APPLIED SCGM(1,1)$_C$ MODEL AND WEIGHTED MARKOV CHAIN FOR EXCHANGE RATE RATIOS

Shaghayegh KORDNOORI
Research Institute for ICT, Tehran, Iran
sh_kordnourie@yahoo.com

Hamidreza MOSTAFAEI
Islamic Azad University, Tehran, Iran
Institute for International Energy Studies
h_mostafaei@iau-tnb.ac.ir

Shirin KORDNOORI
Islamic Azad University,Tehran,Iran
shirin_noori1371@yahoo.com

Abstract: *The importance of predicting the fluctuations of exchange rate ratios is noticeable. In relation to markov model and grey system theory, using a single gene system cloud grey SCGM(1,1)c model to adjust the development trend of time series, its error index is randomly fluctuated. Markov chain model is appropriate to forecasting of a random dynamic system, choosing weighted markov chain to predict the error index. We applied a weighted markov SCGM(1,1)c model for predicting the U.S. Dollar /Euro, U.S. Dollar/Japan Yen, U.S. Dollar/Swiss franc and U.S. Dollar/Trade –Weighted Index. The forecasting results are reliable and show that the weighted markov SCGM(1,1)c model has high prediction precision.*

Keyword: Weighted Markov Chain, SCGM(1,1)c Model, Exchange Rate Ratios

Introduction

Economic system is complicated and can be defined by deterministic or random models. Forecasting the currency exchange rates is essential for the global economy and financial markets. Analyzing and predicting the movements of exchange rates attach much attention from policy makers now days. The market expectations about the economic and policies and activities are demonstrated by the exchange rates. 11 member states of European and Union make Euro as their currency in 1999. Japanese Yen is the third most commercial currency and Swiss Franc is ranked among five most notable currency of the word. Trade – Weighted Index is a weighted average of exchange rates of the dollar against the currencies of a group of U.S. trading partners. The fluctuations of U.S. Dollar tuese currencies (Figure 1, 2) are a vital issue of macroeconomic analysis. In spite of its significant, predicting the exchange rates have been a dispute for market analyzers.

