Forecast of Stock Index Volatility Using Grey GARCH-Type Models

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Abstract: This paper integrated genetic algorithm (GA) and grey forecasting (GM(1,1)) model into three GARCH-type models and proposed GAGM-GARCH-type models. GM(1,1) model was used to modify the error terms of the GARCH-type models to improve the volatility forecasting performance of the traditional GARCH-type models. Meanwhile, as for the shortcomings on parameters estimation of GM(1,1) model, GA was adopted to find the optimal grey parameters of GM(1,1) model. Using the stock data of China stock market, the paper compared the performance of the GAGM-GARCH-type models in out-of-sample volatility forecasting with those of the GM-GARCH-type, RGM-GARCH-type, and GARCH-type models. It is indicated by the values of the evaluation criteria that the GAGM-GARCH-type models have better volatility forecasting performances relative to the other three types of GARCH-type models.

Keywords: Genetic algorithm, grey GARCH-type models, volatility forecasting.

1. INTRODUCTION

Volatility is one of the important variables in financial economy study. Investment portfolio, asset pricing, risk management and monetary policy formulating all depend on volatility. Therefore, it is necessary and important to model and forecast volatility of financial market. To date, there are various models to analyze and forecast financial volatility. Among them, GARCH-type models developed from ARCH model [1] are more popular than the other types of volatility models. What is more, the three GARCH-type models: GARCH [2], EGARCH [3], and GJR-GARCH models [4], are widely used by researchers in modeling and forecasting volatility.

Financial time series usually contains known and unknown information due to the complexity of financial market. So, it is difficult for the traditional GARCH-type models to describe the unknown information in error terms sequence. Grey forecasting (GM(1,1)) model proposed by Deng is mainly used for a system with the uncertain information [5]. It shows advantages such as high short-term forecasting precision, less samples, and simple calculation [6]. Tseng used the forecasting property of GM(1,1) model to modify the error terms of GARCH model and proposed GM-GARCH model [7]. Later, Tseng, and Wang provided GM-EGARCH [8] and GM-GJR-GARCH models [9], utilizing GM(1,1) model to modify the error terms of EGARCH and GJR-GARCH models. The results indicated that the introduction of GM(1,1) model improved the short-term forecasting accuracy of the GARCH-type models to a certain degree. However, Due to the theoretical shortcomings, GM(1,1) model may produces larger forecast error when fore casting the error sequences which are highly volatile. Genetic algorithm (GA) suggested by Holland is a powerful optimization algorithm and has been widely applied to various optimization problems. With the advantages of self-organizing and self-adaption, GA can find the global-optimal solution without trapping in the local-optimal points. Based on these characteristics, it was indicated that GA can enhance the forecasting accuracy of GM(1,1) model [10, 11].

This paper uses GA to estimate the grey parameters of GM(1,1) model to increase the accuracy in error sequences forecasting, and then improve the forecasting performance of the GARCH-type models. The main structure of this paper is arranged as follows. Section 1 introduces the research background and objective of this paper. Section 2 summarizes the theory of GARCH-type and GM-GARCH-type models. Section 3 describes the theory of GA briefly and designs the procedure of GA-based parameter optimization for GM(1,1) model. The empirical research on two stocks in China stock market is presented in Section 4. Finally, the conclusions and suggestions are provided in Section 5.

2. GREY GARCH-TYPE MODELS

2.1. GARCH-Type Models

Generalized autoregressive conditional heteroscedasticity (GARCH) model introduced by Bollerslev is the extension of ARCH model, which assumes that the current conditional variance associated with the past conditional variances and the past random error. GARCH (p, q) model with Gaussian disturbance can be expressed as:

\[ \varepsilon_t = \sigma_t v_t \sim N(0,1) \]  

\[ \sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 \]  

(1)

(2)
where \( \omega \) denotes the uncertainty of the conditional variance. And \( \alpha_i, \beta_j \) denote the short-term and long-term influence on the conditional variances, respectively. These parameters should satisfy the restrictions:

\[
\sum_{i=1}^{q} \alpha_i + \sum_{j=1}^{q} \beta_j < 1 \tag{3}
\]

\[
\omega, \alpha_i, \beta_j \geq 0 \tag{4}
\]

The GARCH model has the ability of describing the phenomenon of volatility clustering and the distribution of fat tails existed in the financial assets returns, but it cannot explain the asymmetric features of the returns.

