,..., $A_i \rightarrow \tilde{A}_{kp}$, and THEN the value of Fv_t is calculated as follows:

20) Chen (1996).

$$Fv_t = \frac{\tilde{A}_{k1} + \tilde{A}_{k2} + ... + \tilde{A}_{kp}}{p}$$

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

A bivariate fuzzy time series is defined as follows:

Definition 6. Let F and G be two fuzzy time series. Suppose that $F(t\text{-}1)=A_i$, $G(t\text{-}1)=B_k$, and $F(t)=A_j$. A bivariate FLR is defined as $A_i, B_k \rightarrow A_j$, where A_i, B_k are referred to as the LHS and A_j as the RHS of the bivariate FLR.

In the present paper, the first order bivariate FLRs are constructed with life expectancy and LFI series for forecasting one period ahead LFI.

2. Bivariate long term fuzzy inference

The current fuzzy time series models utilize discrete fuzzy sets to define their fuzzy time series. Their discrete fuzzy sets are defined as follows:

Assume there are m intervals, which are $u_1 = [d_1,d_2]$, $u_2 = [d_2,d_3]$, $u_3 = [d_3,d_4]$, $u_4 = [d_4,d_5]$,..., $u_{m\text{-}3} = [d_{m\text{-}3},d_{m\text{-}2}]$, $u_{m\text{-}2} = [d_{m\text{-}2},d_{m\text{-}1}]$, $u_{m\text{-}1} = [d_{m\text{-}1},d_m]$, and $u_m = [d_m,d_{m+1}]$.

Let $\tilde{A}_1, \tilde{A}_2,..., \tilde{A}_k$ be fuzzy sets which are linguistic values of the data set. Define fuzzy sets $\tilde{A}_1, \tilde{A}_2,..., \tilde{A}_k$ on the universe of discourse U as follows:

$\tilde{A}_1 = a_{11}/u_1+a_{12}/u_2+a_{13}/u_3+...+a_{1m}/u_m$,

$\tilde{A}_2 = a_{21}/u_1+a_{22}/u_2+a_{23}/u_3+...+a_{2m}/\mathrm{u}_m$,

... ...

$\tilde{A}_k = a_{k1}/u_1+\mathrm{a}_{k2}/u_2+a_{k3}/u_3+...+a_{km}/u_m$,

where $a_{ij} \in [0,1]$, $1 \leq i \leq k$, and $1 \leq i \leq m$. 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 $\tilde{A}_k$. Our empirical study about dry bulk shipping index is based on gradients rather than raw data. Using the raw data has several drawbacks such as non-stationarity which decreases generality of proposed study. The percentage changes of both variables are used for inference which are $\frac{\Delta F_t}{F_{t-1}}$ and $\frac{\Delta G_t}{G_{t-1}}$. For the LFI data, eight fuzzy sets are defined ($\tilde{A}_1, \tilde{A}_2, \ldots, \tilde{A}_8$) and for life expectancy data seven fuzzy sets are defined ($\tilde{A}_1, \tilde{A}_2, \ldots, \tilde{A}_7$) by equal fuzzy intervals which are assumed length of standard deviations of transformed datasets.

The fuzzy sets $\tilde{A}_1, \tilde{A}_2, \ldots, \tilde{A}_k$ are defined by

$\tilde{A}_1 = 1/u_1+0.5/u_2+0/u_3+0/u_4+\ldots+0/u_m,$

$\tilde{A}_2 = 0.5/u_1+1/u_2+0.5/u_3+0/u_4+\ldots+0/u_m,$

$\tilde{A}_3 = 0/u_1+0.5/u_2+1/u_3+0.5/u_4+\ldots+0/u_m,$

... ...

$\tilde{A}_{k-1} = 0/u_1+0/u_2+\ldots+0/u_{m-3}+0.5/u_{m-2}+1/u_{m-1}+0.5/u_m,$

$\tilde{A}_k = 0/u_1+0/u_2+\ldots+0/u_{m-3}+0/u_{m-2}+0.5/u_{m-1}+1/u_m,$

The root mean squared error (RMSE), mean absolute error (MAE) and mean absolute percentage error (MAPE) metrics are used for performance evaluation. The RMSE metric gives an average deviation interval, and increases effects of larger errors by squares of them. Eq. (1) indicates the RMSE function.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}\left(Dv_t - Fv_t\right)^2}{n}} \quad (i=1, 2,\ldots, n) \qquad (1)$$

