行政院國家科學委員會專題研究計畫 成果報告

以雲端服務為基礎之期貨避險交易決策支援系統
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中 華 民 國 101 年 10 月 17 日

中 文 摘 要： 本研究提出了一個利用時間序列動態行為的群集分析法，可用來估算期貨避險交易決策所需之最適避險比例，作為發展避險決策輔助系統雲端服務之基礎。市場波動的動態行為可以使用變異數、共變數、期貨和現貨間的價差和這些變數的一階、二階導數來衡量。具有相同行為模式的日資料，則可以利用擴展階層式自我組織映射圖(growing hierarchical self-organizing map，GHSOM)來進行分群，這些具有相似行為的日資料將依照相似程度被分配到階層式的子集合中，配合集群內重新取樣之演算法，來構成以傳統最小變異數法估算避險比例之樣本資料。我們使用了台灣加權指數之期貨與現貨來進行為實證，結果顯示本研究所提出的方法可以顯著的改善避險效能。

中文關鍵詞： 集群分析、財務時間序列、避險比例、擴展階層式自我映射組織圖

英 文 摘 要： In this study, a novel procedure of time series dynamic behaviors clustering is proposed to improve the accuracy of minimum -variance optimal hedge ratio (OHR) estimation for future hedging. The dynamic behaviors of market fluctuation are extracted by measurement of variances, covariance, price spread, and their first and second differences. The behaviors with similar patterns are clustered using a growing hierarchical self-organizing map (GHSOM). The observations for OHR estimation are collected based on the hierarchical cluster structure and processed by within-cluster resampling. The spots and futures of the Taiwan Weighted Index (TWI) are adopted to demonstrate that the futures hedge effectiveness can be significantly improved.

英文關鍵詞： cluster analysis； financial time series； hedge ratio； GHSOM

行政院國家科學委員會補助專題研究計畫 □期中進度報告 ■期末報告

以雲端服務為基礎之期貨避險交易決策支援系統

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中　華　民　國　101 年 10 月 17 日

摘 要

本研究提出了一個利用時間序列動態行為的群集分析法，可用來估算期貨避險交易決策所需之最適避險比例，作為發展避險決策輔助系統雲端服務之基礎。市場波動的動態行為可以使用變異數、共變數、期貨和現貨間的價差和這些變數的一階、二階導數來衡量。具有相同行為模式的日資料，則可以利用擴展階層式自我組織映射圖(growing hierarchical self-organizing map，GHSOM)來進行分群，這些具有相似行為的日資料將依照相似程度被分配到階層式的子集合中，配合集群內重新取樣之演算法，來構成以傳統最小變異數法估算避險比例之樣本資料。我們使用了台灣加權指數之期貨與現貨來進行為實證，結果顯示本研究所提出的方法可以顯著的改善避險效能。

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Abstract

In this study, a novel procedure of time series dynamic behaviors clustering is proposed to improve the accuracy of minimum -variance optimal hedge ratio (OHR) estimation for future hedging. The dynamic behaviors of market fluctuation are extracted by measurement of variances, covariance, price spread, and their first and second differences. The behaviors with similar patterns are clustered using a growing hierarchical self-organizing map (GHSOM). The observations for OHR estimation are collected based on the hierarchical cluster structure and processed by within-cluster resampling. The spots and futures of the Taiwan Weighted Index (TWI) are adopted to demonstrate that the futures hedge effectiveness can be significantly improved.

Keywords-cluster analysis; financial time series; hedge ratio; GHSOM

I. INTRODUCTION

With the emergence of financial derivatives markets in the past two decades, hedging has been of interest to both academicians and practitioners. The goal of hedging is to minimize exposure to unwanted risk. This is carried out by establishing the position of a derivative instrument to offset exposure to price fluctuations opposite to that of underlying assets, such as using futures to hedge a portfolio of risky assets. The primary objective is to estimate the size of the short position that must be held in the futures market (i.e., a proportion of the long position held in the spot market) with minimal risk and specific risk aversion of the hedged portfolio.

Many methods have been used to decide the OHR. Most studies adopt the mean-variance framework, which measures the risk of the hedged portfolio by standard deviation, and which assumes that OHR simply minimizes the variance of hedged portfolios. Many applications of optimal hedging use the criterion of minimum variance to estimate OHR, such as by regressing the spot market return on the futures market return using ordinary least squares (OLS) [1] [2] [3]. However, OHRs estimated via the conventional approach is constant over time. The classical time-invariant OHR appears inappropriate with the time-varying nature of many financial markets. Improvements were made to capture time-varying features, such as by adopting dynamic hedging strategies based on the bivariate generalized autoregressive conditional heteroskedasticity (GARCH) framework [4] [5] [6] [7] [8] or the stochastic volatility (SV) model [9] [10].

These approaches to estimating the OHR are based on sample variance and covariance estimators of returns without considering the underlying distribution of data. The conventional OLS approach ignores the conditional distribution of most financial asset returns, which tends to vary over time. To obtain recent information, most research adopt a rolling window scheme to estimate the variance and covariance of spot and futures returns. However, rolling window estimators use an equally weighted moving average of past squared returns and their cross products. Observations have equal weight in the variance-covariance matrix estimator of the arbitrarily defined estimation period, but they have zero weight beyond the estimation period. GARCH class models are successful in capturing time-varying features for estimating conditional variance-covariance matrices, but they place too much weight on extreme observations [11] when the distribution of data is leptokurtic and fat-tailed.

In this paper, our work employs a different weight for observations in a rolling window OLS estimator of the variance-covariance matrix subsequent to the clustering time series using growing hierarchical self-organizing map (GHSOM) [12]. The weights of observations are determined by the measurement of similar patterns, which are correlated with the sample size of the cluster they belong to in the hierarchy architecture. The observations with different weights in clusters are then used to predict the conditional distribution of spot and futures returns for different hedging horizons in the future. When the conditional distribution of spot and futures returns is predictable, a more efficient estimate of the OHR can be obtained by conditioning on recent information.

The new approach uses GHSOM to cluster time series data, which could decompose financial data into a hierarchical architecture consisting of several familiar clusters. Several applications of cluster analysis to economics and finance time series have been documented in recent literature, including identification of mutual funds styles by analyzing the time series of past returns [13], discovery of companies that share similar behavior with the Dow Jones industrial average (DJIA) index [14], prediction of value at risk [15], prediction of oil futures price [16], and determination of optimal tracking portfolio [17].

The application of GHSOM to clustering time series to improve the conventional OHR estimator has several salient advantages. Observations within the cluster with similar patterns provide a way for examining the dependency of observations, which are generated from long-horizon return series and can provide predictable time patterns. The conditional distribution of returns in the next hedging horizon is predictable by aggregating these clustered observations, which are inspired by the well-established features of many asset returns that their conditional distribution is time-varying and tendency display volatility clustering. Further, the proposed approach is a non-parametric method, which can avoid too many inappropriate assumptions and restrictions found in conventional parametric models.

The rest of the paper is organized as follows: Section II illustrates the idea of the proposed model for the OHR estimation; Section III details the procedure of the proposed model; Section IV presented the experiments design and results; and lastly, conclusions and the future works drawn from the study will be discussed in Section V.

II. The Proposed Model

A. The Two Phases Computational Intelligence Aapproach

Instead of the conventional approach to OHR estimation, which is simply to regress the spot and futures series, two modifications of the conventional approach are proposed based on computational intelligence shown in Fig. 1. The original composition of data for OHR estimation is modified by the selected data with a similar pattern, which is performed in two phases. Phase I is clustering time series, and Phase II is modifying the probability distribution.

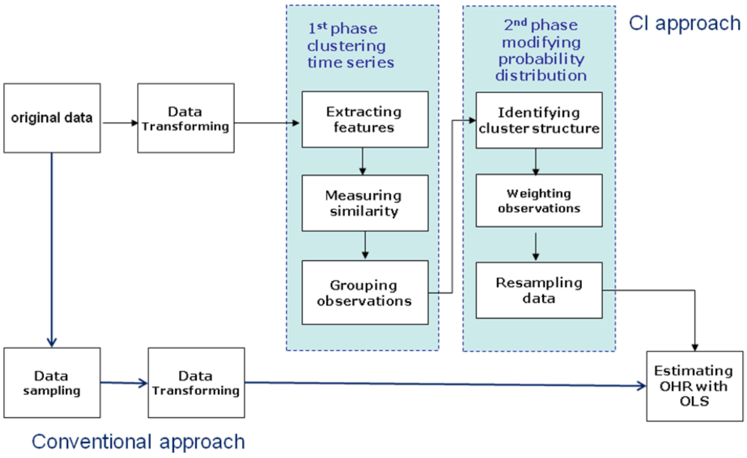

Figure 1. The computational intelligence approach.