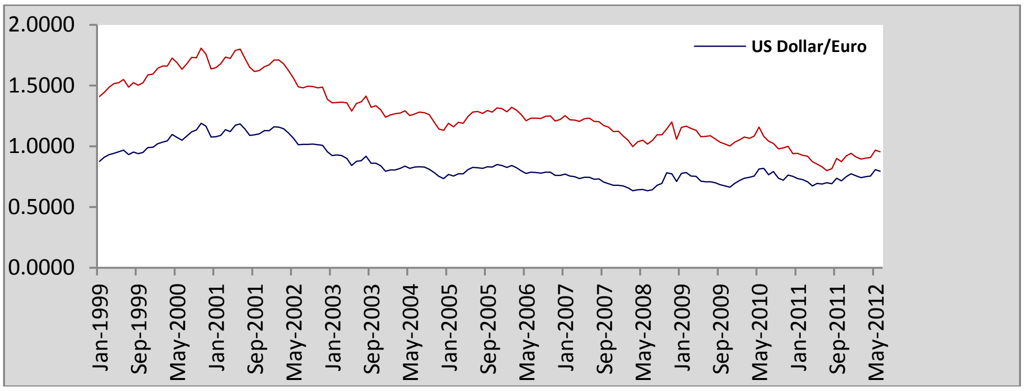

Figure 1. Exchange Rates US Dollar/Euro and US Dollar/Swiss Franc

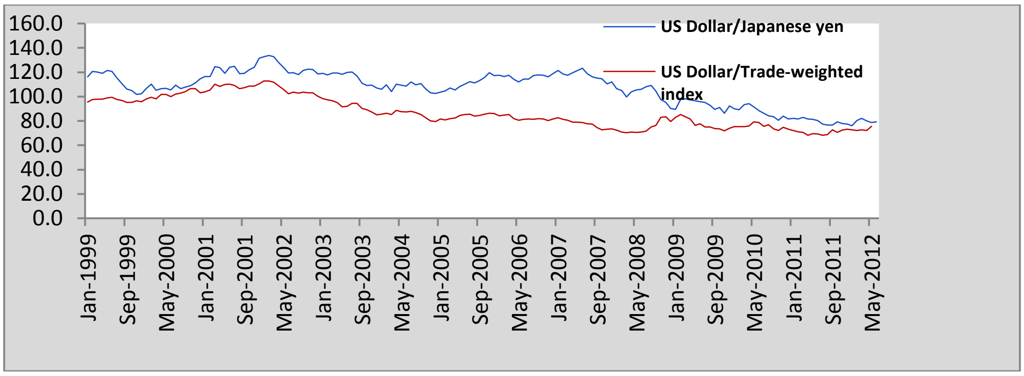

Figure 2. Exchange Rates US Dollar/Japan Yen and US Dollar/Trade Weighted Index

By using different methods exchange rate data have been analyzed in literature. Bianca and et al (2012) suggested an econometric model for the weekly changes in Euro/Dollar rate. Fenz and spritzer (2004) compared the precision of vector autoregressive and vector error correlation models in predicting the Euro/Dollar and Japanese Yen. Huang and et al (2011) proposed a way to exchange rate volatility forecasting by quintile regression. Dunis and et al (2012) studied the application of a neural network in predicting the Euro/Dollar exchange rate. Liu and et al (1994) applied a full, mixed and Bayesian vector autoregressive model for the U.S. Dollar /Yen, U.S. Dollar/Canadian Dollar and U.S. Dollar/Deutsch Mark exchange rates. Yuan(2011) applied multi-state markov switching model with smoothing techniques for an exchange rate forecasting model with smoothing techniques for an exchange rate forecasting. Hanians and Curtis (2008) analyzed the daily data of Dollar/Euro time Series models with chaos theory. Clements and Lan (2006) applied a Monte Carlo simulation for forecasting exchange rates. Alson (2010) used Johannes and stock-Watson procedures to estimates the cointegrating relationship between the real exchange rate and productivity. Andreou and Zombanakis (2006) proposed intelligence methods for forecasting Euro/Dollar and Japanese Yen. Yao and et al (1996) compared neural network model with ARMA model for forecasting GBP, DEM, JPY, CHF, AUD/Dollar exchange rate. Philip and et al (2011) proposed artificial neural network for forecasting foreign exchange rate. Kurita (2012) applied ARCH time series models for examine the dynamics of Yen – Dollar exchange rate Mc Grey and et al(2012) studied the Euro ,Swiss, Franc and Yen against the Dollar exchange rates by using factor analyzing . Pacelli (2012) compare artificial neural network, ARCH, and GARCH model to predict the daily exchange rates Euro/Dollar.

The system with incomplete unknown construction, properties and parameters is called a grey system. This system has grey appearance with complexity property and multiple solutions. Since there is always some unpredictability in real life, every system can be regarded as a grey system. Grey model could be considered as a powerful approximation for deriving system dynamic information with only a limited amount of data. The advantage of the grey system theory is its applications with poor information uncertainty and any distribution in small samples. System analysis, modeling, data processing, prediction, control and decision making are the fields which covered by grey theory. the grey system theory has been extensively and satisfactorily applied to different systems such as energy ([15] [16] [17] [18]),Economic and Financial([19][20][33][21][30][34]), Business ([31]), Geology ([22]), Transportation ([23]), Engineering([24][25]),Hydrological ([26]), Social ([32]), Agricultural ([27][28]) and Medical ([29]) systems.

This paper is established on the Grey Theory, which combines the advantages of Markov Chain and SCGM(1,1)c model. By using the Weighted Markov SCGM(1,1)c model we predict the ratios of currency exchange rates as U.S. Dollar/Euro, Japanese Yen, Swiss Franc and Trade-Weighted Index.

Mathematical Models

Let $X^{(0)}$ as the initial time series as follow:

$$X^{(0)} = \{X^{(0)}(1), X^{(0)}(2), \dots, X^{(0)}(n)\} \quad (1)$$

Indispensable transform of $X^{(0)}$ is

$$\bar{X}^{(1)}(k) = \sum_{m=2}^{k} \bar{X}^{(0)}(m), (k = 2,3,\dots,n) \quad (2)$$

Where

$$\bar{X}^{(1)}(k+1) = \frac{X^{(0)}(k+1) + X^{(0)}(k)}{2} \quad (3)$$

This can be represented as

$$\bar{X}^{(1)} = \{\bar{X}^{(1)}(2), \bar{X}^{(1)}(3), \dots, \bar{X}^{(1)}(n)\} \quad (4)$$

By assuming a discrete exponential function of non-homogenous $f_r(k) = be^{a(k-1)} - c$ and time series $\{\bar{X}^{(1)}(k)\}$ is a well –being trend relationship, the system cloud grey SCGM(1,1)c is

$$\frac{dX^{(1)}(k)}{dk} = aX^{(1)}(k) + U, (k \geq 2) \quad (5)$$

The response function is as follow:

$$\hat{X}^{(1)}(k) = \left(\hat{X}^{(1)}(k) + \frac{U}{a}\right)e^{ak} - \frac{U}{a} \quad (6)$$

