EMD Copula based Value at Risk Estimates for Electricity Markets

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Abstract

In this paper we propose an Empirical Mode Decomposition Copula based approach for analyzing the portfolio risk and estimating VaR at Risk. The copula theory is introduced to analyze the time-varying microscopic dependence structure between New South Wales (NSW) and Queensland (QLD) in Australian electricity market, and test the existence of the symmetrical dependence structure between them. The EMD algorithm is combined with copula theory to construct a new based EMD-Copula model for estimating Value-at-Risk (VaR) of electricity market. Results from the empirical analysis show that compared with the benchmark DCC-GARCH model, the proposed model outperforms the DCC-GARCH model, in terms of estimation reliability.

Keywords: Copula Theory; Bivariate EMD Algorithm (BEMD); copula GARCH; Value at Risk (VaR); Electricity Market;

1. Introduction

As the fluctuation of electricity price becomes more and more intense and the dependence between the electricity markets becomes more time varying, the electricity market price risk becomes more significant and complicated to understand and model. It is of utmost importance for investors to measure the risk level of electricity market reliably and accurately for better risk management strategies and decisions.

Till now, there has been some limited studies for the risk measurement in the electricity markets. For example, [1] measures the risk of electricity market in Columbian by addressing a based Fuzzy Logic model [1]. [2] proposes a swarm intelligence meta-heuristic optimization technique for managing the long-term risk of electricity market [2]. [3] adopts the long-term equilibrium technology mix to analyze the risk-aversion in an electricity market [3]. [4] combines neural networks with extreme value model to predict the electricity spot prices for hedging against risk [4]. [5] propose a computationally tractable robust optimization method for minimizing the CVaR of a portfolio using L1norm [5]. In this paper we adopt the VaR for risk measurement. Value at risk (VaR) is defined as the maximum expected loss which may be incurred by a financial asset or a portfolio over a holding period and at a given level of confidence under normal market conditions. There are different methods to estimate VaR. Typical method include historical simulation method, variance-covariance method and Monte Carlo.
simulation method. There are some frequently used way to estimate the mean, such as ARMA (Auto-Regressive and Moving Average Mode) and VAR (Vector Autoregression), and the common method to predict the variance include EWMA (Exponentially Weighted Moving-Average), GARCH (Generalized AutoRegressive Conditional Heteroskedasticity) and DCC-GARCH, and so on.

For example, [6] discusses the concept and calculation method of VaR for measuring investment risk, and investigates the VaRs of stock in Shenzhen market under different confidence level [6]. [7] proposes a EVT-based model to forecast out-of-sample VaR, and proves that it can provide an appropriate interval coverage in predicting VaR in electricity markets [7]. [8] confirms that VaR can provide a useful approach to judge whether the formed risk control scheme is acceptable by constructing a layered framework of risk management for electric energy trading [8]. [9] develops a two-stage stochastic integer programming model using conditional Value-at-Risk constraint to avert risk in the electricity sector, and demonstrated that this based conditional VaR model can allow acceptance of contracts at lower prices [9]. [10] estimates the risk measures Value-at-Risk and Expected Shortfall on the electricity forward market by applied a group of multivariate volatility model, such as EWMA, BEKK and DCC model, and the predicted results are well [10]. [11] proposes self-exciting market point process Shortfall on the electricity forward market by applied a group of multivariate volatility model, such as EWMA, GARCH-M and DCC-GARCH, and so on.