The philosophy of the proposed approach is that data with similar dynamic behaviors may appear in the future with higher probability than dissimilar ones. Therefore, the objective of Phase I is to identify higher probability data, which would occur in the next hedging horizon based on the whole data set, and ignore lower probability data. In Phase II, the data omposed by the higher probability data are expected to be more approximate to the normal distribution than the original data, suggesting decreased inaccuracy caused by leptokurtic and fat-tailed distributions. Details of the proposed model are described in the following sections.

B. Clustering Time Series

Phase I of our proposed approach is clustering time series. Cluster analysis is an unsupervised learning method that can gather similar data in the same group by feature extraction and similarity measurement. Consequently, the features of time series and the algorithm for measuring similarity should be determined when applying the proposed approach. Many research works indicate that dynamic behaviors exist in financial time series, and these dynamic behaviors are helpful for time series forecasting [18] [19]. The dynamic behaviors often refer to the velocity and the acceleration of a moving object, which are computed by the first-order and second-order differencing of the object position, respectively. In other words, dynamic behaviors can be defined as the speed of change and the acceleration of change. OHR estimation is relative to bivariate random variable analysis, which considers the joint probability distribution of spot and futures return series, and focuses on variance and covariance analysis. Dynamic behaviors—the interest of this study—are the variance of spot and futures return series, as well as the speed and acceleration of variance change. Furthermore, the time series of financial asset returns often exhibits the volatility clustering property. As noted by Mandelbrot [20], "large changes tend to be followed by large changes, of either sign, and small changes tend to be followed by small changes." Therefore, the variance, speed of variance change, and acceleration of variance change are adopted as dynamic behaviors, which represent the features of time series and are extracted for clustering. The other features of the time series that are helpful for OHR estimation, such as price spread [21] and covariance of joint distribution, are also considered and tested in this study.

The cluster algorithm chosen in this study is GHSOM, but not k-mean, SOM, and others, because of three main reasons. The first relates to the benefits of the hierarchical structure. Cluster algorithms can be classified into two categories, non-hierarchical and hierarchical. For the non-hierarchical structure, the degree of similarity for each cluster is obtained by measuring the distance between cluster centers. When we want to collect a certain number of observations (i.e., the most similar), the distance of cluster centers for measuring the similarity is hardly determined. However, for the hierarchical structure, the degree of similarity for each cluster can be obtained in a more natural manner depending on the layer it belongs to in the hierarchical structure. Second, the result of GHSOM is stable regardless of cluster number. Many cluster algorithms should determine the number of clusters prior to their application. However, the best number of clusters for analysis is unknown, and the clustering results are often unstable with the cluster number. GHSOM can grow and expand the hierarchy of a cluster by parameter setting, which can determine the number of clusters automatically and is not sensitive to clustering results. The last reason is that the similarity measurement function of various cluster algorithms are not sensitive to the clustering results [22]. Therefore, GHSOM is adopted in this study for clustering time series.

C. Modifying the Probability Distribution

Many properties of financial time series are time variant. We suggest that the probability distribution should be time variant, and estimated and updated by the latest time series data. We are also interested in the accuracy of forecasting. Observations with similar behavior may occur more frequently in the future and should be more emphasized than the dissimilar ones. However, when data are grouped by cluster analysis, the original data are divided into several groups, with each group only containing partial data. The number of similar data is far less than the original data. Reducing sample size causes inaccuracy when OLS for OHR estimation is employed [23]. To overcome this problem, we propose to adopt with-in cluster resampling. With-in cluster resampling has been used for solving sample-reduced problems in the biometric field [24] [25]. The observations of the cluster are replicated to expand the sample size. This idea is inspired by the stratified resampling scheme and bootstrap resampling method. The architecture of hierarchical cluster is very similar to the hierarchical stratified resampling scheme, in which the observations are divided into several groups according to their properties. Each group is weighted by the number of observation replications. Bootstrap method, which replicates the observation randomly to simulate the status in the future based on few observations, has been commonly used in finance and economics models. Therefore, in this study, observations in the cluster are randomly replicated until the sample size reaches the number size of the population.

III. PROCEDURE OF THE PROPOSED MODEL

A. Data Transformation

The original data for OHR estimation gathered from the financial market are the daily closing (or settlement) prices of spot and futures. Generally, these price series are transformed into return series in consideration of payoffs in finance. The return series can be obtained by differencing the price series. We consider continuously compounded data and magnify the scale by multiplying by 100 to avoid a small scale. The return series is expressed as the price change:

$$\Delta S_t, \Delta F_t = \ln(P_t / P_{t-1}) \times 100 \tag{1}$$

where ΔS and ΔF are price changes of spot and futures, respectively; P is the price series; and t refers to the time at present.

These return series are then divided into two parts, in-sample estimating period and out-of-sampling testing period. The hedge portfolio in this study is adjusted every hedging horizon according to the latest estimated OHR until the out-of-sample testing period is due. A rolling window scheme is applied to achieve the dynamic hedging strategy. The rolling windows scheme estimates the OHR at time t according to the conditioning on the time t-1 data set, which is exhibited in Fig. 2. Herein, e denotes the in-sample estimating period while h is the hedging horizon. The length of the rolling window is e+h.

OHR is estimated based on the observations in the in-sample estimating period, from t-e to t, then used for hedging from t to t+h. Next, the window is rolled one hedging horizon ahead in order to reestimate the OHR based on the observations from t+h-e to t+h. Then, we use the new OHR for the next hedging horizon, from t+h to t+2h. OHR is reestimated every h day, and then used to adjust the hedging portfolio until the out-of-sample testing period is due.

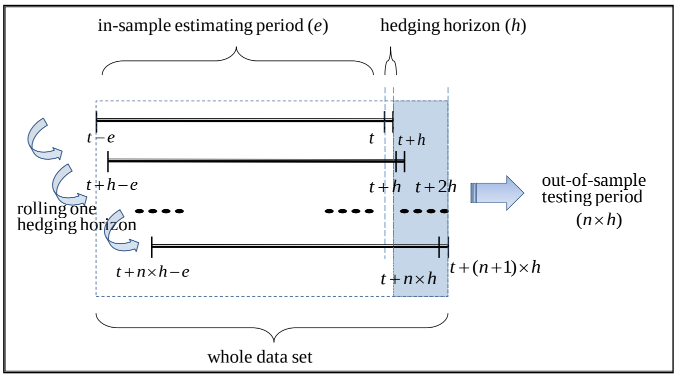

Figure 2. The rolling windows scheme.

TABLE I. FEATURES OF THE OBSERVATION

Input Variables	Notations
Variance	
Variance of spot return series	$Var(\Delta S)$
First order differential of $Var(\Delta S)$	$Var'(\Delta S)$
Second order differential of $Var(\Delta S)$	$Var''(\Delta S)$
Variance of futures return series	$Var(\Delta F)$
First order differential of $Var(\Delta F)$	$Var'(\Delta F)$
Second order differential of $Var(\Delta F)$	$Var''(\Delta F)$
Covariance	
Covariance of spot and futures return series	$Cov(\Delta S, \Delta F)$
First order differential of $Cov(\Delta S, \Delta F)$	$Cov'(\Delta S, \Delta F)$
Second order differential of $Cov(\Delta S, \Delta F)$	$Cov''(\Delta S, \Delta F)$
Price spread	
Spread of spot and futures price series	$Spread(S, F)$
First order differential of $Spread(S, F)$	$Spread'(S, F)$
Second order differential of $Spread(S, F)$	$Spread''(S, F)$

B. *Dynamic Behaviors Feature Extracting*

In this study, variance, covariance, price spread, and their first and second differencing are adopted as the features of time series. These features are calculated using the data in the most recent hedging horizons just before the present; it is denoted by h. These features are calculated as follows:

$$Var(\Delta S_t) = Var[\Delta S_{t-h}, \ldots, \Delta S_t] \tag{2}$$

$$Var(\Delta F_t) = Var[\Delta F_{t-h}, \ldots, \Delta F_t] \tag{3}$$

$$Cov(\Delta S_t, \Delta F_t) = Cov\begin{bmatrix} \Delta S_{t-h}, \ldots, \Delta S_t \\ \Delta F_{t-h}, \ldots, \Delta F_t \end{bmatrix} \tag{4}$$

$$Spread(S_t, F_t) = F_t - S_t \tag{5}$$

The first and second order difference of these features are shown as

$$X_t' = \frac{X_t - X_{t-1}}{X_{t-1}} \quad (6)$$

$$X_t'' = \frac{X_t' - X_{t-1}'}{X_{t-1}'} \quad (7)$$

where X represents the functions of Var, Cov, and $Sperad$. These extracted features from a period of data can represent the dynamic behavior of time series in the recent hedging horizon. Twelve values listed in Table I are selected to describe an observation and used as the input variables of GHSOM.