Where

$$a = \ln \frac{\sum_{k=3}^{n} \bar{X}^{(0)}(k-1)\bar{X}^{(0)}(k)}{\sum_{k=3}^{n} (\bar{X}^{(0)}(k-1))^2} \quad (7)$$

$$b = [(n-1)\sum_{k=2}^{n} e^{2a(k-1)} - (\sum_{k=2}^{n} e^{a(k-1)})^2]^{-1}. [(n-1)\sum_{k=2}^{n} e^{a(k-1)}\bar{X}^{(1)}(k) - (\sum_{k=2}^{n} e^{a(k-1)})(\sum_{k=2}^{n} \bar{X}^{(1)}(k))] \quad (8)$$

$$c = \frac{1}{n-1}[(\sum_{k=2}^{n} e^{a(k-1)})b - \sum_{k=2}^{n} \bar{X}^{(1)}(k)] \quad (9)$$

$$U = ac \quad (10)$$

$$\hat{X}^{(1)}(1) = b - c \quad (11)$$

Replacing $\hat{X}^{(1)}(k)$ yields the system cloud grey SCGM(1,1)c as

$$\hat{X}^{(0)}(k) = \frac{2b(1-e^{-a})}{(1+e^{-a})} . e^{a(k-1)} \quad (12)$$

The deviation degree between the raw data and fit value is obtained by the grey precision index as

$$Y(k) = \frac{X^{(0)}(k)}{\hat{X}^{(0)}(k)} \quad (13)$$

The rage of $Y(k)$ is identified as a non-stationary random process, therefore markov processes are applied to evaluated the fluctuation rule of grey precision to enhance the prediction precision of SCGM(1,1)c model, moreover ,the weighted markov chain forecasting model can assure a more precise forecasting result when the data is random fluctuating dynamic process.

The most convential stochastic models for dynamic system are markov models. A markov process $\{X(t), t \geq 0\}$ satisfies the markov property as follows:

$$P\{X_t \leq i \middle| X_{t_n} = i_n, \ldots, X_{t_1} = i_1, X_{t_0} = i_0\} = P\{X_t \leq i \middle| X_{t_n} = i_n\}$$

$\forall\, t, t_n, \ldots, t_1, t_0$

such that $$t > t_n > \cdots > t_1 > t_0 \quad (14)$$

Weighted grey markov SCGM(1,1)c model employs weighted markov chain to identify state transition regularity and applies grey theory to show the variation trend of time series data , hence accuracy of high volatile time series data is improved.

Any state of $Y(k)$ is state as

$$S_i \in [\otimes_{1i}, \otimes_{2i}], i = 1,2, \ldots, m \quad (15)$$

Where the lower and upper bounds of the i th state are i th $\otimes_{1i} = Y(k) + A_i$, $\otimes_{2i} = Y(k) + B_i$ respectively, S_i is the i th state, A_i and B_i are considered as constant.

The transition probability is

$$p_{ij}^{w} = \frac{N_{ij}^{(w)}}{N_i}, i, j = 1,2, \ldots, m \quad (16)$$

Where $N_{ij}^{(w)}$ is the number of transitions from state S_i to sate S_j through w steps in $Y(k)$ index. So the $m \times m$ step matrix of state transition probability is obtained as

$$P^{(w)} = \begin{pmatrix} p_{11}{}^{(w)} & p_{12}{}^{(w)} & \ldots & p_{1m}{}^{(w)} \\ p_{21}{}^{(w)} & p_{22}{}^{(w)} & \ldots & p_{2m}{}^{(w)} \\ \vdots & \vdots & \vdots & \vdots \\ p_{m1}{}^{(w)} & p_{m2}{}^{(w)} & \ldots & p_{mm}{}^{(w)} \end{pmatrix} \quad (17)$$

Compute the w order autocorrelation coefficient of data and normalize the outcomes as the weighted coefficients of markov model:

$$r_w = \frac{\sum_{l=1}^{n-w}(Y(l)-\bar{Y})(Y(l+w)-\bar{Y})}{\sum_{l=1}^{n}(Y(l)-\bar{Y})^2} \quad (18)$$

$$\theta_w = \frac{|r_w|}{\sum_{w=1}^{m}|r_w|} \quad (19)$$

Where m is the maximum order by prediction inquiry, commonly take $|r_w| \geq 0.3$.