MAPE is defined by:

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{X_i - Y_i}{X_i}\right| \times 100 \quad (i=1, 2,\ldots, n) \qquad (2)$$

MAE is defined by:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|X_i - Y_i\right| \qquad (i=1, 2,\ldots, n) \qquad (3)$$

An additional error metrics is normalised RMSE (NRMSE) which is ratio of RMSE over range of observed values. NRMSE is also reported in results.

$$NRMSE = \frac{RMSE}{x_{\max} - x_{\min}} \qquad (4)$$

The detailed application steps can be described as follows:

Step 1. Collect and arrange the historical data. Transform to percentage change series, Dv_t. Define the universe of discourse U. Find the mean Dmean and the standard deviation σ.

Step 2. Calculate fuzzy sets which are in equal lengths of standard deviations. Mean of data is located in the middle of fuzzy set and upper bound and lower bound is in distance of σ/2. Other fuzzy sets are defined in σ intervals from mean value. Mean of LFI gradient series is 0.03 and fuzzy intervals are u_1=[-0.57, -0.33], u_2=[-0.33, -0.09], u_3=[-0.09, 0.15], u_4=[0.15, 0.39], u_5=[0.39, 0.63], u_6=[0.63, 0.87], u_7 = [0.87, 1.11] and u_8 = [1.11, 1.35].

Mean of life expectancy gradient series is 0.001 and fuzzy intervals are u_1=[-0.0095, -0.0065], u_2=[-0.0065, -0.0035], u_3=[-0.0035, -0.0005], u_4=[-0.0005, 0.0025], u_5=[0.0025, 0.0055], u_6=[0.0055, 0.0085] and u_7 = [0.0085, 0.0115].

Step 3. Fuzzification of the series.

Step 4. Generate the bivariate FLRs. For all fuzzified data, derive the FLRs according to Definition 5 such as

..., A_3, $B_1 \rightarrow A_2$; A_3, $B_1 \rightarrow A_3$, ...

Step 5. Organize the bivariate FLRs into groups of same LHS fuzzy sets named the FLR Group (FLRG). LHSs of groups indicate input value of one period previous data. RHS is variety of outputs that experienced in estimation 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 bivariate inputs at time t-1 is A_i, B_k.

Rule 1. IF the FLRG of A_i, B_k is not existing; Ai, $B_k \rightarrow \phi$, THEN the value of Fvt is A_i, and calculate centroid of the fuzzy set A_i ,which is located on midpoint, for inference point forecast.

Rule 2. IF the FLRG of A_i, B_k is A_i, $B_k \rightarrow \tilde{A}_k$, 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 A_i, B_k is A_i, $B_k \rightarrow \tilde{A}_{k1}$, A_i, $B_k \rightarrow \tilde{A}_{k2}$, A_i, $B_k \rightarrow \tilde{A}_{k3}$,..., A_i, $B_k \rightarrow \tilde{A}_{kp}$, and THEN the value of Fv_t is calculated as follows:

$$Fv_t = \frac{\tilde{A}_{k1} + \tilde{A}_{k2} + \ldots + \tilde{A}_{kp}}{p}$$

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

3. Brief description of benchmark methods

The present paper consists of five empirical calculations. One of them is the proposed method, BiFTS, which already defined in the previous section.

The method of Chen is the conventional univariate case of the proposed method which is also described in the process of fuzzy time series. The main contribution of Chen is to improve calculations and make it simpler.

As statistical benchmarks of the tested methods, Box-Jenkins type ARIMA (autoregressive integrated moving average) and Holt-Winters exponential smoothing methods are applied to univariate LFI series. An additional method which is known as Näive I is also applied for no change case. Näive I refer to forecasted value at time t is the actual value of time t-1. It is conventionally used in forecasting science as a base alternative since the method is the most basic approach.

Autoregressive moving average (ARMA) approach is first suggested by Wold.[21] Wold combined AR and MA forms into ARMA process and indicated

21) Wold (1938).

that it is very useful in many stationary time series. ARMA process is defined as:

$$x_t=\Phi_1 x_{t-1}+ \Phi_2 x_{t-2}+\ldots+ \Phi_p x_{t-p}+e_t-\theta_1 e_{t-1}- \theta_2 e_{t-2}-\ldots- \theta_q e_{t-q} \tag{5}$$

where x_t is the stationary time series and et is the error term.