C. Clustering by GHSOM

Each observation can extract a feature vector from the data from the previous hedging horizon. The feature vectors of the observations in the estimation interval include input matrix of GHSOM for OHR estimation. The GHSOM algorithm in this study is implemented in MATLAB [26]. When applying the GHSOM, the parameters related to network topology need to be determined first. We set the depth parameter as 0.001 and the breadth parameter as 0.8. Items that cannot be expanded are restricted when they are less than 100. The topology of the clusters is automatically determined by the data and related with the threshold setting of width and depth expansion. The feature vectors are processed by min-max normalization, which maps the value of the vector from -1 to 1. Normalization can ensure stable results.

The historical financial time series data are then hierarchically clustered by the GHSOM with similar patterns. Results show that the hierarchical architecture consists of many clusters distributed in different layers. The relations of hierarchical clusters are illustrated in Fig. 3. The sample size of each cluster is different. Clusters in the upper layers of the hierarchical architecture contain more samples of observations than those in the lower layers. The hierarchical architecture also represents the degree of similarity. Any observation can be identified on the cluster based on the layer it belongs to. The host cluster in the lowest layer contains the least data but has the highest similarity with the forecasting data. In addition, similarity with data is decreased in the upper layer clusters.

With regard to the latest observation in the estimation interval, similar observations can be obtained based on the group it belongs to in each layer. To forecast the fluctuation of the spot and futures for the next hedging horizon, we collect the observations which are one hedging horizon ahead the similar observations in the same clusters. Fig. 4 illustrates the observations collection for forecasting. These observations are weighted by similarity based on the cluster they belong to, and are used to modify the probability distribution for OHR estimation.

D. Data Resampling and Weighting

Regardless of similarity in data, every observation in the estimation interval is given equal weight for OHR estimation in the conventional model. In our proposed CI approach, for OHR estimation, the observation is given a different weight according to similarities. Although the size of the clusters obtained by GHSOM is different, the more similar data in the lower level clusters would be given more weight than the upper level clusters in the resampling process. The weights of observation are suggested for data replication. The more similar data will be replicated more frequently, thus increasing the occurrence probability in the whole population.

Figure 3. An example of the hierarchical clustered data.

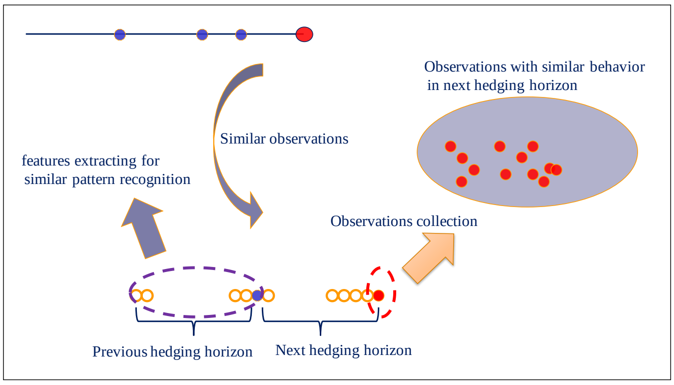

Figure 4. The observations collection for forecasting

For each layer in the hierarchical cluster, the data in the same cluster are replicated randomly until the sample size coincides with the original sample size of the estimation period. The sample size is expanded by multiplying the layer of the hierarchical architecture. For example, in the conventional approach, if the size of observations in the estimating period is 1000, the OHR for the next hedging horizon is estimated based on 1000 observations. In the proposed CI approach, if 1000 observations are clustered into three layers by GHSOM, the OHR will be estimated based on triple observations, all generated by resampling. The expansion of sample size avoids the small sample effect and increases the accuracy of OHR estimation.

After data resampling, we can obtain a collection of observations composed of similar data in the cluster and consequent observations in the following hedging horizon with different weight.

E. Estimating OHR with OLS

The basic concept of hedging involves the elimination of fluctuations in the value of a spot position by tracking futures contracts that are opposite to the position held by the spot market. For a long position in the spot market, the return of a hedged portfolio is given by

$$\Delta HP = \Delta S - r \times \Delta F \tag{8}$$

where ΔHP is the change in the value of the hedge portfolio; ΔS and ΔF are the changes in the spot and futures prices, respectively; and r is the hedge ratio. Changes in spot and futures prices are also considered as returns, which are calculated by Equation (1). OHR is the value of r that maximizes the expected utility of the investor; it is defined as the expected return and risk of the hedged portfolio. The expected return of futures is 0 when the futures price follows a martingale;

hence, the futures position will not affect the expected return of the portfolio.

The risk of the hedge portfolio is defined by its variance in the mean-variance framework. Therefore, OHR is simply the value of r that minimizes the variance of Equation (8), which is given by

$$\frac{\partial Var(\Delta HP)}{\partial r} = 2r \times Var(\Delta F) - 2Cov(\Delta S, \Delta F) = 0 \tag{9}$$

where $Var(\Delta F)$ is the variance of the futures return and $Cov(\Delta S, \Delta F)$ is the covariance between the spot return and the futures return. OHR is determined by solving Equation (9):

$$r^* = \frac{Cov(\Delta S, \Delta F)}{Var(\Delta F)} \tag{10}$$

The OHR given by Equation (10) can be estimated by regressing the spot return on the futures return using OLS, which corresponds to conventional OHR.

In this study, OHR estimation is improved by replacing the original observations in the estimation period with the collection of observations, which is composed of similar data in the cluster. Their consequent observations in the following hedging horizon have different weights. The traditional OLS method for OHR estimation, expressed by Equation (10), is modified to Equation (11), in which $\Delta\tilde{S}$ and $\Delta\tilde{F}$ refer to the collection of observations derived from spot and futures return series, respectively.

$$r^* = \frac{Cov(\Delta\tilde{S}, \Delta\tilde{F})}{Var(\Delta\tilde{F})} \tag{11}$$

F. Model Evaluating Criteria

Hedging Effectiveness: Hedging performance is typically evaluated by hedging effectiveness (HE). The degree of hedging effectiveness is measured by the percentage reduction in the variance of portfolio after hedging (Geppert, 1995). The variance of hedge portfolio with estimated OHR can be expressed as

$$Var_{hedged} = Var(\Delta HP) = Var(\Delta S_t - r \times \Delta F_t) \tag{12}$$

where r is the OHR. Therefore, HE can be expressed as

$$\begin{aligned} HE &= \frac{Var_{un-hedged} - Var_{hedged}}{Var_{unhedged}} \times 100\% \\ &= \frac{Var(\Delta S) - Var(\Delta HP)}{Var(\Delta S)} \times 100\% \\ &= (1 - \frac{Var(\Delta HP)}{Var(\Delta S)}) \times 100\% \end{aligned} \tag{13}$$

The value of HE can be used to evaluate the model of OHR estimation. A higher HE represents better OHR estimation, and vice versa.

White's Reality Check: In comparing the different OHR estimation models and to test the statistical significance of variance deduction, we apply White's Reality Check [27], which has been used to compare hedging models [28]. The Reality Check consists of a non-parametric test that checks if any of the numbers in the concurrent methods yield forecasts that are significantly better than a given benchmark method; then, it corrects the data snooping bias. Data snooping bias may occur when a given dataset is reused by one or more researchers for model selection. The null hypothesis that the performance of the proposed hedging model has no predictive superiority over the conventional model is not rejected. The hypotheses are as follows:

H0: No method is better than the benchmark.

H1: At least one method is better than the benchmark.

The detailed process of White's Reality Check can be found in [27] and [28].

