Comparative analysis of statistical and fuzzy integrated time series and judgmental forecasting: an empirical study of forecasting dry bulk shipping index

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Contents

Abstract

This paper investigates the accuracy of some statistical, judgmental and fuzzy time series methods for dry cargo freight market forecasting purposes. For statistical extrapolation, the X12 ARIMA, TRAMO/SEATS and Holt-Winters exponential smoothing methods are applied. In judgmental prediction, traditional expert opinion and Delphi group decision are performed in an expert group. Additionally, the recent method, fuzzy time series, is used as Chen (1996)'s procedure. Judgmental forecasting improved its superiority among the most of the benchmark methods. Fuzzy time-series methodology also provided relatively better accuracy than the statistical extrapolation.

1. Introduction

Forecasting shipping markets is attempted by many scholars and various methods are applied. Most of the techniques are based on time series analysis and econometric causal models. Especially in regular seasons of freight markets, such a statistical approach give comparatively accurate results. However, freight markets had several unexpected fluctuations due to war fare, sporadic economic boom/bust cycles, structural breaks etc. In long term forecasting, causal models give a baseline and important drivers like productivity or population can be quantitatively embedded to the models except technology cycles. Technology cycles should be judgmentally reviewed and predicted. In short run, there are many judgmental factors effecting freight markets such as political declarations, crowd feed etc. (Duru and Yoshida, 2008a, b). Prediction of freight rates between weeks and months still has difficulties both in statistical methods and judgmental methods.

The main research motivation of this paper is forecasting in weeks and months. For statistical extrapolation, we choose automatic prediction tools such as the X12 ARIMA and TRAMO/ SEATS, and an exponential smoothing method, Holt-Winters' algorithm. In judgmental forecasting, traditional expert opinion and Delphi group decision methods are applied in a small expert group. Finally, an expert system method, Fuzzy integrated time series methodology is also compared.

A new generation forecasting tool is the fuzzification of time series and forecasting with fuzzy logical rules. Rule based forecasting is suggested by Collopy and Armstrong (1992) for structuring dynamics of systems by its features, and it presents an expert system procedure of prediction and combining of multiple methods under predetermined rules of the series. Collopy and Armstrong (1992) proposed a procedure which mainly driven by IF-THEN rules. IF-THEN modelling strategy is also employed by fuzzy logic type expert systems similarly for computer intelligence integration. Rather than a complex procedure, fuzzy time series is building rules for historical pattern. Fuzzy method is also capable to analyze chaotic time series (Palit and Popovic, 2005). As one of the benchmark methods, fuzzy time series approach will be compared with judgmental results.

Song and Chissom (1993a, b) first attempted to implement fuzzy set theory for forecasting task. The famous data set, the student enrolments of University of Alabama, is frequently used in the next studies to compare with previous fuzzy applications. Shortly afterward, a stream of fuzzy time series existed to improve accuracy of the current approaches. Chen (1996) developed the initial study and also ensured robustness of the forecasts. The main difference is presented that the study uses simplified arithmetic operations instead of max-min composition operations of Song and Chissom (1993a). Huarng (2001) introduced heuristic fuzzy time-series model. High order fuzzy time series approach is also suggested by Chen (2002). A time-invariant fuzzy forecasting model is based on fuzzy logical relationships such as $\tilde{A}_i \rightarrow \tilde{A}_j$, and consolidates these logical connections as their rules for forecasting values. Chen (1996)'s methodology is one of the accurate model for prediction, and this paper purposes to implement this method for freight rate task.

Forecasting practice is carried out on Baltic Dry Index (BDI) which is a composite price of various cargoes, routes and ship sizes. BDI is fixed for every trading day by Baltic Exchange, London and it is also reflecting both voyage domain and time domain contracts.

2. Methodology

Forecasting of BDI index is conducted with three statistical methods, judgmental forecasting and fuzzy time-series method. The brief description of methods used in this research is as follows:

2.1 Statistical Forecasts: X12 ARIMA, Tramo-Seats and Holt-Winters exponential smoothing

The present paper applied two automatic extrapolation method, the X12 ARIMA and TRAMO/SEATS, and an exponential smoothing method, Holt-Winters' algorithm. The X12 ARIMA seasonal adjustment algorithm is an improved version of the X11 ARIMA (Shiskin et.al., 1967; Findley et.al., 1998). The method automatically detects seasonal ARIMA configurations and applies for forecasting. TRAMO/SEATS program can treat missing observations and outliers, and also estimate unobserved data. As in the X12 ARIMA, TRAMO/ SEATS also uses ARIMA-model-based methodology for extrapolation (Gómez and Maravall, 1996).