Nelson proposed exponential GARCH (EGARCH) model to capture the leverage effects of the assets price varying on conditional variance by adding an asymmetric term into the GARCH model. Different from GARCH model, EGARCH model defines the conditional variance as the logarithm form, which has no restrictions on the parameters \( \alpha_i \) and \( \beta_j \). The conditional variance equation of EGARCH \((p, q)\) is written as:

\[
\ln \sigma_t^2 = \omega + \sum_{i=1}^{q} \left( \alpha_i \frac{\varepsilon_{t-i}}{\sigma_{t-i}} - \frac{2}{\pi} \right) + \sum_{j=1}^{q} \beta_j \ln \sigma_{t-j}^2 \tag{5}
\]

where the parameter \( \gamma_j \) reflects the asymmetry of the returns. \( \gamma_j > 0 \) represents the positive return gives bigger impact on the volatility, \( \gamma_j < 0 \) represents the negative return gives bigger impact on the volatility and there is no asymmetric effect when \( \gamma_j = 0 \).

Glosten et al. added another asymmetric term into the GARCH model for account for the asymmetry of the return behavior. They called the proposed model as GJR-GARCH model. The conditional variance equation of GJR-GARCH \((p, q)\) is represented as:

\[
\sigma_t^2 = \omega + \sum_{i=1}^{q} \left( \alpha_i \varepsilon_{t-i}^2 + \gamma_i S_i \varepsilon_{t-i}^2 \right) + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 \tag{6}
\]

where \( S_i \) is a dummy variable. \( S_i = 1 \) when \( \varepsilon_{t-i} < 0 \), and \( S_i = 0 \) when \( \varepsilon_{t-i} \geq 0 \). \( \gamma_i < 0 \) indicates no asymmetric effect, while \( \gamma_i \neq 0 \) indicates the presence of asymmetric effect. Additionally, the parameters of EGARCH model should meet the following restrictions:

\[
\sum_{i=1}^{q} \alpha_i + \sum_{j=1}^{q} \beta_j + \frac{1}{2} \sum_{j=1}^{q} \gamma_j < 1 \tag{7}
\]

\[
\omega, \alpha_i, \beta_j \geq 0, \int \alpha_i + \gamma_j \geq 0 \tag{8}
\]

2.2. GM-GARCH-Type Models

According to the GARCH-type models, the current conditional variance \( \sigma_t^2 \) essentially depends on the past error terms \( \varepsilon_{t-\tau}, \tau < t \), but this is not consistent with the actual situation. In the actual financial market, with the exclusion of the past price, the error terms are also affected by the uncertain factors, such as the economic, political, environmental and other complex factors. These factors will cause the errors changing all the time. Thus, the current error may have impact on the current conditional variance \( \sigma_t^2 \), while the traditional GARCH-type models just neglect this point.

Grey forecasting model is the core model of the grey system theory. Using the accumulated generating operation (AGO) to preprocess the original data, grey forecasting model finds and grasps the development law of the system, and then forecasts the future state of the system quantitatively. GM \((1,1)\) model is the commonly used grey forecasting model.

To strength the impact of the current error on the current conditional variance, GM \((1,1)\) model was used to continuously modify the squared error term sequences of GARCH-type models (GM-GARCH-type models). That is, the one-step-ahead forecasted error values obtained from GM \((1,1)\) model are put into the conditional variance equations for enhancing the forecasting ability of the GARCH-type models, as shown in literatures [7-9]. The conditional variance equations of the GM-GARCH-type models are written as:

\[
\sigma_t^2 = \omega + \sum_{i=1}^{q} \left[ \alpha_i \left( \varepsilon_{t-i} - \hat{\varepsilon}_{t-i} \right) + \gamma_i S_i \varepsilon_{t-i} - \hat{\varepsilon}_{t-i} \right] + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 \tag{9}
\]

\[
\ln \sigma_t^2 = \omega + \sum_{i=1}^{q} \left( \alpha_i \left[ \frac{\varepsilon_{t-i} + \hat{\varepsilon}_{t-i}}{\sigma_{t-i}} - \frac{2}{\pi} \right] + \gamma_i S_i \varepsilon_{t-i} - \hat{\varepsilon}_{t-i} \right) + \sum_{j=1}^{q} \beta_j \ln \sigma_{t-j}^2 \tag{10}
\]

\[
\sigma_t^2 = \omega + \sum_{i=1}^{q} \left[ \alpha_i \left( \varepsilon_{t-i} + \hat{\varepsilon}_{t-i} \right) + \gamma_i S_i \varepsilon_{t-i} + \hat{\varepsilon}_{t-i} \right] + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 \tag{11}
\]

where \( \hat{\varepsilon}_{t} \) are the random error forecasts obtained by using the GM\((1,1)\) model.

