The Dynamic Analysis of Baltic Exchange Dry Index

Yueh-Ju Lin *
Department of Accounting, Kainan University
No. 1 Kainan Road, Luzhu, Taoyuan County 33857, Taiwan
* Corresponding author

Chi-Chen Wang
Department of Financial Management
National Defense University
No 70, Sec 2, Zhongyang N.Rd, Peitou District, Taipei, Taiwan

Abstract

Baltic Exchange Dry Index (BDI) is an independent response of maritime market information for the trading and settlement of physical and derivative contracts. In this paper, we propose fuzzy set theory and grey system for modeling the prediction of BDI, and employ the ARIMA model for the calibration of the data structure to depict the trend. The empirical results indicate that for both short-term and long-term BDI data, the fuzzy time series model has the lowest prediction error; the structural change ARIMA model fits better for prediction in the long term, while the GM (1,1) model compared to proposed models has the greatest prediction error. Moreover, the relationship between current BDI and previous BDI is highly significant. In addition, the external interference is negatively related to the current BDI index. The conclusion of this paper provides the bulk shipping industry with a beneficial reference for market and risk assessment.

Keywords: Baltic Dry Index; Derivative contracts; Fuzzy Time Series; Grey Theory; Grey-Markov Model; ARIMA
Introduction

Through the trends of globalization and regional economic integration, global trade has witnessed continuous growth, leading to the expansion of marine transport. The freight rate of the bulk shipping market has been determined by both supply and demand for a long time. The supply perspective is mainly decided by new vessel orders and overage vessel disassembly, and the demand by global economic cycles, seasons, climate, and politics. With virtually perfect competition, freight rate volatility can occur at any time in the bulk shipping market. The changes in freight rates are not easy to master for management decision-making. Bulk shipping companies are thus confronted with business risks and uncertainties in the ocean transportation industry [22].

The Baltic Freight Index (BFI) was created by the London Baltic Exchange in 1985, and replaced by the Baltic Dry Index (BDI) in 1999. After 2006, BDI was calculated as the average of the Baltic Capesize Index (BSI), Baltic Panamax Index (BPI), Baltic Supramax Index (BSI), with a multiplier of 0.99800799. When the Baltic Handysize Index (BHSI) was introduced, the new BDI account is equal to the same weight of the four indices multiplied by 1.192621362 to maintain BDI continuity. Thus, BDI reflects bulk shipping market sentiment as a price reference for transaction platforms of bulk shipping companies and investors.

As a price follower in the market, one bulk shipping company cannot change the equilibrium freight of the market. If there is a mechanism for management to evaluate the changes in ocean freight, then business risks and uncertainties can be reduced (Cullinane, 1995). For the prediction problem, using dynamic BDI historical data for judging short-term trends should be an effective approach. However, only few studies have devoted their attention to the problem. Most have mainly included regression models and traditional time series models. Using these models for prediction still needs to meet some statistical conditions, otherwise the risk of inadequate model-to-data fitting may occur.

The characteristic of BDI data is that it changes with each transaction and has multi-variability. In each transaction period, there is the highest/lowest price and closing/opening price. The Baltic Exchange Center considers the closing price as the benchmark price level. The closing price is a fixed value that simply reflects the final conditions of a market transaction, unable to express the whole pattern. The index in nature seems to be accurate but has implications. Consequently, the reality of BDI data is not easily described by the traditional 0-1 logical concept. Fuzzy set theory (Zadeh, 1965) describes a fuzzy continuum logic which transits from “non-membership” to “membership.” It can define a clear boundary for some uncertain data to quantify the data for calculation. In dealing with the limitation of binary logic, the concept of fuzzy set theory is widely employed for social systems, environment, and machine control. Today, the fuzzy theory is merged with linguistic variables, membership functions, and fuzzy relation matrices for application to social forecasting problems.
In this paper, we proposed the concept of fuzzy set grey theory to construct a BDI prediction model for short-term dynamic trends. In the meantime, the traditional time series model and grey theory was used for the comparison of prediction capability and stability. Lastly, the economic implications of different prediction models were interpreted based on the prediction results of the models.

The remainder of this paper is organized as follows: Section 2 introduces fuzzy prediction and the BDI-related literature; Section 3 presents the construction of the fuzzy time series model, GM (1,1) and Grey-Markov Model and solving; Section 4 provides the data source and empirical results; Section 5 gives conclusions and suggestions.

Literature Review

1. Factors that influence shipping price

Kavussanos (1996) used ARCH to discuss price fluctuation of very large crude carriers and found the prices of different vessels have different responses to exogenous shocks. Lundgren (1996) considered bulk cargo shipping price variation was related to the price variation in Organization of Petroleum Export Countries (OPEC) countries. Cullinane (1992) analyzed the fitness of time series models (MA, AR, ARMA, ARIMA) for BFI (Baltic Freight Index) prediction and selected the best method for application. Chang and Chang (1996) analyzed the relationship between BFI and BIFFEX through linear regression for prediction of the bulk cargo market. Veenstra and Franses (1997) used error term to correct the models for forecasting the voyage charter price of Capesize and Panamax carriers, and considered there was a long-run equilibrium relationship between routes. The shipping price is not easily foreseen due to its unpredictable nature.