Holt-Winters' exponential smoothing is well known time series method which frequently used in forecasting practice (Makridakis, Wheelwright, and Hyndman, 1998). Holt (1957) and Winters (1960) extended the classical form of exponential smoothing and consolidated some improvements. Holt-Winters method can be applied to both additive and multiplicative trended series.

Since the present paper attempts to use the mentioned statistical methods, the detection of whether seasonal factors have unit roots has a critical role. Many scholars indicated about the drawbacks of routine adjustment of seasonality (Barsky and Miron, 1989, Hyllberg et. al. 1990). Barsky and Miron (1989) pointed out that the routine elimination of the seasonal cycles is concluded by losing important information about the fluctuations. In existence of stochastic seasonality, Box-Jenkins type ARIMA modelling can be proper for a univariate series. However, it is reported that spurious regression results are probable if the series is not differenced at the seasonal frequency. Hyllberg et. al. (1990) suggested a testing procedure for seasonal unit roots (HEGY test), and that method is also developed for monthly frequencies by Franses (1990) and Beaulieu and Miron (1993).

A seasonal unit root test is performed for the series of the BDI, and the results are prospective. The historical backgrounds of two empirical studies have seasonal unit roots, and adjustment or seasonal differencing will be rational. The tests are conducted by monthly HEGY test for the models that is based on intercept only, intercept and trend, and intercept, trend and seasonal dummies. Constant, trend and seasonal dummy variables are found insignificant in most. The significance tests of seasonal frequencies are conducted by the reference t-test and F-test tables of Franses and Hobijn (1997). The single and joint existence of seasonal unit roots is indicated present in the applied datasets. Therefore, smoothing and adjustment of seasonal differences will be consistent as in the X12 ARIMA, Tramo/Seats and Holt-Winters' methods.

2.2 Fuzzy time-series extrapolation

After the development of fuzzy set theory, time-series forecasting is one of the good example of fuzzy extended studies. Zadeh (1965) introduced fuzzy numbers, and it is used for many different applications in the last half century. Fuzzy logic algorithms are implemented for various engineering problems which mainly include some degree of uncertainty. Uncertainty is one of the unique problems of several time series and it can be improved by fuzzification of the data.

Fuzzy time-series methodology is appeared to implement the uncertainty of series and in some empirical studies, it provides higher accuracy. The basic principals of fuzzy set theory and fuzzy time series are as follows:

A *fuzzy set* A in a universe of discourse U is characterized by its membership function I_A which is a map $I_A: U \rightarrow [0, 1]$. The value of $I_A(\theta)$ is the *degree of membership* of the point θ in the fuzzy set A. The fuzzy sets with boundaries that are not precise, it is possible to take into account the uncertainties inherent in the systems.

Definition 1. $Y(t)$ (t =...,0,1,2,...), is a subset of R. 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 $F(t) = \tilde{A}_j$, 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 and right-hand side of the fuzzy logical relationship, respectively.

The current fuzzy time series models (Song and Chissom, 1993a, b, 1994; Chen, 1996, 2002; Hwang et al., 1998; Chen and Hwang, 2000; Huarng, 2001a, b; Lee and Chou, 2004) utilize discrete fuzzy sets to define their fuzzy time series. Fuzzy sets can be based on triangular or trapezoidal shapes. The present work applies trapezoidal fuzzy numbers (Liu, 2007).

The research steps of the fuzzy time series extrapolation of Chen (1996) can be described as follows:

Step 1. Collect the historical data Dv_t.

Step 2. Define the universe of discourse U. Find the maximum D_{max} and the minimum D_{min} among all Dv_t. For easy partioning of U, two small numbers D_1 and D_2 are assigned. The universe of discourse U is then defined by:
$U = [D_{min} - D_1 , D_{max} + D_2]$

Step 3. Determine the appropriate length of interval l. Here, the average-based length method (Huarng, 2001b) can be applied to determine the appropriate l. The length of interval l is computed by the following steps:
a. Calculate all the absolute differences between the values Dv_{t-1} and Dv_t as the first differences, and then compute the average of the first differences.
b. Take one-half of the average as the length.
c. Find the located range of the length and determine the base (Table 2).
d. According to the assigned base, round the length as the appropriate l.