IV. EXPERIMENTS AND RESULTS

A. *Experimental Design*

Fig. 5 shows the framework of the experiments. The feature-extracting process of the proposed model is tested in different settings to achieve the best parameters. The feature vectors that represent the dynamic behaviors of time series for GHSOM similarity measurement are composed of variance, covariance, price spread, and their first and second order differences. We design six combinations of these parameters, which are adopted in the experimental models and denoted by CI_1, CI_2, CI_3, CI_4, CI_5, and CI_6, respectively, to verify the performance over various hedging horizons. Table II presents the parameter settings of these models.

Moreover, the optimal hedge ratio is estimated by the proposed model concerned with the hedging horizon, and the performances are compared with conventional models. For each hedging horizon in the testing period, the hedged portfolio is adjusted once according to the latest OHR at the beginning of a hedge horizon and lasts until the beginning of the next hedging horizon. At the end of the testing period, hedging effectiveness is calculated based on the variance of the hedging portfolio in each hedging horizon. Hedge horizons in the experiments are set at 1, 7, 14, 21, and 28 days, which cover the intervals from short-term to long-term. The superiority of the proposed model is verified using two conventional models, the OLS and naïve models, both of which are widely used in OHR research on different hedging horizons [29] [30].

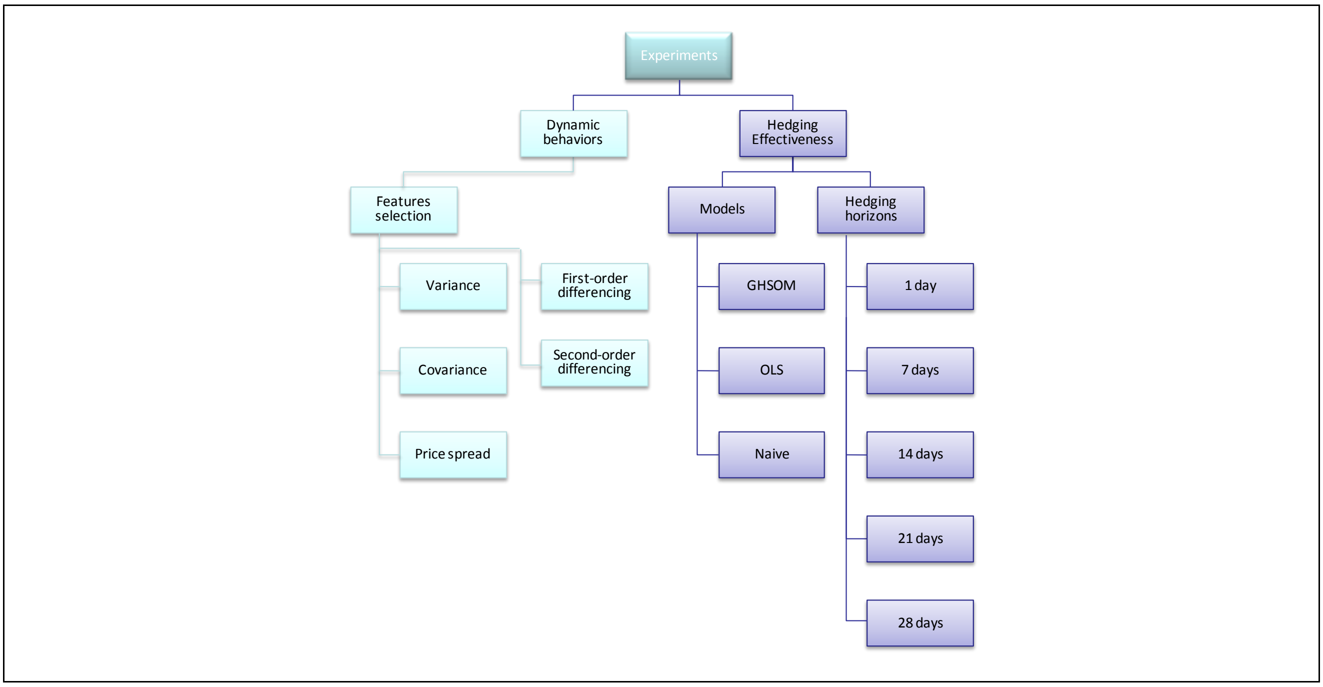

Figure 5. Experiment framework

TABLE II. PARAMETER SETTINGS FOR TESTING DYNAMIC BEHAVIORS

Model	Parameter setting: Variance	Covariance	Price spread
CI_1	$Var(\Delta S)$, $Var(\Delta F)$		
CI_2	$Var(\Delta S)$, $Var(\Delta F)$ $Var'(\Delta S)$, $Var'(\Delta F)$ $Var''(\Delta S)$, $Var''(\Delta F)$		
CI_3	$Var(\Delta S)$, $Var(\Delta F)$	$Cov(\Delta S, \Delta F)$	$Spread(S, F)$
CI_4	$Var(\Delta S)$, $Var(\Delta F)$ $Var'(\Delta S)$, $Var'(\Delta F)$ $Var''(\Delta S)$, $Var''(\Delta F)$	$Cov(\Delta S, \Delta F)$	$Spread(S, F)$
CI_5	$Var(\Delta S)$, $Var(\Delta F)$	$Cov(\Delta S, \Delta F)$ $Cov'(\Delta S, \Delta F)$ $Cov''(\Delta S, \Delta F)$	$Spread(S, F)$ $Spread'(S, F)$ $Spread''(S, F)$
CI_6	$Var(\Delta S)$, $Var(\Delta F)$ $Var'(\Delta S)$, $Var'(\Delta F)$ $Var''(\Delta S)$, $Var''(\Delta F)$	$Cov(\Delta S, \Delta F)$ $Cov'(\Delta S, \Delta F)$ $Cov''(\Delta S, \Delta F)$	$Spread(S, F)$ $Spread'(S, F)$ $Spread''(S, F)$

TABLE III. EXPERIMENT DATA

Index (Spot)	Exchange (Futures)	Observations
Taiwan Weighted Index (TWI)	Taiwan Futures Exchange (TAIFEX)	2217

Note: Data period is from July 21, 1999 to July 18, 2008.

B. *Experiment Data*

This study obtained empirical trading data of the daily closing price from Taiwan stock and futures markets. Table III lists the stock market index and exchange of their correlative futures contracts trade. All data were obtained from the Thomson Datastream database in the same period from July 21, 1999 to July 18, 2008. The futures prices series was gathered from the nearest month contracts and rolled over to the next nearest contracts on the maturity day due to the consideration of liquidity and price spread risk. Among the total observations, the first 90% is considered the estimation period, and the remaining 10% is considered the testing period.

C. Results of the Dynamic Behavior Prediction

Table IV presents the hedging effectiveness for all models. Results indicate that based on the same experiment data, the

TABLE IV. COMPARISONS OF DYNAMIC BEHAVIORS

Market/model		Hedging effectiveness				
		Hedging horizon (days)				
		1	7	14	21	28
TWI						
CI	1	93.3309% *	97.1661% **	99.2656%	99.3811%	99.3131%
	2	93.3905% **	97.1534% *	99.2480%	99.3942%	99.3556% *
	3	93.2715%	96.9289%	99.2751%	99.3947%	99.3160%
	4	93.0998%	96.8809%	99.2879% *	99.4342% *	99.3802% **
	5	93.1081%	97.0102%	99.3111% **	99.4327%	99.3431%
	6	93.1798%	96.9169%	99.2047%	99.4666% **	99.3470%
OLS		93.3055%	97.0244%	99.1612%	99.3860%	99.3089%
Naïve		90.6982%	96.0278%	98.5331%	99.0888%	98.8415%

Note: ** and * represent the best and second best HE among eight models at the same hedging horizon, respectively.

CI-based model can obtain the best performance compared with the traditional OLS and naïve models. A comparison of the six experiment models indicates that the best CI-based model is different over different hedging horizons. The results imply that the ability to capture fluctuation under various timescales is different for CI-based models. Short-term dynamic behavior may be captured by variance and its first and second differences. Long-term tendency may need more variables for its description than short-term tendency by adding covariance and price spread.

D. Results of the Hedging Performance

For a comparison of hedging performance, we list the best CI-based model from the six experiments models, and the two conventional models (naïve and OLS) in Table V. The hedging performance of the model is evaluated using hedging effectiveness and statistic testing for significance of superiority. The hedging effectiveness of the model is calculated using the variance reduction of the hedged portfolio (Table IV). Table V presents the variance of unhedged and hedged portfolios employed in White's reality check to verify the significance of superiority.