Cullinane et al. (1999) used ARIMA to forecast BDI index, and found the ARIMA mode has highest density and best prediction results. Akatsuka and Leggate (2001) investigated two shipping countries to analyze the influence of exchange rates on the shipping companies in those countries. Foreign exchange rate is one of the key factors in the shipping business. Kavussanos and Alizadeh-M (2002) analyzed the seasonal effect on the bulk shipping market by using seasonality patterns and studied rent, contract period, and market. Kavussanos (1996) used the ARCH model to analyze relative risks of different tanker types and operation modes for tanker owners and operators. Kavussanos and Nomikos (2003) analyzed the correlation between spot price and BIFFEX. Alizadeh-M and Nomikos (2003) discussed price relations between five-year used Capesize, Panamax, Handymax carriers with the correlation analysis method, VAR and Granger correlation method, and considered used-ship market price had a positive correlation with activities on the buyer’s market and the seller’s market. Kavussanos et al. (2004) discussed the correlation among the trading volume of forward freight agreements and charter hire and voyage charter.
Chen and Wang (2004) found large carriers have a higher variable ratio; the larger the dry bulk carrier is, the larger the concentration of cargo. Small carriers have greater variability. The findings showed ship tonnage supply, grain, and Asian steel demands are significantly related to BDI fluctuation. Batchelor (2007) used ARIMA, VAR, VECM, and S-VECM to forecast spot rate and forward rate of Panamax carriers. The empirical findings show the seasonal factor of shipping price is not significant, and the previous raw material price may affect the next shipping price index.

2. Fuzzy Set Theory

Since Zadeh (1965) proposed fuzzy set theory as a tool to test uncertain membership, it has served as the theory framework in research of many fields and has solved the 0-1 logic value limitation of traditional sets. The fuzzy theory has been successfully applied in decision analysis, artificial intelligence, economics, psychology, and control theory. Song and Chissom (1993a) established a fuzzy relationship for fuzzy time series model, and introduced fuzzy theory into the prediction domain. Other relevant prediction-related studies are introduced as follows. Chen (1996) simplified the fuzzy matrix construction procedure of Song and Chissom (1993a, b, 1994), and used a simple mathematical equation instead of the complex Max-Min equation, suggesting a fuzzy logical relationship group. The empirical data are superior to the results from the model created by Song and Chissom (1994).

Huarng (2001a, b) proposed two heuristic models to improve the model by Chen (1996), constructed two fuzzy logical relationship groups of previous and next periods, and introduced a threshold value to construct three fuzzy logical relationship groups of previous and next periods. Meanwhile, distribution-based and average-based approaches were proposed to explain that too long of an interval may cause fuzzy time series to not fluctuate. The historical data variation trend cannot be known, and prediction accuracy lowers; too short of an interval may conflict with the nature of the fuzzy time series model.

Hwang et al. (1998) proposed a differential mode for stabilization of historical data to predict future variation and not the value. The predicted value is equal to the variation plus previous-period value. A fuzzy correlation matrix is constructed to differentiate window basis and operation matrix. The fuzzy correlation matrix is more rational, operation time is more co-efficient, and predicted value is superior to the model (Song and Chissom, 1993a, b, 1994). Cheng et al. (2008a, b) used trapezoidal membership functions to fuzzify historical data and suggested the minimize entropy principle approach (MEPA) to find appropriate interval median points and form unequal interval segmentation. The trapezoid fuzzification approach (TFA) is different from the triangular membership function approaches in the previous literature. In the segmentation of various intervals, more than one membership is 1.

Yu (2005a, b) considered that the fuzzy logical relationship should be assigned with proper weights, reflecting the data, and employed two interval segmentation
methods by Huarng (2001a, b) to construct models. Huarng and Yu (2005) proposed a heuristic type-2 model to increase research variables and to facilitate efficiency of prediction models. Huarng and Yu (2006a) introduced a neural network nonlinear structure and employed back propagation for prediction. Huarng and Yu (2006b) suggested the unequal-length interval segmentation and firmly believed the same variation value has unequal validity in different intervals.

Cheng et al. (2006) built a fuzzy relation matrix based on the entropy concept and tested the model with secular trend data. Li and Cheng (2007) considered that the fuzzy logic relationship group created by Chen (1996) is the factor that leads to prediction uncertainty and thus suggested a backtracking system to establish a sole definite fuzzy logic relationship; the findings are inconsistent with the conclusion made by Huarng (2001a). Cheng et al. (2008) extended the concept by Wang and Hsu (2008) and Yu (2005b) and made a linear correction with linear and non-linear concepts after nonlinear fuzzy logic relationship, and assigned suitable weight to the difference between predicted value and the actual value of the previous period.

Chen and Hwang (2000) first introduced two variables into fuzzy time series prediction to forecast main variables in combination with the concept by Hwang et al. (1998). Cheng et al. (2008) applied a novel fuzzy time series method to resolve student enrollment at the University of Alabama as well as Taiwan stock TAIEX data. Recently, Wong et al. (2010a) compared the three fuzzy prediction models in the literature and found that the heuristic fuzzy time series model has the lowest prediction error. Further, a single-variable model is better than a multi-variable model. This conclusion disproves the past literature (Huarng and Yu, 2005). Later, Wong et al. (2010b) suggested that the predicting decision of an optimal fuzzy model is correlated with the type of time series data.

After a review of the BDI-related literature, it is noted that most discussed the correlation analysis of shipping price variation; however, authors seldom paid attention to the BDI prediction. These studies mainly applied a regression model and the traditional time series model. Fuzzy set theory aims to solve fuzzy phenomena in the real world and is a quantitative description tool. It is used to describe some fuzzy concepts, especially for human language. In this paper, the grey systems concept is applied to expressing the characteristic of BDI data for the forecasting problem. For the comparison purpose of modeling the traditional ARIMA and GM models were used for the same data test.