The copula theory is used to describe the dependence structure between financial variables, including both the unconditional and conditional version [14, 15, 16]. Regarding unconditional copula, [17] determines the portfolio with minimum risk in the foreign exchange market by using Archimedean Copula [17]. [18] adopts it to capture the long-range dependence and tail dependence between international equity markets [18]. [19] use unconditional SJC (Symmetrized Joe-Clayton) copula function to investigate the dependence structure between the Canadian stock returns and the USD/CAD exchange rate returns, and found that the returns are more dependent in the left than in the right tail of their joint distribution [19]. Furthermore, [20] models the dependence structure between stock index returns and foreign exchange rate returns by applying the copula theory, and the empirical results show that there is no dependence between two developed economies (Hongkong and Singapore) while three emerging markets (Indonesia and South Korea) have much stronger lower tail dependency than right tail [20]. [21] analyzes the coomovement between crude oil prices and exchange rate using copula, and verify that the dependence between them is in general very weak [21]. [22] utilizes the unconditional copula model to discuss the dynamic dependence between crude oil price and stock markets in ten countries across the Asia-Pacific region, and prove that there exists a generally weak dependence, but it is positive before the global financial crisis [22]. Compared with unconditional copula, a larger number of scholars use the conditional copula to investigates the dependence structure. For example, [23] computes the VaR of stock portfolios composed of NASDAQ and TATEX by ultimating conditional copula-GARCH, and testify that compared with traditional methods, the model can captures the VaR more accurately [23]. Other some studies, such as [24] also successfully introduce this model into the VaR measurement for stock market [24]. In addition, [25] estimates the VaR of an equally weighted portfolio comprising crude oil futures and natural gas futures in energy market using time-varying copula-GARCH model [25]. [26] uses copula-GARCH-EVT model to calculate the portfolio risk in carbon market, and proves that the based copula method is better than the traditional covariance metric method [26]. [27] make an empirical study about the correlation between the conditional skeweness in return distribution and time-varying risk attitude by proposing a GARCH-M model with a time-varying coefficient of the risk premium, and the results indicates that the coefficient of the risk premium are time-varying [27].

We have witnessed some promising results using the unconditional copula method in the electricity markets. For example, [28] introduces copula to analyze the dependence in electricity markets [28]. [29] utilizes the student’s t, Gumbel and time-varying normal copulas to capture the dependence structure between spot and futures
of electricity [29]. [30] uses a non-symmetric copula to model the evolution of electricity and gas prices, and found that option prices are significantly influenced with the seasonality of the underlying prices [30]. [31] uses copula to study the dependence structure between spot electricity prices of Australian regional electricity markets in NSW, QLD, SA, TAS and VIC, and there exists a positive dependence between prices from all markets [31]. [32] also adopts skew t copula to model for the dependence between regional spot prices in the Australian electricity market, and obtained relative better results [32]. However, few research has been done using the conditional copula in the electricity economics literature.

Meanwhile, few research has been identified to analyze and model the multiscale structure of the dependence structure, both in the unconditional and conditional form. There are important literature gaps in the field. The recently emerging Empirical Mode Decomposition (EMD) algorithm is a self-adaptive multi scale processing method of signal time-frequency. It decomposes the time series into a series of intrinsic mode functions (IMF) which are independent each other. Each IMF is a nearly periodic zero mean function with variable amplitude and frequency at different time. The Bidimensional Empirical Mode Decomposition (BEMD) is a extension to EMD. In comparison to EMD, the complex data can be better decomposed by BEMD into some independent pairs of IMFs. Up till now, most researches concerning BEMD are mainly applied in image compression, image denoising, watermark embedding and texture analysis, the applications by employing BEMD to measure VaR of portfolio in electricity market are relatively few [33, 34, 35, 36, 37].

Thus in this paper we propose the EMD Copula based approach to estimate Value at Risk in the electricity markets. We collect Australian regional electricity markets in NSW and QLD as the representative to explore the microcosmic dependence between Australian electricity markets based on copula theory, and then propose a based EMD-copula model for estimating VaR. The empirical results shows that the proposed VaR model is better in accuracy and prediction performance.

The rest of this paper is organized as follows. Section 2 briefly reviews the copula theory and BEMD theory, as well as illustrate the proposed BEMD-copula-GARCH model to measure VaR. The empirical analysis is presented in Section 3 by selecting the respective average daily price of NSW and QLD as the study objective, followed by a conclusion in Section 4.