Box and Jenkins developed ARMA by providing differencing operation to ensure stationarity of time series.[22) The term 'Integrated' is inserted to the model by means of order of differencing (ARIMA). Thereafter, ARIMA is mentioned with the name of Box and Jenkins. ARIMA method provided an additional function that uses autocorrelation and partial autocorrelation for definition of order of ARMA terms. Finally, outline of the procedure is defined as follows:

(1) Testing for stationarity and definition of order of differencing,
(2) Testing for seasonality and definition of order of seasonal differencing,
(3) Definition of order of ARMA model,
(4) Estimating model parameters,
(5) Diagnostic checks for residual white noise assumption.

For example, first order autoregressive and first order moving average terms under the first order differencing are figured out as ARIMA (1,1,1).

Another benchmark method is Holt-Winters's exponential smoothing algorithm. Holt and Winters[23) extended traditional exponential smoothing and improved forecasting performance. The structure of the Holt-Winters exponential smoothing is made up by local trend (Tt), level of series (Ft) (smoothed value) and seasonality (St). Eq. (6) shows the level of series smoothed by the constant α. Eq. (7) shows the seasonality component smoothed by the constant β. Eq. (8) shows the trend component smoothed by

22) Box and Jenkins (1970).
23) Holt (1957); Winters (1960),pp.324-342.

the constantγ. Eq. (9) is the Winters's forecasting function that includes the components as follows:

$$F_t = \alpha X_t / S_{t-p} + (1-\alpha)(F_{t-1} + T_{t-1}) \quad (6)$$
$$S_t = \beta X_t / F_t + (1-\beta)S_{t-p} \quad (7)$$
$$T_t = \gamma(F_t - F_{t-1}) + (1-\gamma)T_{t-1} \quad (8)$$
$$W_{t+m} = (F_t + mT_t)S_{t+m-p} \quad (9)$$

where X_t is actual value for period t, m is the number of period ahead to be forecasted and p is the number of periods in the seasonal cycle. Smoothing constants are based on ordinary least squares estimates.

III. The empirical results and validation

Empirical works are carried out on univariate and bivariate cases. The univariate LFI transformed series is estimated by Chen's method and the bivariate LFI-Life expectancy transformed series is estimated by the first order bivariate FTS (BiFTS). As benchmark, Näive I (no change model), Box-Jenkins type ARIMA and Holt-Winters exponential smoothing results are presented.[24] LFI series is tested for stationarity and first order differencing applied since the levels of LFI have unit roots (Augmented Dickey-Fuller test, p: 0.000).[25] Specification of ARIMA is defined ARIMA (2, 1, 3) by review of autocorrelations, partial autocorrelations and significance of coefficients (p<0.05). Non-seasonal Holt-Winters model (non-β) is based on α=0.87 and γ=0.03 according to the best fit. Since the LFI series is annual base, non-seasonal data (except probable business cycles), seasonality is out of scope.

Results for ARIMA and Holt-Winters method are calculated by E Views 6.0©QMS LLC software. Table 2 indicates results for five methods.

According to RMSE, NRMSE and MAE metrics, BiFTS exposes superiority

24) Box and Jenkins (1970); Holt (1957); Winters (1960), pp.324-342.
25) Dickey and Fuller (1979).

among the benchmark methods (See table 2). However, MAPE metric indicates simple no change model can outperform several complicated methods while the difference between Näive I and BiFTS is just 1%. Use of MAPE is discussed by many scholars and it is noted that MAPE may cause incomparable deviations.[26] Therefore, the present study introduces results for MAPE as a benchmark, but priority will be based on RMSE, MAE and particularly NRMSE metrics.

<Table 2> *RMSE, MAE, MAPE* and *NRMSE* results of empirical works.

	Näive I	Chen (1996)	BiFTS	ARIMA (2, 1, 3)	Holt-Winters
RMSE	107.1	101.24	82.41*	99.30	112.24
MAE	39.51	41.55	36.62*	50.06	43.85
MAPE	15*	17	16	20	16
NRMSE	0.0492	0.0467	0.0421*	0.0433	0.0489

* The most accurate.