**Research Method**

1. **Fuzzy Time Series Model**

   The core concept of fuzzy set theory is membership degree. It can describe fuzzy set characteristics, quantify the fuzzy set and handle linguistic information through two-value logic. Fuzzy sets can express a set of specific things with
indistinct boundaries, and membership function denotes the fuzzy set relation that elements belong to; the fuzzy set is often denoted by $[0,1]$.

The membership function can be divided into the discrete function and the continuous function. Proper membership function transformation can easily quantify interval data for numerical calculation. The fuzzy time series model applies fuzzy logic in the data series analysis to solve fuzzy problems in linguistic degree, membership members and fuzzy relation.

1.1. Fuzzy Time Series

Suppose that $\{y(t) \in R, t=1,2,\ldots,n\}$ is a time series, $U$ denotes its universe of discourse, and an ordered partition set is given to $U$, represented by $\{G_i, i=1,2,\ldots,m\}, \cup_{i=1}^m G_i = U$. Relatively, the linguistic variable is $\{A_i, i=1,2,\ldots,m\}$, assume that the time series $Y(t)$ experiences linguistic variable $\{A_i\}$ and corresponds to $F(t)$, which is called a fuzzy set. The membership function of the fuzzy set $F(t)$ is $\{u_i(Y(t), u_2(Y(t), \ldots, u_m(Y(t))\}$ where $0 \leq u_i(Y(t)) \leq 1$, and the fuzzy set $F(t)$ can be expressed by the discrete function:

$$F(t) = \sum_{i=1}^m \frac{\mu_i(Y(t))}{A_i} = \frac{\mu_1(Y(t))}{A_1} + \frac{\mu_2(Y(t))}{A_2} + \ldots + \frac{\mu_m(Y(t))}{A_m}$$

where $\frac{\mu_i(Y(t))}{A_i}$ denotes the membership and membership degree of original time series $Y(t)$ after experiencing linguistic variable $\{A_i\}$; “+” denotes a connecting symbol; $\mu: R \rightarrow [0,1]$, and $\sum_{i=1}^m u_i(Y(t)) = 1, t=1,2,\ldots,n$.

1.2. Fuzzy Logic Relation

Suppose that the fuzzy time series $F(t)$ and $F(t-1)$ of previous and next periods have a fuzzy relation, expressed by $R(t-1, t)$. Let $F(t) = F(t-1) * R(t-1,t)$ and the relation between $F(t)$ and $F(t-1)$ can be represented by $F(t-1) \rightarrow F(t)$. Assume that $F(t-1) = A_i$, $F(t) = A_j$, and the two-value fuzzy relation can be represented by $A_i \rightarrow A_j$ where $A_i$ is called LHS, and $A_j$ is called RHS.

If the fuzzy time series $F(t)$ is affected by several previous series $F(t-1), F(t-2),\ldots, F(t-n)$, the fuzzy logic relationship between the series can be represented by $F(t-1), F(t-2),\ldots, F(t-n) \rightarrow (t)$. This is called the n-order fuzzy time series model. If $n=1$, it is a first-order fuzzy time series model.

If the fuzzy time series $F(t)$ has a multi-group fuzzy relationship, the same fuzzy relationships can be arranged into a fuzzy logic relationship group. For example, all fuzzy logic relationships of $A_i$ include $A_i \rightarrow A_{i1}, A_i \rightarrow A_{i2}, \ldots, A_i \rightarrow A_{in}$, and the arranged fuzzy logic relationship group is $A_i \rightarrow A_{i1}, A_{i2}, A_{in}$. 
1.3. Time-Invariant Fuzzy Time Series

If the fuzzy time series $F(t)$ is impacted by $F(t-1)$, and the fuzzy relationship $R(t-1, t)$ is not related to time, $F(t)$ is a time-invariant fuzzy time series, otherwise it is a time-variant fuzzy time series.

In the fuzzy time series $F(t)$, it has multi fuzzy logical relationship group, $A_1 \rightarrow A_{j1}, A_{j2}, A_{jn}$; if the intervals in the fuzzy group $\{A_j\}$ are $u_1, u_2, \ldots, u_k$, and the interval median values are $m_1, m_2, \ldots, m_k$, the predicted fuzzy value is the mean of the middle points in each group, as shown in the following equation:

$$Y(t) = \frac{f_{im1} + f_{im2} + \ldots + f_{imk}}{K_2}$$  

After corresponding to the fuzzy relationship, fuzzy group $\{A_j\}$ is an empty set, and the fuzzy predicted value is group midpoint $u_j$.

The algorithm of objective value for the fuzzy time series model is expressed by five steps as follows:
1. Define universal time series.
2. Define interval length, fuzzy set, and fuzzify data in a linguistic manner.
3. Establish the time series fuzzy logic relationship.
4. Integrate fuzzy logic relationships and construct a model.
5. Make prediction and defuzzify.