Combining the initial state S_i as the corresponding state of grey precision index in the foregoing one year with the row vector of its corresponding transition probability matrix results in state transition probability vector in the year as

$$P_i^{(w)} = \left(p_{i1}{}^{(w)}, \quad p_{i2}{}^{(w)}, \quad \ldots \quad p_{im}{}^{(w)}\right), i \in E \quad (20)$$

The m-order weighted state transition probability matrix is obtained as follows:

$$\begin{pmatrix} p_{\alpha 1}{}^{(w)} & p_{\alpha 2}{}^{(w)} & \ldots & p_{\alpha m}{}^{(w)} \\ p_{\beta 1}{}^{(w)} & p_{\beta 2}{}^{(w)} & \ldots & p_{\beta m}{}^{(w)} \\ \vdots & \vdots & \vdots & \vdots \\ p_{\gamma 1}{}^{(w)} & p_{\gamma 2}{}^{(w)} & \ldots & p_{\gamma m}{}^{(w)} \end{pmatrix} \quad \alpha, \beta, \gamma \in S, \alpha, \beta, \gamma \leq m \quad (21)$$

Therefore state transition probability of grey precision index to forecasted year is

$$P_i = \sum_{w=1}^{m} \theta_w \,.\, P_{.i}^{(w)}, i \in S \qquad (22)$$

The forecasted state of grey precision index by weighted markov chain is $\max\{P_i, i \in S\}$.

Calculate the predicted value $\hat{Y}(n+1)$ using linear interpolation:

$$\hat{Y}(n+1) = \otimes_{1i} \times \frac{P_{i-1}}{P_{i-1}+P_{i+1}} + \otimes_{2i} \times \frac{P_{i+1}}{P_{i-1}+P_{i+1}} \qquad (23)$$

Finally the predicted value in the $(n+1)th$ year is

$$\tilde{X}^{(0)}(n+1) = \hat{Y}(n+1).\hat{X}^{(0)}(n+1) \qquad (24)$$

For evaluating the prediction precision of the model the mean absolute percentage error (MAPE) is applied as

$$MAPE = \frac{1}{n}\sum_{k=1}^{n} \left| \frac{X^{(0)}(k) - \tilde{X}^{(0)}(k)}{X^{(0)}(k)} \right| 100\% \qquad (25)$$

Aplications

Economic systems can be modeled by stochastic models. This paper applies the weighted markov SCGM(1,1)c model to monthly fluctuations of U.S. Dollar against Euro, Japanese Yen, Swiss Franc and trade-weighted index. To formulated system cloud grey SCGM(1.1)c model , monthly data of U.S. Dollar/Euro, Japanese Yen, Swiss Franc and trade weighted index are used from January 2010 to respectively march 2012 may 2012, may 2012 and April 2012 . The data are listed in table 1.

Table 1.Data

Date	U.S. Dollar / Euro	U.S. Dollar / Japanese Yen	U.S. Dollar /Swiss Franc	U.S. Dollar / Trade weighted index
Jan.2010	0.7178	89.9	1.054	75.2
Feb.2010	0.7361	89.3	1.077	75.4
March 2010	0.7454	93.4	1.066	75.4
April 2010	0.7551	94.1	1.084	75.9
May 2010	0.8129	91.5	1.156	79.2
June 2010	0.8188	88.5	1.082	78.9
July 2010	0.7655	86.4	1.042	75.5
Aug. 2010	0.7909	84.2	1.024	76.8
Sep.2010	0.7366	83.4	0.978	72.1
Oct.2010	0.7201	80.6	0.978	74.8
Nov.2010	0.7639	84.1	1.001	73.2
Dec.2010	0.7524	81.5	0.938	72.1
Jan. 2011	0.7350	52.1	0.942	71.2
Feb.2011	0.7269	81.7	0.927	70.5
March2011	0.7073	82.8	0.918	68.2
April 2011	0.6738	81.6	0.873	69.5
May 2011	0.6954	81.4	0.854	69.2
June 2011	0.6895	80.4	0.931	68.3
July 2011	0.6996	77.5	0.800	68.9
Aug. 2011	0.6929	76.6	0.816	72.8
Sep.2011	0.7374	76.6	0.899	70.5
Oct.2011	0.7147	79.2	0.874	72.4
Nov.2011	0.7500	77.9	0.920	73.3

Dec.2011	0.7727	77.5	0.941	72.6
Jan. 2012	0.7580	76.2	0.914	72.1
Feb.2012	0.7416	80.4	0.894	72.4
March 2012	0.7487	82.0	0.902	72.3
April 2012	*	80.1	0.907	*
May 2012	*	78.8	0.969	*

We get:

U.S. Dollar /Euro: $\hat{X}^{(0)}(k) = 0.7427\ e^{a(k-1)}$

$$a = -0.000949 \quad ,b = -782.449347$$

U.S. Dollar /Japanese Yen: $\hat{X}^{(0)}(k) = 87.3956\ e^{a(k-1)}$

$$a = -0.004792 \quad ,b = -18237.8586$$

U.S. Dollar /Swiss Franc: $\hat{X}^{(0)}(k) = 1.0079\ e^{a(k-1)}$

$$a = -0.005561 \ ,b = -181.253478$$

U.S. Dollar /Trade Weighted Index: $\hat{X}^{(0)}(k) = 73.7541\ e^{a(k-1)}$

$$a = -0.00161 \quad ,b = -45810.03114$$

We calculate the grey precision indices (Table 2) with equation (13) which show the trend of exchange rate ratios.