Step 4. Define fuzzy numbers. The number of intervals (fuzzy numbers), m, is computed by

$$m = (D_{max} + D_2 - D_{min} + D_1) / l. \qquad \text{Eq. 4}$$

Thus, there are m intervals and m fuzzy numbers, which are u_1, u_2,...,u_m, and $\tilde{A}_1$, $\tilde{A}_2$, ..., $\tilde{A}_m$, respectively. Assume that the m intervals 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 $u_m = [d_m,d_{m+1}]$. The fuzzy numbers, $\tilde{A}_1$, $\tilde{A}_2$, ..., $\tilde{A}_m$ can be defined as follows:

$$\begin{aligned}
\tilde{A}_1 &= (d_0,d_1,d_2,d_3),\\
\tilde{A}_2 &= (d_1,d_2,d_3,d_4),\\
\tilde{A}_3 &= (d_2,d_3,d_4,d_5),\\
&\cdots \quad \cdots\\
\tilde{A}_{m-1} &= (d_{m-2},d_{m-1},d_m,d_{m+1}),\\
\tilde{A}_m &= (d_{m-1},d_m,d_{m+1},d_{m+2}),
\end{aligned}$$

Step 5. Fuzzify the historical data. If value of Dv_t is located in the range of u_j, then it belongs to fuzzy number $\tilde{A}_j$. All Dv_t must be classified into the corresponding fuzzy numbers.

Step 6. Generate the fuzzy logical relationships. For all fuzzified data, derive the fuzzy logical relationships based on Definition 4. The fuzzy logical relationship is like $\tilde{A}_j \rightarrow \tilde{A}_k$, which denotes that "if the Dv_{t-1} value of time t-1 is $\tilde{A}_j$, then that of time t is $\tilde{A}_k$."

Step 7. Establish the fuzzy logical relationship groups. The derived fuzzy logical relationships can be arranged into fuzzy logical relationship groups based on the same

fuzzy numbers on the left-hand side of the fuzzy logical relationships.
The fuzzy logical relationship groups are like the following:

$$\tilde{A}_j \rightarrow \tilde{A}_{k1},$$
$$\tilde{A}_j \rightarrow \tilde{A}_{k2},$$
$$\tilde{A}_j \rightarrow \tilde{A}_{k3},$$
$$\ldots$$
$$\tilde{A}_j \rightarrow \tilde{A}_{kp},$$

Step 8. Calculate the forecasted outputs. The forecasted value at time t, Fv_t, is determined by the following three heuristic rules. Assume the fuzzy number of $Dv_{t\text{-}1}$ at time t-1 is $\tilde{A}_j$.

Rule 1. If the fuzzy logical relationship group of $\tilde{A}_j$ is empty; $\tilde{A}_j \rightarrow \phi$, then the value of Fv_t is $\tilde{A}_j$, which is $(d_{j\text{-}1}, d_j, d_{j+1}, d_{j+2})$.

Rule 2. If the fuzzy logical relationship group of $\tilde{A}_j$ is one-to-one; $\tilde{A}_j \rightarrow \tilde{A}_k$, then the value of Fv_t is $\tilde{A}_k$, which is $(d_{k\text{-}1}, d_k, d_{k+1}, d_{k+2})$.

Rule 3. If the fuzzy logical relationship group of $\tilde{A}_j$ is one-to-many; $\tilde{A}_j \rightarrow \tilde{A}_{k1}$, $\tilde{A}_j \rightarrow \tilde{A}_{k2}$, $\tilde{A}_j \rightarrow \tilde{A}_{k3}$,..., $\tilde{A}_j \rightarrow \tilde{A}_{kp}$, and then the value of Fv_t is calculated as follows:

$$Fv_t = \frac{\tilde{A}_{k1} + \tilde{A}_{k2} + \ldots + \tilde{A}_{kp}}{p}$$
$$= \left(\frac{d_{k1\text{-}1} + \ldots + d_{kp\text{-}1}}{p}, \frac{d_{k1} + \ldots + d_{kp}}{p}, \frac{d_{k1+1} + \ldots + d_{kp+1}}{p}, \frac{d_{k1+2} + \ldots + d_{kp+2}}{p} \right).$$

where $\tilde{A}_{k1} = (d_{k1\text{-}1}, d_{k1}, d_{k1+1}, d_{k1+2})$, $\tilde{A}_{k2} = (d_{k2\text{-}1}, d_{k2}, d_{k2+1}, d_{k2+2})$,...,and $\tilde{A}_{kp} = (d_{kp\text{-}1}, d_{kp}, d_{kp+1}, d_{kp+2})$.