2. GM (1,1)

In GM Theory, one uses the generation method to pre-process the raw data, which are usually incomplete and uncertain, and construct a grey model through differential equations to reduce data randomness. The GM (1,1) is the forecasting model in grey system theory, consisting of a one-order difference equation and one variable. It calculates data and describes the implications through parameters $a$ and $b$ in the model (Deng, 1989). The GM (1,1) model is described as follows:
1. After the Accumulated Generating Operation (AGO), the time series $x^{(0)}(k) = (x^{(0)}(1), x^{(0)}(2), \ldots, x^{(0)}(n))$ can be transformed into:

   $$x^{(1)}(k) = (x^{(1)}(1), x^{(1)}(2), \ldots, x^{(1)}(n))$$

   where

   $$x^{(1)}(k) = \sum_{i=1}^{k} x^{(0)}(i) \quad k = 1, 2, \ldots, n \tag{3}$$

2. Use Equation (3) to construct a data matrix $B$ and constant matrix $Y$:

   $$B = \begin{bmatrix} -x^{(0)}(2) & 1 \\ -x^{(0)}(3) & 1 \\ \vdots & \vdots \\ -x^{(0)}(n) & 1 \end{bmatrix}, \quad Y = \begin{bmatrix} x^{(0)}(2) \\ x^{(0)}(3) \\ \vdots \\ x^{(0)}(n) \end{bmatrix} \tag{4}$$
where: \( x^{(0)}(k) = \frac{x^{(1)}(k) + x^{(1)}(k-1)}{2} \), \( k = 2, 3, \ldots, n \); and let \( \frac{dx^{(1)}}{dx} + ax^{(1)} = b \).

3. Use the method of least squares to solve coefficients \( a \) and \( b \) in (4) as follows;

\[
(B^T B)^{-1} B^T Y_n = \begin{bmatrix} a \\ b \end{bmatrix}
\]

(5)

4. Substitute \( a \) and \( b \) into the differential equation, and the function can be obtained:

\[
x^{(1)}(t+1) = (x^{(0)}(1) - \frac{b}{a} a^{-at} + \frac{b}{a}, t = 1, 2, \ldots, n
\]

(6)

where \( (x^{(0)}(1))^{-at} \) is the initial value term, \( \frac{b}{a} (1 - e^{-at}) \) is the constant term.

5. Use the function derived from IAGO to restore \( x^{(0)}(t+1) \), and \( G(1,1) \) can be obtained:

\[
x^{(0)}(t+1) = (1 - e^a)(x^{(0)}(1) - \frac{b}{a} a^{-at}
\]

(7)

where \( x^{(0)}(t+1) \) denotes the predicted value, and \( t \) denotes the period.

This study used posterior accuracy to verify prediction fitting capability of \( GM(1,1) \), and posterior error rate \( (C) \) is expressed by:

\[
c = \frac{s_1}{s_2} = \sqrt{\frac{1}{n} \sum_{k=4}^{n} (e(k) - \bar{e})^2}
\]

(8)

where: \( s_1 \) denotes the RMSE of predicted residual \( q(0)(k) \), \( s_2 \) denoted RMSE of original data \( Y(0)(k) \), and the small error frequency rate \( (p) \) is

\[
p = \text{prob}\left\{ q^{(0)}(k) - \bar{q} < 0.6745 s_2 \right\}
\]

(9)

where \( \bar{q} \) is the mean of \( q(0)(k) \). The smaller posterior error ratio is, the better it is. This means that the elements in the Eq. (8) are small. The predicted residual has lower degree of dispersion and \( GM(1,1) \) has better stability. The GM accuracy grade is shown in Table 1.

<table>
<thead>
<tr>
<th>Grade</th>
<th>P</th>
<th>C</th>
<th>level</th>
</tr>
</thead>
<tbody>
<tr>
<td>One</td>
<td>( \geq 0.95 )</td>
<td>( \leq 0.35 )</td>
<td>Good</td>
</tr>
<tr>
<td>Second</td>
<td>( \geq 0.80 )</td>
<td>( \leq 0.50 )</td>
<td>Qualified</td>
</tr>
<tr>
<td>Third</td>
<td>( \geq 0.70 )</td>
<td>( \leq 0.65 )</td>
<td>Just</td>
</tr>
<tr>
<td>fourth</td>
<td>( \leq 0.70 )</td>
<td>( \geq 0.65 )</td>
<td>Unqualified</td>
</tr>
</tbody>
</table>

Deng (1989)
The greater the error frequency ratio, the better it is. This means that the
difference between the residual and the mean residual is mostly smaller than
0.6745xS2, similar with the significance of the C value.

3. Grey-Markov Model

The Grey-Markov model is based on the grey prediction model combined with
the Markov process. It can handle a dynamic system that changes randomly and is
a transition probability process relying on all dimensions of state evolution,
including two characteristics: First, the model consists of the i state set \( \{E_i, E_2, E_3, \ldots, E_i, i=1,...,n\} \), in which \( E_i \in \{\oplus_{i1}, \oplus_{i2}\} \), elements \( \oplus_{i1} \) and \( \oplus_{i2} \) are state margin, i would change with time. Thus, state division \( E_i \) is a function that changes with time; second, it is composed of a group of transition probabilities \( P_{ij} \)
\( (i,j=1,2,...,n) \), and \( P_{ij} \) reflects the degree and regularity of random influence in the
system. According to the two characteristics, the Markov model is applied to
process the data with a greater random variation in the system. Markov transition probability is represented by \( P_y^{(t)} \), as shown in Eq. (10):

\[
P_y^{(t)} = \frac{m_{ij}^{(t)}}{M_i}, \quad i=1,2,\ldots, j=1,2,\ldots, t=1,2,\ldots,n
\]

where \( P_y^{(t)} \) denotes the probability of transition from state \( E_i \) to state \( E_j \) after \( t \)
step; \( m_{ij}^{(t)} \) denotes the times of transition from state \( E_i \) to \( E_j \) after \( t \) step; \( M_i \) denotes
the occurrence number of state \( E_i \). The matrix \( R^{(t)} \) with \( t\)-step transition probability is represented by:

\[
R^{(t)} = \begin{bmatrix}
    P_{11}^{(t)}, P_{12}^{(t)}, \cdots, P_{1j}^{(t)} \\
    P_{21}^{(t)}, P_{22}^{(t)}, \cdots, P_{2j}^{(t)} \\
    \vdots & \vdots & \ddots & \vdots \\
    P_{ij}^{(t)}, P_{j2}^{(t)}, \cdots, P_{jj}^{(t)}
\end{bmatrix}, \quad t=1,2,\ldots,n
\]