Table V shows that increasing the hedging horizon will increase the variance of unhedged portfolio but will be effectively reduced by the hedging model. The percentage of variance reduction, shown as hedging effectiveness in Table IV, is higher in a long hedging horizon than in a short one.

The value of hedging effectiveness is slightly different in these models. To test the significance of these models' performance improvements, we perform White's reality check. When OLS is treated as the benchmark, the null hypothesis of no improvement of CI-based model over benchmark is rejected for 28 days hedging in TWI at the significance level of 1%. Results of the reality check provide evidence that the proposed CI-model can improve the OLS model, especially in long-term hedging.

TABLE V. VARIANCE OF THE PORTFOLIO

Market/models	Variance				
	Hedging horizon				
	1	7	14	21	28
TWI					
Unhedged	2.7527	20.5443	41.8060	35.5709	39.9629
Naïve	0.2561	0.8161	0.6132	0.1840	0.1698
OLS	0.1843	0.6113	0.3507	0.1454	0.1546
CI-based	0.1819 ***	0.5822 ***	0.2880 ***	0.1148 ***	0.1056 ***
Reality check p value	0.134	0.026 *	0.015 *	0.085	0.000 **

Note: (1) The benchmark model for White's reality check is the OLS model. (2) * and ** represent significance at the 5% and 1% levels, respectively. (3) *** represents the minimum variance among the naïve, OLS, and CI-based hedged portfolios.

V. CONCLUSION AND FUTURE WORK

In this study, we propose a novel computational intelligence approach to estimate the time-varying minimum variance hedge ratio. Clustering time series are employed to recognize the observations with similar time series patterns. Observations with a high possibility of occurrence in the future are selected when hedging. These observations are used to modify the distribution probability of time series data using a resampling process with different weights given based on cluster result. The empirical findings in this study are consistent with the following notations. First, hedging horizon will increase hedging effectiveness. When hedge horizon is increased, hedging effectiveness is also increased. Second, the proposed CI-based model can improve the typical OLS model, especially in long-term hedging.

This study evidences that the proposed model is superior to the conventional OLS model in hedging effectiveness, but the usability of this computational approach is worse than conventional OLS model. Many factors, such as the breadth and depth parameters of GHSOM, the period of data for feature extraction, which may influence the performance of the proposed model, should to be determined appropriately in practical use. Further, most non-parametric models based on computational intelligence are challenged that the experiment results of non-parametric model are more unstable than parametric model when repeating the experiments.

Although this research still have some restriction of model parameters selection, this novel approach based on computational intelligence can improve the performance of traditional approach without too many inappropriate assumptions and restrictions. Consequently, the proposed model can also be considered as a powerful tool to investigate any financial market, in which the probability distribution of data is unrestricted and not necessary to fit any type of probability distribution.

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計畫成果自評

本研究之成果與原申請計畫內容大致相符。原規劃兩年研究期間，後經核定為一年，因此我們主要著重在原計畫之第一年，避險交易決策支援模型的建立，而原第二年雲端運算服務設計與實作的部分，則先進行初步的探討。研究中我們建構出一個避險比例估算的模型，適合部署到雲端服務的架構中，可用來發展雲端化的交易決策支援系統，並就避險交易之決策支援系統進行實證，相關成果已發表於澳洲舉辦的IEEE IJCNN 2012 (WCCI 2012)國際研討會中。

唯原先規劃第二年的雲端服務建構與部署，需要建構高效能運算的伺服器，這個部分以目前計畫主持人所能應用的研究資源並無法支援後半部雲端化的研究，而本計畫所提之電腦設備補助也未獲通過，在缺少硬體資源環境下，我們採取了先導試驗的作法，嘗試以國家高速電腦中心所發展的免費Ezilla雲端虛擬環境，配合幾部已屆使用年限但堪用的個人電腦，架構出雲端服務的環境，來進行雲端化可行性的評估，主要是要驗證研究中所提出來的實驗模型，是否可以分散在多部的虛擬電腦中執行，構成一個雲端化的決策支援系統。未來若有相關的電腦硬體資源，將可延續本計畫之成果，建立一個私有化的雲端決策支援系統，作為投資銀行、基金經理人、公司財務部門，進行期貨避險交易之參考，藉由雲端化的服務達到公司內部多人共用資源的效益，並且可進一步發展出提供一般社會大眾專業理財避險試算服務的商務模式。

相關論文發表

1. Yu-Chia Hsu, An-Pin Chen (2012), "Futures hedging using clusters with dynamic behavior of market fluctuation," Proceedings of the 2012 International Joint Conference on Neural Networks (IJCNN), June 10-15, 2012. Brisbane, Australia. (EI)

國科會補助專題研究計畫項下出席國際學術會議心得報告

日期：101 年 7 月 30 日

計畫編號	NSC 100－2410－H－028－005		
計畫名稱	以雲端服務為基礎之期貨避險交易決策支援系統		
出國人員姓名	許育嘉	服務機構及職稱	國立臺灣體育運動大學 助理教授
會議時間	101 年 6 月 10 日至 101 年 6 月 15 日	會議地點	澳大利亞 布里斯本
會議名稱	(中文) 2012 類神經網路國際聯合研討會 (英文) 2012 International Joint Conference on Neural Networks (IJCNN)		
發表論文題目	(中文)利用市場波動動態行為之群集分析進行期貨避險 (英文) Futures hedging using clusters with dynamic behavior of market fluctuation		

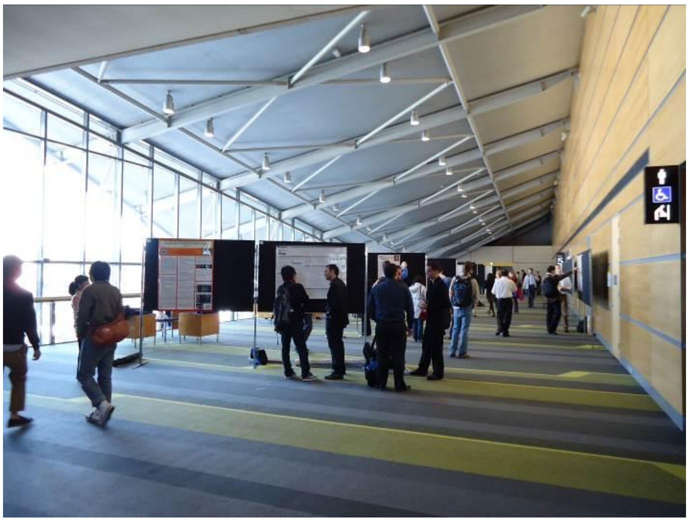
一、參加會議經過

此次 2012 the IEEE International Joint Conference on Neural Networks (IJCNN)舉行之地點在澳大利亞的布里斯本市國際會議中心。這個研討會是 IEEE Computational Intelligence Society 每年必辦的年度計算智慧系列研討盛會，也就是目前計算智慧規模最大的 IEEE World Congress on Computational Intelligence (IEEE WCCI 2012)研討會，與 2012 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE 2012)和 IEEE Congress on Evolutionary Computation (IEEE CEC 2012)共同舉辦。本次國科會專題研究計畫的部分成果，很榮幸的被接受了，安排在 Computational Intelligence In Finance, Economics and Management Sciences 的 session 中報告。

研討會舉辦的第一天，在正式議程開始前安排了許多場次的 workshop，而這些 workshop 是需要另外付費的，因考量到研究領域的獨特性與專業性，以及旅途中搭機的疲累，因此未參加。正式的會議於第二天才展開，開場安排由會議主席、主辦單位人員上台致詞，而後則安排了研討會的專題演講，之後則開始了正式的分組論文簡報，三個研討會的場地幾乎涵蓋了整個國際會議廳，同步舉行。往後的幾天時間，大部分的時間我們選擇參加與本研究相關的金融決策支援系統與計算智慧相關主題，來了解國際上相關研究的進展現況。

我們的論文告被安排在最後五天下午的場次。而參加該 session 的人數約有 30 幾位，而報告完論文後，可能是因為金融資訊研究領域的獨特性，因此所提出來的發問不多，僅 session chair 就部分細節進行發問，也許是因為以英語報告流暢度的關係，以致於未引起大量的討論。