2. BEMD Copula Algorithm for Value at Risk Estimate

Firstly we assume a multiscale structure of risk. This would translate to the aggregated risk from the individual risks for the bivariate time series data at different scales. Assume a bivariate time series coded as the complex time series, we use the EMD algorithm to decompose this structure, as follows.

1. identify the number of projection directions N and compute the projection directions:

   \[ \varphi_n = \frac{2n\pi}{N}, \quad 1 \leq n \leq N \]  

2. Project the complex valued signal \( x(t) \) on directions \( \varphi_n \):

   \[ P_{\varphi_n}(t) = \text{Re}[e^{-j\varphi_n}x(t)] \]  

3. Extract all local maxima of \( P_{\varphi_n}(t) \), namely \( \{(t^n_i, P_{\varphi_n}(t^n_i))\} \) (i is denoted as the number of individual local maxima);

4. Interpolate the set \( \{(t^n_i, P_{\varphi_n}(t^n_i))\} \) by spline interpolation to obtain the partial envelop curve in direction \( \varphi_n \), and repeat (2)-(4) until the envelop curves in all N projection directions are got.

5. Calculate the mean of all envelop curves according to the following equation:

   \[ m(t) = \frac{1}{N} \sum_{n=1}^{N} e_{\varphi_n}(t) \]  

6. Extract \( m(t) \) and obtain \( h(t) \) as in such:

   \[ h(t) = x(t) - e(t) \]
7. Check whether h(t) is an IMF. If not, replace x(t) with h(t) and repeat steps 8. (2)-(6) until h(t) is an IMF. Otherwise, repeat the step from the step 2 on the residual signal.

9. The original signal x(t) can be expressed as the following equation:

\[ x(t) = \sum_{k=1}^{K} h_k(t) + r(t) \]  

(5)

where k indicates the total number of IMFs, and \( h_k(t) \) and \( r(t) \) represent the k-th subtracted complex IMF and residue, respectively.

Secondly, we estimate the conditional mean and conditional standard deviation at the individual level. We assume that the conditional mean follows the VAR processes. The conditional mean matrix is estimated as follows:

\[ Y_t = C + \sum_{i=1}^{k} \Phi Y_{t-i} + \epsilon_t \]  

(6)

Where \( \epsilon_t \) denotes the random disturbance term at k order, and \( Y_t \) is the multivariate time series.

We assume that the conditional covariance follows the Copula-GARCH model as in (7).

\[ r_{it} = \mu_{it} + \epsilon_{it} \]

\[ \epsilon_{it} = \epsilon_{it}\sigma_{it}, \epsilon_{it} \rightarrow F_{i}(\cdot) \]

\[ \sigma_{it}^2 = \omega_i + \alpha_1\epsilon_{it-1}^2 + \beta_1\sigma_{it-1}^2 \]

\[ (\epsilon_{1t}, \epsilon_{2t}) \mid I_{t-1} \rightarrow C_1(F_{1}(\epsilon_{1t}), F_{2}(\epsilon_{2t}) \mid I_{t-1}) \]  

Where \( r_{it} \) indicates the returns series of each asset, \( n=1, 2 \). \( \epsilon_{it} \) is independent and identical distributed and it follows \( F_{i}(\cdot) \) distribution with zero mean and one variance. \( C_1 \) denotes the copula function, and \( I_{t-1} \) is the innovation at \( t-1 \) time. Besides, \( \sigma_{it}^2 \) is the conditional variance. The time-varying correlation coefficient is can obtained by \( R_{ij} = (\text{diag}(Q_i))^{-\frac{1}{2}} Q_i (\text{diag}(Q_i))^{-\frac{1}{2}} \), in where \( Q_i = (1 - \alpha - \beta) \hat{Q}_i + \alpha \epsilon_{i,t-1}^2 + \beta Q_{i,t-1} \).