Transition matrix \( R^{(t)} \) shows that regular transposition patterns of various states
in the system, Eq. (10) and (11) is the foundation of the Markov model transition
probability. After the transition state of a system is determined, the possible
falling point state of \( i \) period can be predicted. Assuming that the falling point
state is \( j \), the state interval range \( E_j \in \{\oplus_{i1}, \oplus_{i2}\} \), and predicted value of \( j \) period
takes a middle point between the upper and lower boundaries of the state (He
Yong 1992). Eq.(12) is presented by:

\[
\hat{X} = \frac{1}{2}(\oplus_{ij} + \oplus_{2j})
\]

The algorithm of the objective value for the Grey-Markov model can be
expressed in five steps as follows:
Yueh-Ju Lin and Chi-Chen Wang

1. Solve the residual error of GM(1,1),
2. Divide the relative state of residual error,
3. Calculate the transition probability of various states,
4. Establish the transition probability matrix,
5. Predict residual error.

4. Measurement of Prediction Accuracy

Lewis (1982) uses MAPE to divide the model prediction capability into four levels, as shown in Table 2. This study used mean absolute percentage error (MAPE) to measure prediction model accuracy. The equation is used to test the percentage of data which is not explained by the prediction model. The smaller the MAPE is, the closer is the predicted result of the model to the historical data, the higher the prediction capability of the model. The MAPE value can be represented by:

$$MAPE = \frac{1}{n} \sum_{k=1}^{n} \frac{|x^{(0)}(k) - \hat{x}^{(0)}(k)|}{x^{(0)}(k)} \times 100\%$$

(13)

where $x^{(0)}(k)$ denotes the actual value; $\hat{x}^{(0)}(k)$ denotes the predicted value of the model; $n$ denotes the number of periods.

Table 2 The prediction level of MAPE

<table>
<thead>
<tr>
<th>Level</th>
<th>MAPE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Excellent</td>
<td>&lt;10%</td>
</tr>
<tr>
<td>Good</td>
<td>10%~20%</td>
</tr>
<tr>
<td>Rational</td>
<td>20%~50%</td>
</tr>
<tr>
<td>Un-rational</td>
<td>&gt;50%</td>
</tr>
</tbody>
</table>

Lewis (1982)

Empirical Analysis and Discussion

In this study, the BDI time series data were selected from January 2006 to April 2010. There were 52 monthly closing prices of market transactions in the Baltic Exchange Center. The data were divided into three sections for discussing the model prediction stability. They are long term, medium term, and short term: 1) from January 2006 to April 2010, there were 52 long-term data; 2) from January 2006 to April 2008, there were 28 medium-term data; 3) from January 2006 to February 2007, there were 14 short-term data. For the 14 short-term and 28 medium-term data, this study applied the fuzzy model and GM for prediction as ARIMA cannot be implemented with fewer data; the 52 long-term data were used for the three models. The result of the data predictions are discussed in the next section.
1. Prediction Result of ARIMA

The result of BDI data from the ARIMA \((p,d,q)\) model is expressed as follows (Box & Jenkins, 1976):

\[
\Delta \text{BDI}_t = 0.974614 \Delta \text{BDI}_{t-1} - 0.392752 \epsilon_t
\]  \hspace{1cm} (13)

where \(\Delta \text{BDI} = \text{BDI}_t - \text{BDI}_{t-1}\), adjusted \(R^2=0.883732\), SBC=16.67470. Equation (13) represents the ARIMA \((1,1,1)\) model, and the original BDI data presents a stable sequence after one-order difference; the autoregressive coefficient is 0.974614 which means a high margin effect. It indicates that the previous BDI variation is positively related to the current BDI variation, meaning the margin effect is high. In addition, from Equation (13), the residual term is negatively related to the current BDI variation.

As the original BDI data had twice the volatility, it is uncertain whether the volatility reflected major economic changes. This study considered the structural change of the data and implemented a Chow Breakpoint for the model test. The log-likelihood was 7.406407 (P< 0.05). The structural change of the original BDI data was statistically significant. This structural change occurred in December 2007. Therefore, the ARIMA model needed to be re-estimated while considering the occurrence of the structural change. The results are shown in Equation (14):

\[
\Delta \text{BDI}_t = 1.97518 \Delta \text{BDI}_{t-1} - 0.174640 D_t \Delta \text{BDI}_{t-1} - 0.352198 \epsilon_t
\]  \hspace{1cm} (14)

Equation (14) represented the ARIMA model taking the structural change into account, where \(D_t=0\) (period is smaller than December 2007); \(D_t=1\) (period is larger or equal to December 2007), adjusted \(R^2=0.897334\), SBC=16.60747. The adjusted \(R^2\) (0.897334) of the ARIMA model (14) was greater than that (0.883732) of the model (13), and the SBC (16.60747) of the model (14) was smaller than that (16.67470) of the model (13). The test statistic was significant. When the data time passed December 2007, \(D_t=1\). The model considered the occurrence of structural change, and the previous BDI variation interacted the data, and was negatively related to the current BDI variation. BDI trended from a low point in January 2006 (2,081) to a high point in November 2007 (10557). After December 2007, the index had a larger turning point and went down. In January 2008, the drop stopped. The index rose to a second high point in May 2008 (10,807), and afterwards fell to its lowest point in December 2008 (743).