以下摘錄幾場參加 Panel Sessions 以及 Poster Sessions 等所拍攝的紀錄相片供參考。



圖一、Poster Sessions

圖二、Panel Sessions

圖三、研討會分組報告

圖四、晚宴

二、與會心得

這次研討會收穫良多，茲將心得整理如下：

- 會議的多元化：

    這次的研討會由於是三個研討會共同舉辦，因此共安排的 Panel Sessions 和 Keynote Speech 場次相當多。儘管有一些演講、論文報告與我們所從事的領域不盡相同，但藉由研討會的參與友有機會了解相近領域的學者所從事的研究，也未嘗不是在將來進行跨領域整合研究的基礎。

- 學者之交流：

    這個研討會參與的人數相當的多，而海外的華人也占了一大部分的比例。在會議報告空檔間以及晚宴的交流中，認識了來自新加坡大學的一位陳教授，而他也是

CEC 會議的組織委員之一，比較遺憾的是由於會議規模與場地分布實在太大了，很多學者專家除了 Keynote speaker 的演講場地之外，不容易再遇到第二次。甚至有一些原本在台灣就認識的專家學者，到了會議現場也不容易遇到。

- 研究方向的肯定：

  從這次研討會許多學者得報告中，都提到了計算智慧中「權重」得計算，這跟本研究中所提出的將權重依據日期的遠近以及動態行為的相似度來計算的觀念是不謀而合，只是各領域的學者以不同的方式來演繹出不同的演算法。這給了我們很大的啟發，如果金融投資決策的相關主題不為一般計算智慧的期刊所接受，其實可以改變一下投稿的策略，將其中的演算法與模型獨立提出，再以金融上的應用來做實證，不外乎是一個很可行的期刊投稿策略，也希望在將來這篇研討會論文的延伸，可以獲得重要期刊的接受刊登。

三、考察參觀活動(無是項活動者省略)

於會議的空檔中自費參加團體一日遊前往摩頓島參觀，很巧的是小團體的成員大都是此次研討會的學者，而研討會每日的傍晚結束後，幾乎整個布里斯本市區，都是參加會議的學者，整個研討會的規模是我前所未見的。

四、建議

很感謝國科會提供補助可以讓我增加國際研討會發表的經驗，有助於針對目前的研究主題，更進一步地發表至期刊中。藉由聆聽、觀摩其他場次及研究主題，也有助於研究上的創新。而對於一位本土培養的博士而言，語言能力大致可以進行論文報告沒有問題，但在社交活動上的閒聊與交談，則還需加強英語會話能力。

五、攜回資料名稱及內容

1. 會議議程手冊
2. 會議論文集 USB
3. 會議紀念品(小背袋、T shirt)
4. 會議期間交流學者名片

六、其他

1. 論文接受證明
2. 論文全文

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IJCNN 2012 Paper #226 Decision Notification

1 封郵件

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Congratulations! On behalf of the IJCNN 2012 Program Chairs, we are pleased to inform you that your paper:

Paper ID: 226
Author(s): Yu-Chia Hsu and An-Pin Chen
Title: Futures Hedging Using Clusters with Dynamic Behavior of Market Fluctuation

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Sincerely, Kate Smith-Miles <ijcnn2012@ieee-cis.org>

REVIEWERS' COMMENTS

REVIEW NO. 1

Originality: Strong Accept
Significance of topic: Strong Accept
Technical quality: Strong Accept
Relevance to IJCNN 2012: Strong Accept
Presentation: Strong Accept
Overall rating: Strong Accept

Reviewer's expertise on the topic: High
Suggested form of presentation: Oral
Best Paper Award nomination: No

Comments to the authors:
This paper is rigorously written, and has quite eloquently extended the self-organizing maps to clustering financial time series for hedging purpose. The paper is rather well balanced developed and I don't have specific comments except one reference. The idea of using self-organizing maps to cluster financial time series was first initial by Chen and He (2003). This citation, unfortunately, is missing in the literature review. This paper can be more self-contained if this pioneering citation can be added.

Chen, S.-H, He H (2003) Searching financial patterns with self-organizing maps. In S.-H. Chen and P. P. Wang (eds.), Computational Intelligence in Economics and Finance, Springer-Verlag, 2003, pp. 203-216.

REVIEW NO. 2

Originality: Accept
Significance of topic: Accept
Technical quality: Accept
Relevance to IJCNN 2012: Accept
Presentation: Accept
Overall rating: Accept

Reviewer's expertise on the topic: High
Suggested form of presentation: Any
Best Paper Award nomination: No

Comments to the authors:
This is a well-done and interesting paper. It uses an ANN model made of independent growing self-organizing maps to develop a pattern for optimal hedge ratios. This new approach to clustering time series data is well-documented and explained. This paper will be of interest to anyone working in financial markets.

REVIEW NO. 3

Originality: Accept
Significance of topic: Accept
Technical quality: Accept
Relevance to IJCNN 2012: Accept
Presentation: Accept
Overall rating: Accept

Reviewer's expertise on the topic: Medium
Suggested form of presentation: Any
Best Paper Award nomination: No

Comments to the authors:

The paper demonstrates a novel method of hedging, using clustering. It is close to being ready for publication 'as is'. The displayed understanding of the financial aspects is very good, and the maths seems in order too. A brief description or more explicit reference to the naive method of hedging would be useful. The English in 'Conclusions and Future Work' should be improved.

Futures Hedging Using Clusters with Dynamic Behavior of Market Fluctuation

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***Abstract*—In this study, a novel procedure of time series dynamic behaviors clustering is proposed to improve the accuracy of minimum -variance optimal hedge ratio (OHR) estimation for future hedging. The dynamic behaviors of market fluctuation are extracted by measurement of variances, covariance, price spread, and their first and second differences. The behaviors with similar patterns are clustered using a growing hierarchical self-organizing map (GHSOM). The observations for OHR estimation are collected based on the hierarchical cluster structure and processed by within-cluster resampling. The spots and futures of the Taiwan Weighted Index (TWI) are adopted to demonstrate that the futures hedge effectiveness can be significantly improved.**

Keywords-cluster analysis; financial time series; hedge ratio; GHSOM

I. INTRODUCTION

With the emergence of financial derivatives markets in the past two decades, hedging has been of interest to both academicians and practitioners. The goal of hedging is to minimize exposure to unwanted risk. This is carried out by establishing the position of a derivative instrument to offset exposure to price fluctuations opposite to that of underlying assets, such as using futures to hedge a portfolio of risky assets. The primary objective is to estimate the size of the short position that must be held in the futures market (i.e., a proportion of the long position held in the spot market) with minimal risk and specific risk aversion of the hedged portfolio.

Many methods have been used to decide the OHR. Most studies adopt the mean-variance framework, which measures the risk of the hedged portfolio by standard deviation, and which assumes that OHR simply minimizes the variance of hedged portfolios. Many applications of optimal hedging use the criterion of minimum variance to estimate OHR, such as by regressing the spot market return on the futures market return using ordinary least squares (OLS) [1] [2] [3]. However, OHRs estimated via the conventional approach is constant over time. The classical time-invariant OHR appears inappropriate with the time-varying nature of many financial markets. Improvements were made to capture time-varying features, such as by adopting dynamic hedging strategies based on the bivariate generalized autoregressive conditional heteroskedasticity (GARCH) framework [4] [5] [6] [7] [8] or the stochastic volatility (SV) model [9] [10].

These approaches to estimating the OHR are based on sample variance and covariance estimators of returns without considering the underlying distribution of data. The conventional OLS approach ignores the conditional distribution of most financial asset returns, which tends to vary over time. To obtain recent information, most research adopt a rolling window scheme to estimate the variance and covariance of spot and futures returns. However, rolling window estimators use an equally weighted moving average of past squared returns and their cross products. Observations have equal weight in the variance-covariance matrix estimator of the arbitrarily defined estimation period, but they have zero weight beyond the estimation period. GARCH class models are successful in capturing time-varying features for estimating conditional variance-covariance matrices, but they place too much weight on extreme observations [11] when the distribution of data is leptokurtic and fat-tailed.

In this paper, our work employs a different weight for observations in a rolling window OLS estimator of the variance-covariance matrix subsequent to the clustering time series using growing hierarchical self-organizing map (GHSOM) [12]. The weights of observations are determined by the measurement of similar patterns, which are correlated with the sample size of the cluster they belong to in the hierarchy architecture. The observations with different weights in clusters are then used to predict the conditional distribution of spot and futures returns for different hedging horizons in the future. When the conditional distribution of spot and futures returns is predictable, a more efficient estimate of the OHR can be obtained by conditioning on recent information.