The conditional variance matrix is estimated as in \( \sigma_{it}^2 R_{ij} \).

Thirdly, as we assume the independence between the conditional mean and conditional standard deviations among different scales, the aggregated conditional mean and conditional standard deviation are constructed as the summation of the estimates at the individual level. Then we estimate the VaR with the estimated aggregated conditional mean and conditional standard deviation. Suppose that the distribution of a portfolio follows the Normal distribution, and the holding period is \( h \), then portfolio VaR at \( \alpha \) confidence level can be calculated in 8.

\[ \text{VaR}(h, \alpha) = [-hw\mu + \sqrt{h} \sum w^T z_{\alpha}]P \]  

(8)

Where \( \mu \) and \( \Sigma \) separately denote the estimated mean matrix estimated with VAR (Vector autoregressive) model and conditional variance-covariance matrix estimated with Copula-GARCH model, and \( w \) is the weight vector which consists of the proportion of each asset in portfolio. \( P \) represents the total asset value of portfolio, and \( Z_{\alpha} \) is the quantile of order.

3. Empirical Studies

In this study, the average daily closing electricity price of New South Wales (NSW) and Queensland (QLD) in Australian electricity market are collected as the sample data set, from the official website of AEMO. The data span from January 1, 2004 to February 14, 2015, excluding non joint trading daily data, with a total of 4055 observations. In data preprocessing, the original price is processed as \( r_t = \ln(p_{t-1}) - \ln(P_t) \), where \( r_t \) and \( p_t \) refer to the returns and prices respectively. During the empirical study, the data set is divided into two parts. The 70% of the data set, i.e. 2838 daily observations, are reserved as the training set for in-sample estimate. The remainder
30% of the data set, i.e. 1216 daily observations, are used as the test set for the out-of-sample test to evaluate the performance of the proposed model (30%). The BEMD algorithm is implemented using EMD toolbox. The DCC GARCH and the Copula GARCH model are implemented using the USCD-GARCH and Dynamic copula toolbox, respectively.

Table 1 lists the descriptive statistics of returns for the two electricity markets.

| Markets | mean  | std   | Skewness | Kurtosis | Jarque-Bera | P-value |
|---------|-------|-------|----------|----------|-------------|---------|
| rNSW    | 0     | 0.3899| -0.4435  | 39.0942  | 220200      | 0.001   |
| rQLD    | 0     | 0.4456| -0.0521  | 30.5671  | 128370      | 0.001   |

Table 1 summarizes the descriptive statistics of the two returns series. Kurtosis of price in both electricity markets are far greater than 3, indicating that there are greater probability to produce the extreme event in both markets. Besides, the Jarque-Bera statistics reject the null hypothesis of both two returns series follows normal distribution, showing that a series of change of the returns belong to the non-linear dynamic change, which can be certified by the skewness value, namely, there exists a heavy tail in both returns series.

Two types of copula function, including the constant copula function (Normal copula, Student’s t copula, Clayton copula and SJC copula) and the time-varying copula function (time-varying Normal copula, time-varying student’s t copula and time-varying SJC copula), are considered in this article to discuss the microcosmic dependence pattern between electricity price returns, then an appropriate copula function which can better fit the dependence pattern is chosen according to the minimized log-likelihood value (LL), AIC and BIC. The estimated results of copula parameters are illustrated in Table 2 and 3.