3. GM-GARCH-TYPE MODELS WITH GA

3.1. Genetic Algorithm

Genetic algorithm (GA) is a global optimization algorithm, following the mechanics of biological evolution. It mimics the phenomenon of reproduction, mating and mutation happened in the process of natural selection and natural inheritance. Based on the natural law of survival of the fittest, GA produces the preferred individual generation by generation and finds the optimal individual by using the genetic operators such as selection, crossover and mutation. The details on the genetic operators can be found in [12].

GA has its own characteristics apart from all the features of evolutionary computation: (1) GA directly deals with the code set of the decision variables rather than the actual value itself. During the search process, GA neither places any constraints on the continuity of the optimized function nor requires existence of derivative of the optimized function. (2) GA looks for the optimal solution by using multi-point search or group search, which shows high implicit parallelism. (3) GA is an adaptive search technique. The selection, crossover and mutation are operated in a probabilistic man-
3.2. The Optimal Grey Parameters by GA

Grey parameters \( a \) and \( b \) are important for GM (1,1) model. The forecasting performance of the GM (1,1) model is dependent on the accuracy of the parameters solution to \( a \) and \( b \). In GM (1,1) model, the estimators of \( a \) and \( b \) are obtained by the least squares method under the assumption that the random error sequences is normally distributed. However, due to affected by various complex factors, the error sequences don’t follow the normal distribution. As a result, the parameter estimators by the least squares method may be bias and non-consistent. Moreover, when estimating the two parameters, the least squares method should satisfy the restriction of \( \hat{x}^{(1)}(t) = \hat{x}^{(1)}(1) = x^{(0)}(1) \), which will cause larger system error and then impact the forecasting accuracy of GM (1,1) model. To improve the forecasting ability of GM (1,1) model in error terms sequence forecasting, GA is applied to searching for the optimal grey parameters of GM (1,1) model. The general procedure of GA-based parameter optimization to GM (1,1) model for forecasting the error sequences can be summarized as follows:

**Step 1: Preprocessing the data.** Transform the original error terms sequence \( \hat{e}(t) = (\hat{e}(0), \hat{e}(1), \ldots, \hat{e}(n)) \) into the non-negative sequence \( u(t) = \left\{ u^{(0)}(1), u^{(0)}(2), \ldots, u^{(0)}(n) \right\} \), where \( u^{(0)}(t) = e^{(0)}(t) + \min(e^{(0)}(t)), t=1,2,\ldots,n. \) (12)

**Step 2: Initialization population.** Initialize the parameters of GA, consisting of the population size, the number of evolutionary generation, the crossover rate and mutation rate.

**Step 3: Definition objective function.** The objective function is defined based on the criterion of minimizing the mean squares error:

\[
F = \frac{1}{n} \sum_{t=1}^{n} (\hat{u}^{(0)}(t) - u^{(0)}(t))^2
\] (13)

where \( \hat{u}^{(0)}(t) \) and \( u^{(0)}(t) \) are the forecasted and actual error values, respectively.

**Step 4: Evolution operation.** Calculate the objective value of each individual in the population and search for the optimal solution by the steps of selection, crossover, mutation and evolution.

**Step 5: Evolution stops.** Repeat Step 3 to Step 4 until the number of evolutionary generation is met, when the optimal grey parameters \( a^* \) and \( b^* \) are obtained.

**Step 6: Model construction and forecasting.** Using the obtained parameters \( a^* \) and \( b^* \), the GA-based GM (1,1) model (called GAGM (1,1)) is constructed as:

\[
\hat{e}^{(0)}(t) = \left( 1 - e^a \right) \left( e^a - e^{(0)}(t) \right) - \min(e^{(0)}(t)), t=2,\ldots,n. \] (15)

Finally, \( \hat{e}^{(0)}(t) \) is added in the conditional variance equations of the GARCH-type models.