RMSE for BiFTS is around one forth of standard deviation of LFI series (σ: 246). The size of error is quite less than average deviation from long term mean. About the rate of error metrics, Makridakis et al suggests comparative analysis with alternative methods rather than analysing simply size of them.[27]

Especially on long term series, size of deviation has different meanings over the different levels of dataset. In case of BiFTS, 82.41 has crucial importance in the end of 1800s, but it has relatively small size for the end of 1900s. As a cumulative result, size of average error metrics is not straightforward for interpretation.

NRMSE is an adjusted version of RMSE and explicitly indicates superior results of BiFTS for LFI series. BiFTS can be selected for practical use in long term inference by noting that reference methods may outperform in some parts of the term according to different error perceptions (absolute errors vs. squared errors) which is very common among the prediction science.

26) Armstrong (1985); Flores (1986); among others.
27) Makridakis et al (1998).

IV. Conclusions

In this paper, the first order BiFTS is applied to a long term forecasting problem. The LFI is the objective series and life expectancy data is used as a leading indicator. According to results, bivariate FTS indicated more accurate outcome over benchmark methods. Bivariate FTS provides co-trended pattern recognition and its major advantages lie on the data pre-conditions such as needless of stationarity, normality and other diagnostic particulars. Although, it is expressed that there is no requirement for stationarity in the conventional FTS, theoretically it should be obtained.[28)] Such a diagnostic test is still not embedded to traditional FTS methodology. The present paper does not compile raw data and transforms to percentage changes to reduce possible non-linearity.

Although, the present paper utilises LFI, various alternative dataset can easily be applied by FTS and BiFTS. Non-stationarity and non-linearity are two major problems of conventional time series analysis. Computer intelligence such as FTS may simply cope with such complications.

Future works should be based on high order BiFTS case because of that long term LFI data carries signal of long memory cycles. High order model may improve consistency and accuracy.[*]

Acknowledgement

Authors are thankful to four anonymous referees for their time and valuable comments. We also gratefully acknowledge participants and commentators of the 3rd Int'l Conference of the Asian Journal of Shipping & Logistics. Our special thanks and gratitude are due for Prof. Dr. Tetsuji Shimojo for his contributions to shipping economics and for his life devoted to shipping research.

28) Duru (2010).

* Date of Contribution; May 13, 2010
Date of Acceptance; Nov. 30, 2010

References

ARMSTRONG, S. (1985), *Long-range Forecasting,* New York: John Wiley & Sons.

BOX, G.E.P. and JENKINS, G.M. (1976), *Time Series Analysis: Forecasting and Control*, revised edition, Oakland CA: Holden-Day.

BOWERMAN, B.L. and O'CONNELL R.T. (1979), *Time series and forecasting*: an applied approach, New York: Duxbury Press.

CHEN, S.M. (1996), "Forecasting enrolments based on fuzzy time series", *Fuzzy Sets and Systems*, Vol. 81, pp. 311-319.

CHEN, S.M. (2002), "Forecasting enrolments based on high-order fuzzy time-series", *Cybernetics and Systems*, Vol. 33, pp. 1-16.

CHEN, S.M. and HWANG, J.R. (2000), "Temperature prediction using fuzzy time series", *IEEE Transaction on Systems*, Man & Cybernetics, Vol. 30, pp. 263-275.

CHENG, C.H., CHEN T.L., TEOH H.J. and CHIANG C.H. (2008), "Fuzzy time-series based on adaptive expectation model for TAIEX forecasting", *Expert systems with applications*, Vol. 34, pp. 1126-1132.

CHU H.H., CHEN T.L., CHENG C.H. and HUANG C.C. (2008), "Fuzzy dual-factor time-series for stock index forecasting", *Expert systems with applications*, Vol. 36, No. 1, pp. 165-171.

COLLOPY, F. and ARMSTRONG, J.S. (1992), "Rule-Based Forecasting: Development and Validation of an Expert Systems Approach to Combining Time Series Extrapolations", *Management Science*, Vol. 38, No. 10, pp. 1394-1414.

DICKEY, D.A. and FULLER, W.A. (1979), "Distribution of the estimators for autoregressive time series with a unit root", *Journal of American Statistical Association*, Vol. 74, pp. 427-431.

DURU, O. and YOSHIDA, S. (2009), "Long term freight market index and inferences", *Proceedings of the 43rd conference of Japan Society of Logistics & Shipping Economics*, Hitotsubashi University, Tokyo.