Table 2.Grey precision indices for exchange rate ratios

Date	Jan2010	Feb2010	March2010	Ap.2010	May2010	June2010	July2010	Aug.2010	Sep.2010	Oct.2010	Nov.2010	Dec.2010
U.S.Dollar /Euro	0.96647	0.99205	1.00554	1.01959	1.09868	1.1077	1.03658	1.07199	0.99934	0.97788	1.03835	1.02369
U.S.Dollar /Japanese Yen	1.029	1.027	1.079	1.092	1.067	1.037	1.017	0.996	0.992	0.963	1.01	0.983
U.S.Dollar /Swiss Franc	1.046	1.074	1.069	1.093	1.173	1.104	1.069	1.056	1.014	1.029	1.050	0.989
U.S.Dollar /Trade Weighted Index	1.020	1.024	1.026	1.034	1.081	1.078	1.034	1.053	1.009	0.992	1.031	1.010
Date	Jan2011	Feb2011	March2011	Ap.2011	May2011	June2011	July2011	Aug.2011	Sep.2011	Oct.2011	Nov.2011	Dec.2011
U.S.Dollar /Euro	1.00096	0.99087	0.96507	0.92024	0.95064	0.94992	0.9582	0.94992	1.01189	0.98167	1.03113	1.06335
U.S.Dollar /Japanese Yen	0.995	0.995	1.013	1.003	1.006	0.998	0.967	0.96	0.965	1.002	0.99	0.99
U.S.Dollar /Swiss Franc	0.999	0.989	0.984	0.941	0.926	0.906	0.877	0.900	0.997	0.974	1.031	1.061
U.S.Dollar /Trade Weighted Index	0.997	0.986	0.978	0.947	0.987	0.964	0.953	0.963	1.019	0.989	1.017	1.031
Date	Jan2012	Feb2012	March2012	Ap.2012	May2012	June2012	July2012	Aug.2012	Sep.2012	Oct.2012	Nov.2012	Dec.2012
U.S.Dollar /Euro	1.04411	1.02249	1.03326									
U.S.Dollar /Japanese Yen	0.978	1.037	1.063	1.043	1.031							
U.S.Dollar /Swiss Franc	1.037	1.019	1.034	1.046	1.123							
U.S.Dollar /Trade Weighted Index	1.023	1.018	1.028	1.024								

Applying the weighted markov chain, we partition the grey precision indices to states with equal ranges (Table 3).

Table 3.States partition in grey precision index of SCGM(1,1)c

U.S.Dollar/Euro	E1:0.9202-0.9515 E2:0.9515-0.9827 E3:0.9827-1.0140 E4:1.0140-1.0452 E5:1.0452-1.0765 E6:1.0765-1.1077	U.S. Dollar /Japanese Yen	E1:0.96-0.982 E2:0.982-1.004 E3:1.004-1.026 E4:1.026-1.048 E5:1.048-1.07 E6:1.07-1.092
U.S. Dollar /Swiss Franc	E1:0.877-0.926 E2:0.926-0.976 E3:0.976-1.025 E4:1.025-1.074 E5:1.074-1.123 E6:1.123-1.173	U.S. Dollar /Trade Weighted Index	E1:0.974-0.969 E2:0.969-0.992 E3:0.992-1.014 E4:1.014-1.036 E5:1.036-1.058 E6:1.058-1.081

Next calculate all order autocorrelation coefficients of grey precision indices. Autocorrelation curves are shown in figure 3-6.

It is understood that for U.S.Dollar /Euro, Japanese Yen, Swiss Franc and Trade Weighted Index 1,2,3 , 1,2 ,1,2,3.4 and 1,2,3 order autocorrelation coefficients, respectively are satisfied in the conditional $|r_w| \geq 0.3$.