The new approach uses GHSOM to cluster time series data, which could decompose financial data into a hierarchical architecture consisting of several familiar clusters. Several applications of cluster analysis to economics and finance time series have been documented in recent literature, including identification of mutual funds styles by analyzing the time series of past returns [13], searching similar financial patterns [31], discovery of companies that share similar behavior with the Dow Jones industrial average (DJIA) index [14], prediction of value at risk [15], prediction of oil futures price [16], and determination of optimal tracking portfolio [17].

The application of GHSOM to clustering time series to improve the conventional OHR estimator has several salient advantages. Observations within the cluster with similar patterns provide a way for examining the dependency of observations, which are generated from long-horizon return series and can provide predictable time patterns. The conditional distribution of returns in the next hedging horizon is predictable by aggregating these clustered observations, which are inspired by the well-established features of many asset returns that their conditional distribution is time-varying and tendency display volatility clustering. Further, the proposed approach is a non-parametric method, which can avoid too many inappropriate assumptions and restrictions found in conventional parametric models.

The rest of the paper is organized as follows: Section II illustrates the idea of the proposed model for the OHR estimation; Section III details the procedure of the proposed model; Section IV presented the experiments design and results; and lastly, conclusions and the future works drawn from the study will be discussed in Section V.

II. THE PROPOSED MODEL

A. The Two Phases Computational Intelligence Aapproach

Instead of the conventional approach to OHR estimation, which is simply to regress the spot and futures series, two modifications of the conventional approach are proposed based on computational intelligence shown in Fig. 1. The original composition of data for OHR estimation is modified by the selected data with a similar pattern, which is performed in two phases. Phase I is clustering time series, and Phase II is modifying the probability distribution.

The philosophy of the proposed approach is that data with similar dynamic behaviors may appear in the future with higher probability than dissimilar ones. Therefore, the objective of Phase I is to identify higher probability data, which would occur in the next hedging horizon based on the whole data set, and ignore lower probability data. In Phase II, the data

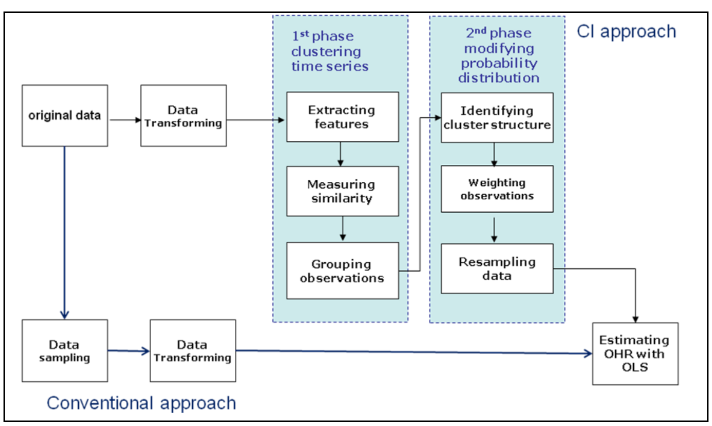

Figure 1. The computational intelligence approach.

composed by the higher probability data are expected to be more approximate to the normal distribution than the original data, suggesting decreased inaccuracy caused by leptokurtic and fat-tailed distributions. Details of the proposed model are described in the following sections.

B. Clustering Time Series

Phase I of our proposed approach is clustering time series. Cluster analysis is an unsupervised learning method that can gather similar data in the same group by feature extraction and similarity measurement. Consequently, the features of time series and the algorithm for measuring similarity should be determined when applying the proposed approach. Many research works indicate that dynamic behaviors exist in financial time series, and these dynamic behaviors are helpful for time series forecasting [18] [19]. The dynamic behaviors often refer to the velocity and the acceleration of a moving object, which are computed by the first-order and second-order differencing of the object position, respectively. In other words, dynamic behaviors can be defined as the speed of change and the acceleration of change. OHR estimation is relative to bivariate random variable analysis, which considers the joint probability distribution of spot and futures return series, and focuses on variance and covariance analysis. Dynamic behaviors—the interest of this study—are the variance of spot and futures return series, as well as the speed and acceleration of variance change. Furthermore, the time series of financial asset returns often exhibits the volatility clustering property. As noted by Mandelbrot [20], "large changes tend to be followed by large changes, of either sign, and small changes tend to be followed by small changes." Therefore, the variance, speed of variance change, and acceleration of variance change are adopted as dynamic behaviors, which represent the features of time series and are extracted for clustering. The other features of the time series that are helpful for OHR estimation, such as price spread [21] and covariance of joint distribution, are also considered and tested in this study.

The cluster algorithm chosen in this study is GHSOM, but not k-mean, SOM, and others, because of three main reasons. The first relates to the benefits of the hierarchical structure. Cluster algorithms can be classified into two categories, non-hierarchical and hierarchical. For the non-hierarchical structure, the degree of similarity for each cluster is obtained by measuring the distance between cluster centers. When we want to collect a certain number of observations (i.e., the most similar), the distance of cluster centers for measuring the similarity is hardly determined. However, for the hierarchical structure, the degree of similarity for each cluster can be obtained in a more natural manner depending on the layer it belongs to in the hierarchical structure. Second, the result of GHSOM is stable regardless of cluster number. Many cluster algorithms should determine the number of clusters prior to their application. However, the best number of clusters for analysis is unknown, and the clustering results are often unstable with the cluster number. GHSOM can grow and expand the hierarchy of a cluster by parameter setting, which can determine the number of clusters automatically and is not sensitive to clustering results. The last reason is that the similarity measurement function of various cluster algorithms are not sensitive to the clustering results [22]. Therefore, GHSOM is adopted in this study for clustering time series.

C. Modifying the Probability Distribution

Many properties of financial time series are time variant. We suggest that the probability distribution should be time variant, and estimated and updated by the latest time series data. We are also interested in the accuracy of forecasting. Observations with similar behavior may occur more frequently in the future and should be more emphasized than the dissimilar ones. However, when data are grouped by cluster analysis, the original data are divided into several groups, with each group only containing partial data. The number of similar data is far less than the original data. Reducing sample size causes inaccuracy when OLS for OHR estimation is employed [23]. To overcome this problem, we propose to adopt with-in cluster resampling. With-in cluster resampling has been used for solving sample-reduced problems in the biometric field [24] [25]. The observations of the cluster are replicated to expand the sample size. This idea is inspired by the stratified resampling scheme and bootstrap resampling method. The architecture of hierarchical cluster is very similar to the hierarchical stratified resampling scheme, in which the observations are divided into several groups according to their properties. Each group is weighted by the number of observation replications. Bootstrap method, which replicates the observation randomly to simulate the status in the future based on few observations, has been commonly used in finance and economics models. Therefore, in this study, observations in the cluster are randomly replicated until the sample size reaches the number size of the population.

III. PROCEDURE OF THE PROPOSED MODEL

A. Data Transformation

The original data for OHR estimation gathered from the financial market are the daily closing (or settlement) prices of spot and futures. Generally, these price series are transformed into return series in consideration of payoffs in finance. The return series can be obtained by differencing the price series. We consider continuously compounded data and magnify the scale by multiplying by 100 to avoid a small scale. The return series is expressed as the price change:

$$\Delta S_t, \Delta F_t = \ln(P_t / P_{t-1}) \times 100 \tag{1}$$

where ΔS and ΔF are price changes of spot and futures, respectively; P is the price series; and t refers to the time at present.

These return series are then divided into two parts, in-sample estimating period and out-of-sampling testing period. The hedge portfolio in this study is adjusted every hedging horizon according to the latest estimated OHR until the out-of-sample testing period is due. A rolling window scheme is applied to achieve the dynamic hedging strategy. The rolling windows scheme estimates the OHR at time t according to the conditioning on the time t-1 data set, which is exhibited in Fig. 2. Herein, e denotes the in-sample estimating period while h is the hedging horizon. The length of the rolling window is $e+h$.