4. EMPIRICAL RESEARCH

4.1. Data Description

Two stock indices of China stock market are examined: HuShen 300 Index (HS300) and HangSeng Index (HSI). The daily trading prices of the two stock indices are extracted from Sina website during July 4, 2011 to July 10, 2014, which includes 1338 observations. The continuously compounded logarithmic returns are calculated by using the daily closing prices: \( r_t = \ln P_t - \ln P_{t-1} \), where \( P_t \) and \( P_{t-1} \) are the daily closing prices for day \( t \) and \( t+1 \), respectively. The descriptive statistics of the daily return series of HS300 and SZCI can be found in Table 1.

It is clear from Table 1 that for the two indices, the means of the return series are close to zero, significantly smaller than the corresponding standard deviation within the considered period. Thus, the conditional mean of the return series can be assign to zero. The J-B test of the return series rejects the null hypothesis of normality at the 1% and 5% level, respectively. Besides, negative Skewness and high Kurtosis are found in the return series, showing that the distribution of the return series is negatively biased and fat-

<table>
<thead>
<tr>
<th>Indices</th>
<th>Mean</th>
<th>Max.</th>
<th>Min.</th>
<th>Std. Dev.</th>
<th>Skewness</th>
<th>Kurtosis</th>
<th>J-B test</th>
<th>LB(20)</th>
<th>LB^2(20)</th>
<th>LM(20)</th>
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<td>HS300</td>
<td>0.0001</td>
<td>0.0646</td>
<td>-0.0737</td>
<td>0.0151</td>
<td>-0.2803</td>
<td>5.0937</td>
<td>17.2411</td>
<td>95.9081</td>
<td>123.6825</td>
<td>120.1993</td>
</tr>
</tbody>
</table>
| SZCI    | 0.0005| 0.0599| -0.0741| 0.0162    | -0.5474  | 4.4599   | 31.6339  | 250.2407| 127.4946|}

Note: JB test is the Jarque-Bera normality test for the distribution of the return series. LB(20), LB^2(20) are the Ljung-Box test for the 20th order serial correlation of the return and squared return series, respectively. LM (20) is the Engle’s (1982) LM test for heteroscedasticity of the return series. a, b denote significance at the 5% and 1% levels, respectively.
tailed. LB(20) statistic for serial correlation suggests that the return series of SZCI has serial correlation at the 5% significance level, while the return series of HS300 has no significant serial correlation. LB(20) and ARCH (20) test support the rejection of the null hypothesis of heteroscedasticity at the 1% and 5% level, indicating that the strongly ARCH effect exists in the two return series. It is reasonable to construct GARCH-type models.

4.2. Empirical Results

The daily returns of HS300 and SZCI, normalized in the range from 0 to 1, are classified into two sections: the first 1000 daily returns are used for model training, and the remaining 337 ones for model evaluation. The rolling forecasting method is used to forecast the stochastic error of the GARCH-type models. When estimate the grey parameters of GM (1,1) model, the control parameters of GA are set as: population size=30; crossover rate=0.95; mutation rate=0.08, number of evolutionary generation=50. For HS300 and SZCI, GAGM (1,1) model forecasts the next error value of the GARCH-type models using the eighteen most recent errors. The forecasted error values were added into the variance equation of the GARCH-type models and the parameters of the GARCH-type models were estimated by using the maximum likelihood estimation (QMLE) method. Then, the constructed GAGM-GARCH-type models were employed to one-step-ahead forecast volatility. To compare the forecasting results of the proposed models, three types of GARCH models are applied to forecasting volatility of HS300 and SZCI with the same data samples. They are GM-GARCH-type, RGM-GARCH-type, and GARCH-type models. Finally, the volatility forecasts are transformed into the original volatility forecasts.