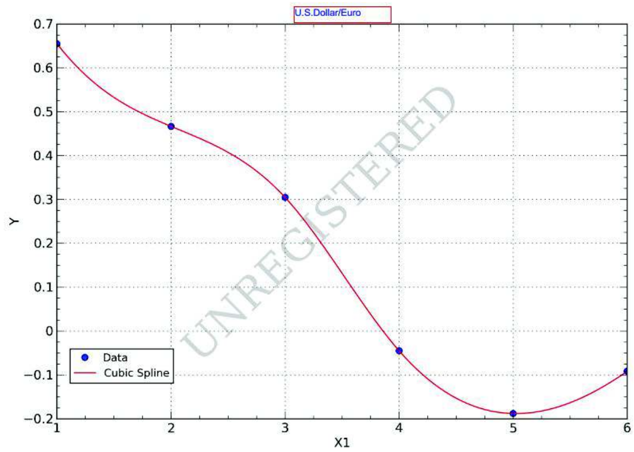

Figure 3.Autocorrelation Curves

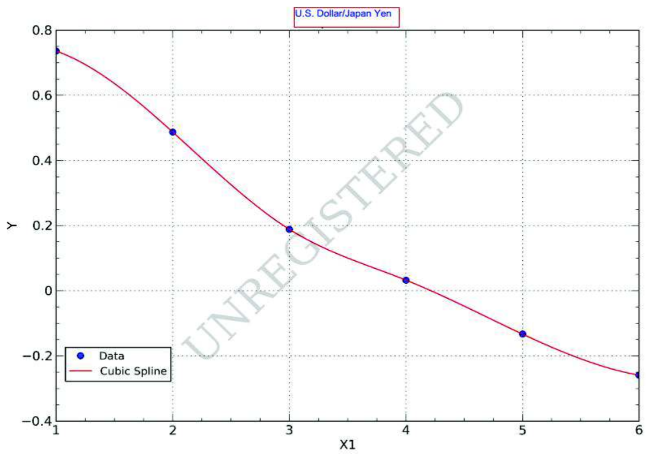

Figure 4.Autocorrelation Curves

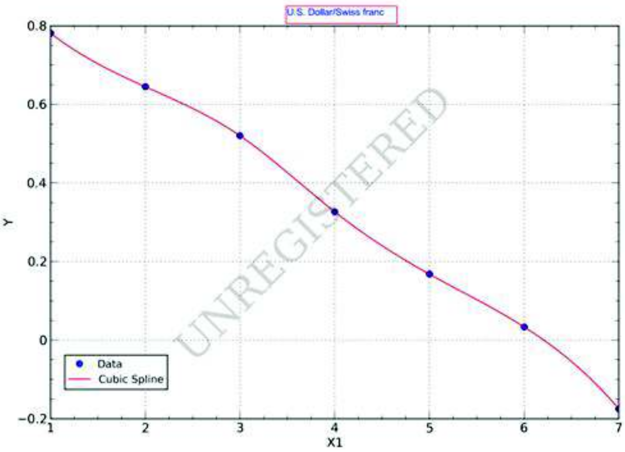

Figure 5.Autocorrelation Curves

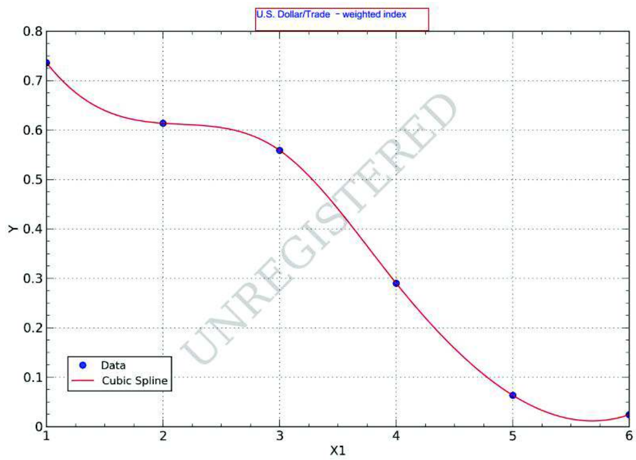

Figure 6 .Autocorrelation Curves

The results of calculating the maximum –order weighted state transition probability of markov chain, normalized autocorrelation coefficients, weighted values θ: of markov chain and weighted markov chain prediction probability P : for every exchange rate ratio are shown in table 4