DURU, O. (2010), "A fuzzy integrated logical forecasting model for dry bulk shipping index forecasting: an improved fuzzy time series approach", *Expert Systems with Applications*, Vol. 37, No. 7, pp. 5372-5380.

FLORES, B.E. (1986), "A pragmatic view of accuracy measurement in forecasting", *Omega (Oxford)*, Vol. 14, No. 2, pp. 93–98.

FOGEL, R.W. (1986), *Nutrition and the decline in mortality since 1700: some additional preliminary findings*, NBER Working Paper No. 1802.

HARVEY, A.C. (1990), *The econometric analysis of time series*, 2nd edition, Cambridge MA: MIT Press.

HOLT, C.C. (1957), *Forecasting seasonal and trends by exponentially weighted moving averages*. Carnegie Institute of Technology.

HUARNG, K. (2001), “Heuristic models of fuzzy time series for forecasting”, *Fuzzy Sets and Systems*, Vol. 123, pp. 369-386.

HUARNG, K. and YU, H.K. (2005), “A type-2 fuzzy time series model for stock index forecasting”, *Physica A*, Vol. 353, pp. 445-462.

HUARNG, K. and YU, H.K. (2006), “The application of neural networks to forecast fuzzy time series”, *Physica A*, Vol. 363, pp. 481-491.

HWANG, J.R., CHEN, S.M. AND LEE, C.H. (1998), “Handling forecasting problems using fuzzy time series”, *Fuzzy Sets and System*, Vol. 100, pp. 217-228.

LEE, H.S. and CHOU, M.T (2004), “Fuzzy forecasting based on fuzzy time series”, *International Journal of Computer Mathematics*, Vol. 81, pp. 781-789.

LIU, H.T. (2007), “An improved fuzzy time series forecasting method using trapezoidal fuzzy numbers”, *Fuzzy Optimization and Decision Making*, Vol. 6, pp. 63-80.

MAKRIDAKIS, S., WHEELWRIGHT, S.C. and HYNDMAN, R.J. (1998), *Forecasting Methods and Applications*, New York: John Wiley and Sons.

PALIT, A.K. and POPOVIC, D. (2005), *Computational intelligence in time series forecasting*, London: Springer-Verlag.

SONG, Q. and CHISSOM, B.S. (1993a), “Fuzzy forecasting enrolments with fuzzy time series-Part 1”, *Fuzzy Sets and Systems*, Vol. 54, pp. 1-9.

SONG, Q. and CHISSOM, B.S. (1993b), “Fuzzy Time Series and Its Models”, *Fuzzy Sets and Systems*, Vol. 54, pp. 269-277.

SONG, Q. and CHISSOM, B.S. (1994), “Fuzzy forecasting enrolments with fuzzy time series-Part 2”, *Fuzzy Sets and Systems*, Vol. 62, pp. 1-8.

SULLIVAN, J. and WOODALL, W.H. (1994), “A comparison of fuzzy forecasting and markov modelling”, *Fuzzy Sets and Systems*, Vol. 64, pp. 279-293.

VEENSTRA, A. and DALEN, J. van (2008), "Price for ocean charter contracts", *the 2nd International Index Measures Congress Proceedings*, Washington D.C., U.S.

WINTERS, P.R. (1960), "Forecasting sales by exponentially weighted moving averages", *Management Science*, Vol. 6, pp. 324-342.

WOLD, H. (1938), A study in the analysis of stationary time series, Stockholm: Almgrist & Wiksell.

YU, H.K. (2005), "Weighted fuzzy time series models for TAIEX forecasting", *Physica A*, Vol. 349, pp. 609-624.

ZADEH, L.A. (1965), "Fuzzy sets", *Information and Control*, Vol. 8, No. 3, pp. 338-353.