Table 2: four constant copula specification and estimation

| Copula     | Parameters | LL     | AIC     | BIC     | upper tail | lower tail |
|------------|------------|--------|---------|---------|------------|------------|
| CopulaNormal | 0.6964    | -1345.2| -2690.484| -2690.482| 0          | 0          |
| CopulaStudent | 0.8273, 2.1000 | -2200.7| -4401.402| -4401.3989| 0.6428     | 0.6428     |
| CopulaClayton | 1.6850    | -1262.5| -2524.9165| -2524.915| 0.6627     | 0          |
| CopulaJC | 0.6120, 0.5582 | -1656.5| -3312.9405| -3312.9374| 0.5582     | 0.612      |

Table 3: three time varying copula specification and estimation

| Copula     | w        | b       | a       | LL      | AIC     | BIC      |
|------------|----------|---------|---------|---------|---------|----------|
| CopulaNormal | -3.3641  | 0.4155  | 3.7497  | -1368.1 | -2736.2875 | -2736.2829 |
| CopulaStudent | -0.7109  | 0.4156  | 3.7485  | -1367.9 | -2735.8134 | -2735.8087 |
| CopulaJC | -1.5286,-3.0678 | -12.0606,-17.855 | 2.88,4.5119 | -1961.3 | -3922.6019 | -3922.5926 |

Compared with copula function, the constant Student’s t copula can better analyze the dependency structure between two electricity markets, followed by the time-varying SJC copula function, showing that there exists a symmetric dependence between them, that is to say, the trend of ups and downs in NSW market is basically similar with QLD market. Besides, the peaks and troughs in NSW market can significantly affect QLD market, and vice versa, which can be concluded by the the value of dependence coefficient. The lowest goodness of fit for clayton copula suggest that the average daily price of two electricity markets dropped to the lowest point at the same time does not appear.

The Kupiec likelihood ratio method is employed to testify the effectiveness of the proposed model. Assuming CL is denoted as the confidence level (95%, 97.5% 99%), and the number of the out-of-sample forecasts is 1216. Besides, if the number of exceedance which is number that actual returns are greater than the value of the forecasted VaR is denoted as N, the N/T is the ratio of VaR exceedances, The Mean Square Error (MSE) value are computed to evaluate the predicted accuracy of the proposed model. Generally speaking, when the MSE value is small enough, the precision of model in describing the original returns is higher.

The following analysis are conducted under the normal distribution. Table 4 lists the number of the exceedance N, N/T and MSE value of DCC-GARCH model, Copula GARCH model and BEMD-Copula-GARCH model at different confidence level.
Table 4: The test results of VaR model for electricity market

| CL  | $N_i$ | $N_i/T_i$ | $MSE_i$ | $N_i$ | $N_i/T_i$ | $MSE_i$ | $N_i$ | $N_i/T_i$ | $MSE_i$ |
|-----|-------|-----------|---------|-------|-----------|---------|-------|-----------|---------|
| 99% | 0     | 0.0000    | 4.1066  | 16    | 0.0132    | 0.7617  | 19    | 0.0156    | 0.9398  |
| 97.5%| 1     | 0.0008    | 2.9322  | 23    | 0.0189    | 0.5576  | 26    | 0.0214    | 0.6841  |
| 95% | 1     | 0.0008    | 2.0828  | 27    | 0.0222    | 0.4100  | 31    | 0.0255    | 0.4993  |

where CL refers to the confidence levels. $N_i, i = 1, 2, 3$ refers to the number of the exceedances of the three models tests, including the benchmark DCC-GARCH model as model 1, Copula-GARCH model as model 2 and BEMD-Copula-GARCH model as model 3 respectively. Results in Table 4 indicate that under different confidence level, the ratio of VaR exceedances for BEMD-Copula-GARCH model are approximately equal to the expected exception, showing that the estimated VaR model can better cover the risk of portfolio includes the two big electricity markets indices. At the same time, the estimated model have a higher predictive accuracy, which can be proved by the MSE values.

4. Conclusions

In this paper we have investigated the dependence structure between electricity markets using the copula methods. We have also proposed the EMD-Copula based approach for estimating Value at Risk, incorporating the microscopic multiscale data feature. We found that t copula provides the best characterization of dependence structure between NSW and QLD markets, which indicates the symmetric dependence relationship between them. We also found that the proposed EMD-Copula VaR algorithm can improve the VaR estimation reliability, compared to the benchmark DCC-GARCH model and the Copula-GARCH model.

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