Table 4. Markov chain prediction probability P

Exchange rate ratio	state	E1	E2	E3	E4	E5	E6	r_ω	θ_ω
U.S.Dollar /Euro	$P_4^{(1)}$	0	0	0.1428571	0.42857	0.28571	0.1428571	0.65510	0.46
	$P_4^{(2)}$	0.166667	0.17143	0.2632653	0.2898	0.4082	0.0680272	0.466697	0.33
	$P_4^{(3)}$	0.055556	0.17092	0.2494461	0.33358	0.07522	0.1152851	0.304744	0.21
	P_i	0.06666687	0.0924651	0.204975496	0.362828	0.1606934	0.112373113		
U.S.Dollar /Japanese Yen	$P_4^{(1)}$	0.5	0.33	0	0.17	0	0	0.7375	0.39836
	$P_4^{(2)}$	0	0	0	0.5	0.25	0.25	0.4871155445	0.601605
	P_i	0.00825	0.1985445	0	0.3014605	0.09959	0.09959		
U.S.Dollar /Swiss Franc	$P_5^{(1)}$	0	0	0	0	1	0	0.781187	0.343649
	$P_4^{(2)}$	0	0	0.182727	0.304545	0.512727	0	0.645032	0.283753
	$P_4^{(3)}$	0.038959	0.0689	0.231166	0.403328	0.217433	0.04	0.520253	0.228862
	$P_3^{(4)}$	0.163966	0.0733	0.252986	0.350645	0.126218	0.04	0.326744	0.143736
	P_i	0.0674015	0.447401	0.194351699	0.30464311	0.36615168	0.025096		
U.S. Dollar /Trade Weighted Index	$P_4^{(1)}$	0	0.083333333	0.083333333	0.666666667	0.083333333	0.083333333	0.73603	0.38563
	$P_4^{(2)}$	0.0277778	0.10466667	0.180555556	0.534722221	0.055555556	0.097222222	0.61373	0.321551
	$P_4^{(3)}$	0.0569444	0.124421296	0.190393519	0.490509259	0.044560185	0.093171296	0.55889	0.292819
	P_i	0.0256064	0.102063649	0.145944493	0.572657563	0.063047847	0.090680062		

From the $max\, P_i$ for each of the exchange rate ratios it is concluded that the state of grey precision index of SCGM(1,1)c model for U.S. Dollar/Euro in April 2012 is mostly state of E4 , for U.S. Dollar / Swiss Franc in June 2012 is state of E5 and for U.S. Dollar / Trade Weighted Index in May 2012 is state of E4 . By considering the neighboring states of these probable states and with formula (23), we get:

U.S. Dollar/Euro: $\hat{Y}(April\ 2012) = 1.02771$

U.S. Dollar/Japanese Yen: $\hat{Y}(June\ 2012) = 1.048$

U.S. Dollar/Swiss Franc: $\hat{Y}(June\ 2012) = 1.07799$

U.S. Dollar/Trade Weighted Index: $\hat{Y}(May\ 2012) = 1.0207$

Finally by formula (24) a prediction value of weighted markov SCGM(1,1)c model for each of exchange rate ratios are calculated (Table 5) . By computing the MSE we find that the predicted values are very close to the actual values.

Forecasting results and their precisions for exchange rate ratios

Table 5.Forecasting results and their precisions for exchange rate ratios

U.S.Dollar/Euro (April 2012)	Predicted Value	Actual Value	Precision	U.S.Dollar /Japanese Yen	Predicted Value	Actual Value	Precision
	0.74397	0.7547	98.58%		79.71	79.4	99.61%
U.S.Dollar/Swiss Franc(June 2012)	0.9247	0.954	96.96%	U.S.Dollar / Trade Weighted Index	71.966	75.6	95%

The forecasting results of a weighted markov SCGM(1,1)c model are reasonable and reliable. Applying this model can achieve a higher precision and a better image.

Conclusions

Forecasting the fluctuation of exchange rate ratios is crucial for all countries. This paper has evaluated the application of weighted markov SCGM(1,1)c model in forecasting the monthly exchange rate ratios as U.S. Dollar/ Euro, Japanese Yen, Swiss Franc and trade weighted index. This model combines the advantages of weighted markov chain and grey system theory. According to the forecasting results we concluded that the prediction error for April 2012 U.S. Dollar /Euro is 1.42%, for June 2012 U.S. Dollar / Japanese Yen is 39% for June 2012 U.S. Dollar/Swiss Franc is 3.04% and for May 2012 U.S. Dollar / Trade Weighted Index is 5%. We can confirm that this model gives a reliable prediction result.

Bibliography

[1] Marcos Dal Bianco ,Maxiamo Camacho ,Gabrell Perez Quiros, 2012,"Short-run forecasting of the euro-dollar exchange rate with economic fundamentals," Journal of International money and finance, vol. 31, no. 2, pp. pp:377-396 .

[2] Alex Yi Han Huang, Sheng-pen peng, Fangjhyli,ching-jieke,2011, "volatility forecasting of exchange rate by quantile regression," International Review of Economics &finance, vol. 2, no. 4, pp. pp:591-606.

[3] Georgirs Serminis, Christian Dunis, Jason Laws , Charalampos Stasinakis,2012 "forecasting and trading the EUR/USD exchange rate with stochastic neural network combination and time-varying leverage," Decision Support Systems.