2. Prediction Result of GM(1,1)

In light of past literature, the predicted error of GM \((1,1)\) is related to the order of past data used. For the purpose of model accuracy, a 4th-8th order GM \((1,1)\) rolling model was constructed to test the MAPE values of various orders in the BDI prediction model. According to the data result, the MAPE values were
sequenced in order as follows: 4th-order 24%, 5th-order 28%, 6th-order 33%, 7th-order 37%, 8th-order 43%, 9-order 51% and 10-order 57%. The 4th-order model had the lowest MAPE value. The MAPE of GM (1,1) became larger as more orders were constructed in the model. The phenomenon was related to GM(1,1) itself. Due to the unstable BDI trend, the index presented irregular fluctuation. At this time, if more previous data were input for the next-period prediction, the effect of grey accumulation generation may deviate from the benchmark of the GM (1,1), and any increase or decrease of data cannot effectively be captured, resulting into a prediction lag. After experiencing 2-3 periods, the model would be self-adjusted. For the BDI data type, this study selected the better 4th-order model in GM (1,1) for typical analysis. After testing the 52 original BDI data, the GM(1,1) prediction model can be obtained:

\[ x^{(0)}(t+1) = (1-e^{-0.0066})(x^{(0)}(t) - \frac{2967.5}{0.0066})e^{0.0066t} \]  (15)

where \(a=-0.0066\), \(b=2967.5\). Different \(t\) periods were substituted into Equation (15) to obtain prediction values of various periods. For example, the predicted value of the grey model was 2971.418 in January 2006. After posterior-error-test of the GM (1,1), the results showed \(S_2=2776.722\), \(S_1=769.8844619\), \(C=0.277263835\), \(P=1\).

3. GM-Markov prediction result

The GM-Markov model used the predicted values from the GM (1,1) 4th order model to calculate residual error between the BDI predicted values and the actual values. The error ratio was used to construct a grey interval. The more Markov states they are, the more complex the solution procedure is. According to the past literature, 5 intervals were commonly divided for the test. Upper and lower boundaries of each state interval are as follows: \(E_1=(-140\%, -70\%]\), \(E_2=(-70\%, -34\%]\), \(E_3=(-34\%, 0\%]\), \(E_4=(0\%, 34\%]\), \(E_5=(34\%, 70\%]\). The grey predicted residual error falling point of each period was used to construct the state. A transposed Markov matrix was constructed through transition probabilities between different states, as shown in Equation (16). The original distribution state of residual error can be transited to a prediction state through the transposed Markov matrix. At last, the predicted value can be determined. For example, in May 2006 the actual value of the grey model was 2,445, the predicted value of GM (1,1) was 2,383, the residual error was \(-62\), and the relative ratio of the residual error was 2.54\%. The membership state was \(E_4\). After transition by the transposed Markov matrix, the most possible falling point state was \(E4\). With the interval range (Eq. 12), the predicted point of the GM-Markov model was calculated to be 2788.11.
4. Prediction Result of Fuzzy Time Series Model

The fuzzy time series model solution followed the above steps (3.1). First, the original BDI data were used to construct the universal of discourse \( U = \{750~\text{to}~10,750\} \). The fuzzy linguistic variables were constructed according to the equal interval principle. The data were corresponded to the fuzzy linguistic variables \( A_i, i=1,2,\ldots,21 \). The linguistic variables can yield the fuzzy relationships. The same fuzzy relationships are arranged into a fuzzy relationship group, as shown in Table (3).

Through Eq.(2), the fuzzy predicted value of each period can be determined. For example, the actual value of February 2006 was 2680, and the corresponding fuzzy linguistic variable was \{A4\}. Thereby the fuzzy relationship was \{A4, A5\}. Through Eq.(2), the predicted point of the fuzzy time series model was 2583. From the Eq.(3), the fuzzy relationship group represents the relationship of fuzzy time series of various orders. The fuzzy relationships would not change with time. Moreover, the model variables adopted BDI, and no auxiliary increment. Accordingly, the model is a univariate-time invariant fuzzy prediction model. The model is one of the common fuzzy time series models, and the solution procedure is simple and accurate (Wong et al. 2010).
Table 3 The fuzzy relationship group for BDI data

<table>
<thead>
<tr>
<th>LHS</th>
<th>RHS</th>
<th>LHS</th>
<th>RHS</th>
<th>LHS</th>
<th>RHS</th>
</tr>
</thead>
<tbody>
<tr>
<td>A1</td>
<td>A1</td>
<td>A8</td>
<td>A8</td>
<td>A8</td>
<td>A8</td>
</tr>
<tr>
<td>A1</td>
<td>A1</td>
<td>A8</td>
<td>A8</td>
<td>A8</td>
<td>A8</td>
</tr>
<tr>
<td>A3</td>
<td>A1</td>
<td>A10</td>
<td>A9</td>
<td>A3</td>
<td>A16</td>
</tr>
<tr>
<td>A3</td>
<td>A3</td>
<td>A9</td>
<td>A3</td>
<td>A16</td>
<td>A20</td>
</tr>
<tr>
<td>A5</td>
<td>A5</td>
<td>A16</td>
<td>A20</td>
<td>A21</td>
<td></td>
</tr>
<tr>
<td>A4</td>
<td>A4</td>
<td>A10</td>
<td>A11</td>
<td>A17</td>
<td>A14</td>
</tr>
<tr>
<td>A5</td>
<td>A5</td>
<td>A16</td>
<td>A20</td>
<td>A21</td>
<td></td>
</tr>
<tr>
<td>A5</td>
<td>A5</td>
<td>A16</td>
<td>A20</td>
<td>A21</td>
<td></td>
</tr>
<tr>
<td>A6</td>
<td>A6</td>
<td>A11</td>
<td>A12</td>
<td>A19</td>
<td>A14</td>
</tr>
<tr>
<td>A7</td>
<td>A7</td>
<td>A12</td>
<td>A11</td>
<td>A20</td>
<td>A21</td>
</tr>
<tr>
<td>A6</td>
<td>A6</td>
<td>A19</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>A7</td>
<td>A7</td>
<td>A13</td>
<td>A14</td>
<td>A21</td>
<td>A20</td>
</tr>
<tr>
<td>A8</td>
<td>A8</td>
<td>A16</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