Appendix A. Long term Freight Index series (LFI)[29)]

Year	LFI	Year	LFI	Year	LFI	Year	LFI	Year	LFI
1741	89.44	1796	213.51	1851	128.44	1906	80.62	1961	140.93
1742	95.71	1797	221.60	1852	139.09	1907	82.91	1962	116.97
1743	143.76	1798	294.47	1853	155.53	1908	71.53	1963	141.59
1744	124.35	1799	295.06	1854	177.66	1909	73.53	1964	149.64
1745	88.88	1800	177.91	1855	179.29	1910	82.00	1965	162.91
1746	69.73	1801	219.70	1856	175.83	1911	93.23	1966	153.76
1747	72.68	1802	302.32	1857	143.15	1912	120.66	1967	156.88
1748	83.69	1803	303.04	1858	146.76	1913	104.82	1968	157.93
1749	92.18	1804	279.54	1859	145.20	1914	92.57	1969	150.67
1750	82.17	1805	240.38	1860	159.72	1915	267.16	1970	231.59
1751	80.24	1806	308.73	1861	195.49	1916	428.95	1971	148.67
1752	65.52	1807	345.09	1862	169.82	1917	887.86	1972	153.13
1753	68.98	1808	383.07	1863	165.22	1918	863.20	1973	347.12
1754	105.25	1809	350.87	1864	124.79	1919	847.46	1974	403.78
1755	160.68	1810	362.93	1865	156.26	1920	501.34	1975	201.94
1756	152.76	1811	344.43	1866	151.96	1921	292.64	1976	222.04
1757	127.08	1812	291.81	1867	156.15	1922	223.60	1977	204.69
1758	154.80	1813	365.89	1868	175.04	1923	170.79	1978	271.21
1759	138.01	1814	369.19	1869	168.08	1924	178.98	1979	374.98
1760	158.46	1815	297.23	1870	160.71	1925	162.92	1980	466.47
1761	183.96	1816	215.78	1871	157.50	1926	193.11	1981	425.56
1762	121.59	1817	159.16	1872	174.05	1927	184.53	1982	285.19
1763	137.38	1818	265.53	1873	210.05	1928	161.55	1983	296.01
1764	110.39	1819	224.32	1874	185.68	1929	156.27	1984	312.36
1765	107.60	1820	260.16	1875	188.07	1930	146.29	1985	289.37
1766	98.16	1821	242.72	1876	168.40	1931	140.38	1986	263.36
1767	95.63	1822	244.68	1877	175.84	1932	130.75	1987	359.82
1768	92.85	1823	220.50	1878	170.51	1933	113.31	1988	500.73
1769	118.50	1824	212.90	1879	165.20	1934	121.32	1989	532.81
1770	134.25	1825	194.16	1880	168.08	1935	116.40	1990	469.59
1771	113.43	1826	216.28	1881	145.87	1936	137.62	1991	545.88
1772	89.17	1827	206.85	1882	151.94	1937	184.11	1992	454.38
1773	105.06	1828	185.97	1883	123.84	1938	173.59	1993	539.41
1774	108.50	1829	182.98	1884	122.36	1939	174.17	1994	536.07
1775	158.12	1830	182.68	1885	110.53	1940	100.11	1995	646.39
1776	162.98	1831	174.37	1886	111.38	1941	124.27	1996	474.79
1777	177.84	1832	185.25	1887	99.47	1942	115.59	1997	472.53
1778	155.58	1833	169.36	1888	114.30	1943	134.48	1998	336.04
1779	177.87	1834	178.42	1889	121.80	1944	123.25	1999	373.64
1780	212.96	1835	169.32	1890	111.93	1945	142.23	2000	555.39
1781	226.95	1836	163.23	1891	103.45	1946	168.97	2001	410.72
1782	179.59	1837	187.84	1892	96.56	1947	166.50	2002	339.55
1783	120.99	1838	199.07	1893	104.12	1948	146.92	2003	785.30
1784	134.91	1839	178.40	1894	81.40	1949	117.47	2004	1488.67
1785	128.44	1840	203.46	1895	89.80	1950	137.36	2005	1212.41
1786	119.84	1841	167.74	1896	97.62	1951	263.86	2006	1093.29
1787	120.02	1842	158.64	1897	97.93	1952	173.26	2007	2360.94
1788	120.71	1843	166.27	1898	110.87	1953	139.62	2008	2120.39
1789	142.99	1844	154.37	1899	106.99	1954	145.61		
1790	141.54	1845	152.87	1900	116.40	1955	227.99		
1791	140.78	1846	168.63	1901	87.05	1956	291.82		
1792	172.18	1847	187.14	1902	77.02	1957	216.76		
1793	218.34	1848	168.23	1903	72.71	1958	117.07		
1794	222.47	1849	147.45	1904	75.85	1959	123.14		
1795	214.79	1850	138.96	1905	80.07	1960	133.71		

29) Duru and Yoshida (2009).