[4] Te-Ru Liu, Mary E.Gerlow,Scott H.Irwin,1994,"the performance of alternative VAR model in forecasting exchange rates," International Journal of Forecasting, vol. 10, no. 3, pp. pp:419-433.
[5] chunming yuan,2011, "forecasting exchange rates :the multi-state markov switching model with smoothing," International Review of economics & finance, vol. 2, no. 2, pp. pp:342-362.
[6] Gerhard Fenz, Martin Spitzer,2004, "Macroeconomic Models and Forecasts for Austria," in workshops, proceedings of OeNB workshops.
[7] Mike P.Hanias,Panayiotis G.Curtis,2008, "time series prediction of Dollar/Euro exchange rate index," International Research Journal of finance and economics, no. 15.
[8] Kenneth W.Clements, Yihui Lan ,2006, "A new approach to forecasting exchange rates".
[9] O. Olson,2010, "Effects of productivity growth and its influence on the Dollar/Euro real exchange rate," International research jounal of finance and economics, no. 39.
[10] Yao J. ,Poh H. ,jasic T.,1996, "Foreign exchange rates forecasting with neural networks," in national university of sangapore working working paper proceeding of the international conference on neural information proceeding , Hong Kong.
[11] T. Kurita,2012, "Dynamic characteristics of the daily yen-dollar exchange rate," CAEs working paper series.
[12] Nelson C. Mark ,Dong ayu Sul, Jyh-Lin Wu ,2012, "exchange rates as exchange rate common factors," Ryan Green away McGrevy.
[13] Vincenzo Pacelli, 2012,"forecasting exchange rates : a comparative analysis," International Journal of Business and Social Science, vol. 3, no. 10.
[14] Sai yang Hu,Songjiang Ma,Dao Cheng Luo.,2012, "Study on the establishment of the modified grey-markov model and its application," advanced material research, Vols. 524-527, pp. 3182-3189.
[15] Zhang Y.,Zhang J.,Zhang S.,Liu S.,Chen Y.,2009, "Establishment of combing grey model with partial least squares regression for city energy consumption forecastin," ieee.
[16] Kumar U.,Jain V.K., "Time series models (grey markov , grey model with rolling mechanism and singular spectrum analysis) to forecast energy consumption in India," Energy, vol. 35, pp. 1709-1716.
[17] Der chiang Lich, che jung-chang,chien-chih chen,Wen-chih chan,2012, "forecasting short term electriity consumption sing the adaptive grey-based approach," An Asian case , vol. 4, no. 6, pp. Omega 767-773.
[18] Hu An, "grey markov chain forecasting application in the stock price,2012," Technology and engineering, vol. 01.
[19] Kuang Yu Huang,Chuen-j,Van Jane,2009, "A hybrid model for stock market forecasting and portfolio selection based on ARX grey system and RS theories," expert systems with applications, vol. 36, no. 3 part 1, pp. 5387-5392.
[20] Shen Yan, 2008,"A novel prediction method for stock index applying grey theory and neural networks," in the 7th international symposium on operation research and its applications , china.
[21] Wu Guang, Yan Tong-Zhen, Zhon Cui-ying , Li Feng-Ming,1990, "grey systems and aspect of environmental geology in china," in first international symposium on uncertaintly modeling and analysis, china.
[22] Ching-Liang Chang,Chiu-Chi Wei,Chie-Bein Chen, "Concurrent maximization of process tolerance using grey theory," robotics and computer, vol. 16, no. 2-3, pp. 103-107, 2000.
[23] Vishnu B.,Symala P., "Grey model for stream flow prediction,2012," Aceh International Journal of science Technology, vol. 1, no. 1, pp. 14-19.

[24] Sheng Doag,Kun Chi,Qiyi Zhang ,Xiang dong zhang,2012, "the application of a grey markov model to forecasting annual maximum water levels at hydrological stations," journal of ocean university of china, vol. 11, no. 1, pp. 13-17.
[25] Jiang Xiang-Cheng ,Chen Sen-fa,2009, "Application of weighted markov SCGM(1,1)C Model to predict Drough Crop Area," Systems engineering -theory & practice, vol. 29, no. 9, pp. 179-185.
[26] Zhou Y.M. ,Yang X.L.,Wang L.R.,2007, "Study on Grey Markov method and its application in agricultural production forecast," in International Conference on Grey systems and intelligent services GSIS2007 IEEE.
[27] Wang Yinao , Wu Shuai , 2007,"Grey system model of medical diseases diagnosis and treatment," in International conference on grey systems and intelligent services IEEE.
[28] Hau Y.,Du J.Wang W.,Wang X,2007, "Grey system model for simulation of economic development," in IEEE,I nternational Intelligent Services, China.
[29] Cheng J.,Cheng K.,2009, "Business failure prediction model based on prediction and rough set," wseas Transactions on Informat science and applications, vol. 6, no. 2.
[30] Xiaoxiang Liu, Weigang Jiang ,Jianwen Xie , "An improves single Variable first - order grey model," in proceedings of the International conferenc on Industrial Mechatronics.