5. Model Results and Discussions

According to the predicted BDI of the fuzzy time series, GM(1,1), GM-Markov, ARIMA and structure ARIMA model, the following two points can be found. First, for model fitness, the error of the GM-Markov model has the lowest dispersion degree, and the predicted MAPE ranged from 0.18% to 38.70%. The second lower dispersion degree is the fuzzy time series GM(1,1) which predicted MAPE was 0.07% ~ 131.41%, 0.0% ~ 74.51%, and MAPE of the was 0.07% ~ 131.41%. The ARIMA model with structural change and ARIMA had a larger error, and they were 0.89% ~ 400.8% and 0.31% ~ 415.5% respectively. From Table 4, the five models had larger error difference.
Table 4 The MAPE of five four models for BDI prediction

<table>
<thead>
<tr>
<th>Period</th>
<th>Fuzzy</th>
<th>GM(1,1)</th>
<th>Grey-Markov</th>
<th>ARIMA¹</th>
<th>ARIMA²</th>
</tr>
</thead>
<tbody>
<tr>
<td>2006.01~2007.02</td>
<td>3.28%</td>
<td>6.31%</td>
<td>4.22%</td>
<td>---</td>
<td>---</td>
</tr>
<tr>
<td>2006.01~2008.04</td>
<td>7.88%</td>
<td>10.89%</td>
<td>9.49%</td>
<td>---</td>
<td>---</td>
</tr>
<tr>
<td>2006.01~2010.04</td>
<td>8.15%</td>
<td>24.34%</td>
<td>12.69%</td>
<td>16.58%</td>
<td>15.08%</td>
</tr>
</tbody>
</table>

¹ ARIMA
² Structure changed ARIMA

For the models, the largest error was similar, which occurred at the period of the BDI sharp drop, i.e. between September 2008 and November 2008. The BDI dropped from 4,953 to 812, down by 84% in total. During this period, the models had significant deviation from the actual value, and could not effectively capture the data trend. However, the largest error produced by both the GM-Markov and fuzzy time series models had a little lower than 84% of BDI. It indicates that the two models have good fitness for BDI data.

Second, for prediction error distribution, the fuzzy model had the largest part of MAPE lower than 10%, revealing a high accuracy level. The fuzzy model had 39, accounting for 76%, and second GM-Markov model had 22, accounting for 46%. The GM (1,1) had 18, accounting for 38%; ARIMA with structural change had 15 respectively, comprising 30%; the ARIMA had 14, comprising 28%. For the MAPE higher than 50% of the irrational level, the GM-Markov model was the best, with no irrational MAPE, and the fuzzy time series model had 1 irrational MAPE, accounting for 2%. The ARIMA with structure change had 6, comprising 12%; GM (1,1) and ARIMA had 7 respectively, accounting for 14%. For the MAPE ranged from 10% ~ 50%, the fuzzy time series model had 11, accounting for 22%, GM(1,1) had 23, accounting for 48%, GM-Markov and ARIMA models with structural change had 26 respectively, accounting for 54% and 50%. ARIMA model had the most, totaling to 29, accounting for 58%.

For the overall prediction accuracy, the fuzzy time series model had the best accuracy, with the high accuracy level accounted for the largest percentage (76%), and MAPE was the smallest 8.15%. The GM-Markov model’s MAPE was 12.69%, the MAPE of the ARIMA model with structural change was 15.08%, the MAPE of the ARIMA was 16.58%, and the MAPE of GM (1,1) was the worst, 24.34%.

The five models may easily cause prediction error when the time data of BDI had a greater fluctuation. The GM (1,1) model had the greatest prediction deviation. If using Markov state transition to modify, GM (1,1) can be corrected, so the effect of the Grey-Markov model is better than GM(1,1), and the deviation was lower. The two ARIMA models had small deviation but could soon capture the BDI variation trend.
In addition, this study further divided the data into different periods, and discussed whether the data number affects the prediction accuracy of the model. Table 4 shows the MAPE comparison of BDI prediction models in different periods. The ARIMA model required a minimum data number; if the data are too few, the model cannot implement prediction (the model limitation). The medium/short term BDI predicted results were not compared. From Table 4, it can be found that (1) when the data period was from January 2006 to February 2007 with 14 monthly data, the fuzzy time series model had the lowest MAPE of 3.28%. The MAPE value for the Grey-Markov model and GM (1,1) was 4.22% and 6.31%, respectively. (2) When the period was January 2006 to April 2008 with data increased to 28, the fuzzy time series model had the better result and its MAPE was 7.88%. The MAPE value of GM (1,1) was 10.87%. (3) When the period was January 2006 to April 2010 with 52 data, the fuzzy time series model had better prediction performance and its MAPE was 8.15%, the MAPE of the Grey-Markov model was 12.69%, the ARIMA with structural change was 15.08%, and the ARIMA was 16.58%. The GM (1,1) had the worst MAPE, 24.34%. Based on the prediction results, from Table 4, the MAPE of the former 3 models was higher with an increase of the data, and the data number had the greatest impact on GM (1,1) prediction error. The fuzzy time series model Grey-Markov model had the lowest MAPE, irrespective of short-term or long-term data, the second is the Grey-Markov model, and the worse is GM(1,1). For the long-term or more data, ARIMA also had the highest prediction accuracy. Additionally, the three different periods had different BDI volatility. The Grey-Markov fuzzy time series model had the smallest MAPE variation, less than 5%, followed by and GM(1,1). The results indicate that the fuzzy time series Grey-Markov had higher prediction stability.