2.3 Judgmental Forecasts

Every forecasting work is subject to managerial review, and some of them will be revised and improved to damp the current factors, and also include judgmental factors. In managerial level or expert group level, judgmental forecasting is one of the unique solutions for sporadic situations and unexpected market movements. When fluctuations depend on judgmental factors, crowd psychology, or political issues, expert judgments can reflect market psychology to the results.

For judgmental forecasting, expert opinion and Delphi group consensus methods are proposed to maintain the subjective exercise of the forecasting study. These methods are implemented in many judgmental forecasting studies. Expert opinion is a basic method based on individual decisions, and it is a single iteration application. Expert decisions are composed of individual forecast of the BDI. Result of expert judgments is consolidated by simple average method. A multi-iteration method, Delphi, is also performed as a second judgmental practice (Rowe and Wright, 1999). The advantages of Delphi exist from its anonymous, multi-session, and feedback structure. A group of experts is required to predict BDI in one and two period ahead horizons. The expert group has no interaction with each other. The group is required to predict twice and in the middle of two iterations, a summary report of the first round is provided.

The judgmental study is performed in a small group (8 experts in expert opinion study and 9 experts in Delphi work) and experts are selected from freight negotiation field such as shipbrokers or chartering managers etc. There are many judgmental works based on a small group (Rowe and Wright, 1999), but the number of experimental work can be considered limited. In practice, organization of such an empirical study has several difficulties. Although we guaranteed to keep information anonymous, most of the experts do not accept to share their opinions. However, most of the shipping companies use their judgments in managerial level in practice. Experts of the present study are mainly from Turkey, but also some of them are from Singapore and U.K.

3. Empirical results

This study attempts to compare statistical extrapolation, fuzzy logic extrapolation and expert judgments for forecasting of the BDI data series. The forecasting accuracy of the methods is assessed with the absolute percentage error (APE) for single predictions and the mean absolute percentage error (MAPE) and root mean squared error (RMSE) metrics for overall accuracy comparison. Table 1 shows the accuracy results of proposed methods. Expert judgments exposed superiority over statistical and fuzzy logical forecasting practice. Statistical methods particularly resulted incapable for short term. Fuzzy logical time-series prediction improved inferior, but adjacent output versus judgmental forecasting. Delphi group consensus practice could not improve prediction accuracy rather than a single iteration expert opinion study.

4. Conclusion

The present study pointed out relative accuracy of judgments and fuzzy time series rather than univariate time series methods. In spite of small number of repetitive works, the study indicates possibility of superior performance in decision methods.

Market intentions have a key role particularly in short term decisions such as trading between spot and time charter markets, assessment of sale and purchase of older fleet, short term asset management. For this type of decisions, managerial decision making strategy and developing company prediction are also crucial. For future extensions of this study, design of company judgmental prediction system or judgmental adjustment of statistical results is considered to be beneficial to improve practical applications.

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Table. Judgmental, statistical and fuzzy time-series forecast errors (MAPE & RMSE)

Forecast horizon	Date	Judgmental	Fuzzy time-series	X12 ARIMA	Holt-Winters	Tramo/ Seats
APE						
Expert opinion based study						
1 month	January '08	31.23	38.08	63.16	72.40	60.54
3 months	March '08	23.19	22.79	45.20	54.46	42.85
6 months	June '08	1.83	3.37	0.96	10.65	0.70
Delphi based study						
1 month	July '08	0.99	15.27	17.95	17.52	25.64
2 months	August '08	24.30	39.14	54.49	50.85	62.38
MAPE		16.31	23.73	36.35	41.18	38.42
RMSE		1535.34	2059.41	3057.47	3428.06	3179.94

Profiles

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