The out-of-sample forecasting performances of each type of models are evaluated by four statistical indices: the root mean squared error (RMSE), the mean absolute error (MAE), the logarithmic error statistic (LL), and the Linear Exponential index (LINEX). These indices are defined by:

\[
\text{RMSE} = \sqrt{T^{-1}\sum_{t=1}^{T}(\hat{\sigma}_t - R_t)^2}
\]

\[
\text{MAE} = T^{-1}\sum_{t=1}^{T}|\hat{\sigma}_t - R_t|
\]

\[
\text{LL} = T^{-1}\sum_{t=1}^{T}\ln(\hat{\sigma}_t) - \ln(R_t)
\]

\[
\text{LINEX} = T^{-1}\sum_{t=1}^{T}\{\exp[\chi(\hat{\sigma}_t - R_t)] - \chi(\hat{\sigma}_t - R_t) - 1\}
\]

where \(T\) is the number of volatility forecasts. \(\hat{\sigma}_t\) is the square root of the volatility forecasts. \(R_t\) is the proxy of the actual daily volatility. In this study, the range-based ex post volatility \(R_t\) is taken as a proxy of the actual daily volatility, expressed as:

\[
R_t = \sqrt{k(\log(P_{i,h}) - \log(P_{i,l}))}\times 100
\]

where \(P_{i,h}\) and \(P_{i,l}\) are the intraday high and intraday low price, respectively. \(k\) is the calibration parameter between the range-based unconditional variance and the return-based unconditional variance. The four statistical indices measure the forecasting errors of the evaluated models. The model with smaller ones shows better volatility forecasting ability.

Table 2 lists the comparison of the results of the four types of models in forecasting volatility of HS300 and SZCI. We can see from Table 2: Firstly, for HS300 and SZCI, GAGM-GARCH-type models generate smaller RMSE, MAE, LL, and LINEX compared to the other types of models, which show a better performance than the other types of models in forecasting volatility. Among the three GAGM-GARCH-type models, compared with GAGM-GJR-GARCH model, GAGM-GARCH model generates smaller RMSE and LINEX but larger MAE and LL, indicating that the forecasting ability of GAGM-GARCH model somewhat mixed compared with that of the GAGM-GJR-GARCH model. GAGM-EGARCH model shows the worst volatility forecasting performance according to the four evaluation criteria. Secondly, with the exception of LINEX of RGM-GARCH type models, GM-GARCH-type models produce smaller RMSE, MAE, and LL than RGM-GARCH-type and GARCH-type models, suggesting that on the whole, GM-GARCH-type models outperform the RGM-GARCH-type and GARCH-type models in volatility forecasting. Thirdly, for HS300, RGM-GARCH-type models provide better volatility forecasting results in term of RMSE, LL, and LINEX. While for SZCI, GARCH-type models seem to provide better volatility forecasting results in term of RMSE, MAE, and LL. Hence, it is difficult to determine which one of these two types model is better in volatility forecasting performance.

The volatility forecasting results of the GAGM-GARCH-type models for HS300 and SZCI are shown in Figs. (1) and (2). As is shown in the two figures, the three GAGM-GARCH-type models can forecast the main volatility varying trend of the two stock indices, where GAGM-GARCH model provides superior volatility forecasts in the smaller fluctuation stage and GAGM-GJR-GARCH model provides superior volatility forecasts in the larger fluctuation stage.

CONCLUSION

To enhance the forecasting performance of the GARCH-type models, i.e., GARCH, EGARCH, and GJR-GARCH models, in this paper, GAGM-GARCH-type models were proposed, which combined genetic algorithm (GA) and GM(1,1) model with three GARCH-type models. GM(1,1) model optimized by GA was used to modify the error terms of the GARCH-type models. The results of the empirical study on HS300 and SZCI indices of China stock market shows that the proposed models have superior performances in out-of-sample volatility forecasting than the GM-GARCH-type, RGM-GARCH-type, and GARCH-type models. The GAGM-GARCH and GAGM-GJR-GARCH models perform better than the GAGM-EGARCH model, but the forecasting performance of the GAGM-GARCH model somewhat mixed compared to the GAGM-GJR-GARCH model. In additional, GM-GARCH-type models, as a whole, produce superior volatility forecasts compared to the RGM-
Table 2. RMSE, MAE, LL, and LINEX of four types of volatility models for HS300 and SZCI.

<table>
<thead>
<tr>
<th>Indices</th>
<th>Models</th>
<th>RMSE</th>
<th>MAE</th>
<th>LL</th>
<th>LINEX</th>
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Fig. (1). HS300 volatility forecasts by GAGM-GARCH-type models.
Fig. (2). SZCI volatility forecasts by GAGM-GARCH-type models.
GARCH-type and GARCH-type models. While for RGM-
GARCH-type and GARCH-type models, they show different
volatility forecasting ability according to different evaluation
criteria, which needs to study further.

CONFLICT OF INTEREST

The authors confirm that this article content has no con-
lict of interest.

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