The GM (1,1) model prediction performance decreased with the increase of BDI data, and its MAPE of the short/long-term data prediction was 10.89% and 24.34%. The result may be related to the model’s monotone increasing or monotone decreasing. GM prediction can be applied to fewer data, but if the data had greater fluctuation during the period, GM (1,1) cannot fit the data well, resulting in greater prediction error. ARIMA is superior to the GM (1,1) in long-term data fitting. If the time series data had greater fluctuation, the ARIMA considering structural change was better than the ARIMA model. Thus, during the three different data periods, through the comparison of the prediction model accuracy, the prediction capability of fuzzy time series model was better than other prediction models.

Figure 1 illustrates BDI predicted value trend of fuzzy time series, GM(1,1), Grey-Markov, ARIMA and ARIMA models considering structural change.
During the period of January 2006 to April 2010, Figure 1 shows that the Grey-Markov fuzzy time series model which fitted the data trend had rather small error in the turning place between the BDI two high points (2007.10, 2008.06) and two lowest points (2008.12). The ARIMA considering structural change can capture the data variation trend when the index fell sharply to a low point and continuously rose from January 2009 to April 2010. The GM(1,1) had overestimation and after modification, Grey-Markov can effectively increase prediction performance for time series data.

Conclusions and Suggestions

The BDI variation trend reflects bulk shipping market sentiment. If the bulk shipping companies can evaluate the trend for shipping freight, market risks and uncertainties can be reduced. Thus, how to use limited information and suitable prediction tool to achieve prediction accuracy is an urgent issue. This study used Baltic Dry Index (BDI) closing prices from London Baltic Exchange and constructed a BDI prediction model using fuzzy set theory, grey theory, and traditional time series models to analyze BDI dynamic trend. The prediction performance of the five four models was also compared. According to empirical analysis, the conclusions are made as follows.

1. Conclusion

The research data were sourced from the BDI between January 2006 and April 2010 with monthly 52 data. MAPE was used to measure the forecasting accuracy
of the models. The empirical results show that the GM-Markov fuzzy time series model had the lowest MAPE, followed by GM-Markov, ARIMA considering structural change and ARIMA model. The GM(1,1) model was the worst. If the research data were divided into short term, medium term and long term to re-evaluate the models, the MAPE of the fuzzy time series and GM models may become large with an increase of time; the GM-Markov fuzzy time series had the smallest error, followed by GM-Markov. GM(1,1) still had the largest error. The model results demonstrate that among the five four models, the GM-Markov with fuzzy time series model can capture the data variation trend and has stable prediction regardless of the long-term or short-term data or different fluctuations.

To know the economic implications of the BDI trend, this study used ARIMA to fit the research data during the period of January 2006-April 2010. The test results indicate that current BDI variation was highly positively related to the previous BDI variation, and the external interference factor was negatively related to the current BDI variation. There were two high points during the research period. This study further used ARIMA considering structural change to fit the data. The result shows that a significant time transition occurred in December 2007. The explanatory ability of the ARIMA model is higher than the model not considering structural change.

Regarding model usability, GM fuzzy time series model has no requirement for a normal distribution of data and sample number, and model construction and solution procedure is simple. This model is an effective tool for business management in decision-making, especially in urgent times. GM also has the same characteristics, but if the data have great fluctuation, the prediction effect is not good. With the Markov state model, GM error can be improved. The traditional time series model needs to meet the statistic requirement for data test and its calculation is complex. For the long-term data, it can capture data variation trends and have accurate prediction.

2. Suggestions

For the predicted objects, considered factors are not unique. Difficulty of information collection, time, cost, and effectiveness of decision should be considered. Moreover, the model should be selected according to the type of data so as to yield the optimal prediction efficiency. In this paper, the models used one set of BDI data. For future study, it is suggested that different types of data are tested to compare the usability of the model.

The fuzzy time series model has advantages in the implementation of prediction, but the prediction often determines some items in a subjective manner, such as equal segmentation, order setting, and Markov state division. The setting may affect model prediction capability. The current literature adopted repeated testing to find out segmentation, order, and state with the lowest error. Future research can use an optimal solution algorithm to produce the maximum efficiency in prediction.
Due to data number limitation, this study did not consider factors influencing BDI in construction of the traditional time series model. If the time series of data is longer, future research can find the variables correlated with the index and introduce them in the prediction model to increase explanation ability and usability of the model, such as a ARIMA transition function or a vector autoregressive model.

References

The dynamic analysis of Baltic exchange dry index


[38] L. A. Zadeh, Fuzzy Sets, Information and control, 8 (1965), 338-353.