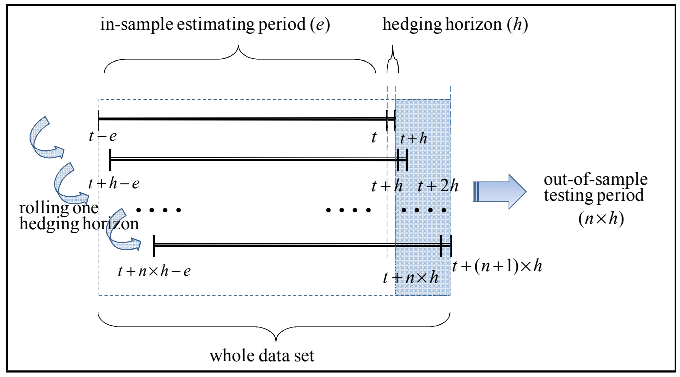

Figure 2. The rolling windows scheme.

TABLE I. FEATURES OF THE OBSERVATION

Input Variables	Notations
Variance	
Variance of spot return series	$Var(\Delta S)$
First order differential of $Var(\Delta S)$	$Var'(\Delta S)$
Second order differential of $Var(\Delta S)$	$Var''(\Delta S)$
Variance of futures return series	$Var(\Delta F)$
First order differential of $Var(\Delta F)$	$Var'(\Delta F)$
Second order differential of $Var(\Delta F)$	$Var''(\Delta F)$
Covariance	
Covariance of spot and futures return series	$Cov(\Delta S, \Delta F)$
First order differential of $Cov(\Delta S, \Delta F)$	$Cov'(\Delta S, \Delta F)$
Second order differential of $Cov(\Delta S, \Delta F)$	$Cov''(\Delta S, \Delta F)$
Price spread	
Spread of spot and futures price series	$Spread(S, F)$
First order differential of $Spread(S, F)$	$Spread'(S, F)$
Second order differential of $Spread(S, F)$	$Spread''(S, F)$

OHR is estimated based on the observations in the in-sample estimating period, from t-e to t, then used for hedging from t to t+h. Next, the window is rolled one hedging horizon ahead in order to reestimate the OHR based on the observations from t+h-e to t+h. Then, we use the new OHR for the next hedging horizon, from t+h to t+$2h$. OHR is reestimated every h day, and then used to adjust the hedging portfolio until the out-of-sample testing period is due.

B. Dynamic Behaviors Feature Extracting

In this study, variance, covariance, price spread, and their first and second differencing are adopted as the features of time series. These features are calculated using the data in the most recent hedging horizons just before the present; it is denoted by h. These features are calculated as follows:

$$Var(\Delta S_t) = Var[\Delta S_{t-h}, \ldots, \Delta S_t] \tag{2}$$

$$Var(\Delta F_t) = Var[\Delta F_{t-h}, \ldots, \Delta F_t] \tag{3}$$

$$Cov(\Delta S_t, \Delta F_t) = Cov\begin{bmatrix} \Delta S_{t-h}, \ldots, \Delta S_t \\ \Delta F_{t-h}, \ldots, \Delta F_t \end{bmatrix} \tag{4}$$

$$Spread(S_t, F_t) = F_t - S_t \tag{5}$$

The first and second order difference of these features are shown as

$$X_t' = \frac{X_t - X_{t-1}}{X_{t-1}} \quad (6)$$

$$X_t'' = \frac{X_t' - X_{t-1}'}{X_{t-1}'} \quad (7)$$

where X represents the functions of Var, Cov, and $Sperad$. These extracted features from a period of data can represent the dynamic behavior of time series in the recent hedging horizon. Twelve values listed in Table I are selected to describe an observation and used as the input variables of GHSOM.

C. *Clustering by GHSOM*

Each observation can extract a feature vector from the data from the previous hedging horizon. The feature vectors of the observations in the estimation interval include input matrix of GHSOM for OHR estimation. The GHSOM algorithm in this study is implemented in MATLAB [26]. When applying the GHSOM, the parameters related to network topology need to be determined first. We set the depth parameter as 0.001 and the breadth parameter as 0.8. Items that cannot be expanded are restricted when they are less than 100. The topology of the clusters is automatically determined by the data and related with the threshold setting of width and depth expansion. The feature vectors are processed by min-max normalization, which maps the value of the vector from -1 to 1. Normalization can ensure stable results.

The historical financial time series data are then hierarchically clustered by the GHSOM with similar patterns. Results show that the hierarchical architecture consists of many clusters distributed in different layers. The relations of hierarchical clusters are illustrated in Fig. 3. The sample size of each cluster is different. Clusters in the upper layers of the hierarchical architecture contain more samples of observations than those in the lower layers. The hierarchical architecture also represents the degree of similarity. Any observation can be identified on the cluster based on the layer it belongs to. The host cluster in the lowest layer contains the least data but has the highest similarity with the forecasting data. In addition, similarity with data is decreased in the upper layer clusters.

With regard to the latest observation in the estimation interval, similar observations can be obtained based on the group it belongs to in each layer. To forecast the fluctuation of the spot and futures for the next hedging horizon, we collect the observations which are one hedging horizon ahead the similar observations in the same clusters. Fig. 4 illustrates the observations collection for forecasting. These observations are weighted by similarity based on the cluster they belong to, and are used to modify the probability distribution for OHR estimation.

D. *Data Resampling and Weighting*

Regardless of similarity in data, every observation in the estimation interval is given equal weight for OHR estimation in the conventional model. In our proposed CI approach, for OHR

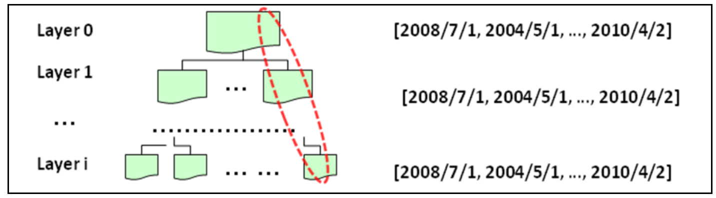

Figure 3. An example of the hierarchical clustered data.

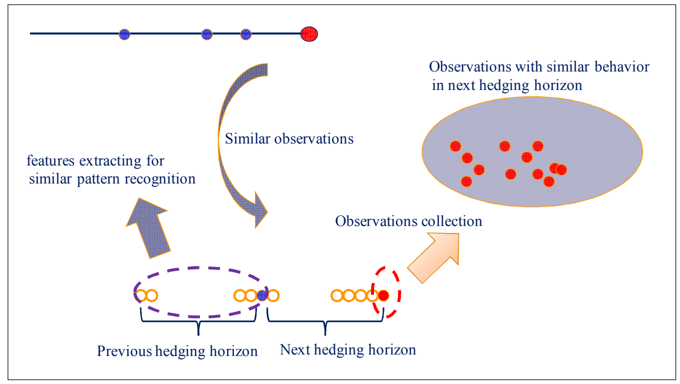

Figure 4. The observations collection for forecasting

estimation, the observation is given a different weight according to similarities. Although the size of the clusters obtained by GHSOM is different, the more similar data in the lower level clusters would be given more weight than the upper level clusters in the resampling process. The weights of observation are suggested for data replication. The more similar data will be replicated more frequently, thus increasing the occurrence probability in the whole population.

For each layer in the hierarchical cluster, the data in the same cluster are replicated randomly until the sample size coincides with the original sample size of the estimation period. The sample size is expanded by multiplying the layer of the hierarchical architecture. For example, in the conventional approach, if the size of observations in the estimating period is 1000, the OHR for the next hedging horizon is estimated based on 1000 observations. In the proposed CI approach, if 1000 observations are clustered into three layers by GHSOM, the OHR will be estimated based on triple observations, all generated by resampling. The expansion of sample size avoids the small sample effect and increases the accuracy of OHR estimation.

After data resampling, we can obtain a collection of observations composed of similar data in the cluster and consequent observations in the following hedging horizon with different weight.

E. *Estimating OHR with OLS*

The basic concept of hedging involves the elimination of fluctuations in the value of a spot position by tracking futures contracts that are opposite to the position held by the spot market. For a long position in the spot market, the return of a hedged portfolio is given by

$$\Delta HP = \Delta S - r \times \Delta F \quad (8)$$

where ΔHP is the change in the value of the hedge portfolio; ΔS and ΔF are the changes in the spot and futures prices, respectively; and r is the hedge ratio. Changes in spot and futures prices are also considered as returns, which are calculated by Equation (1). OHR is the value of r that maximizes the expected utility of the investor; it is defined as the expected return and risk of the hedged portfolio. The expected return of futures is 0 when the futures price follows a martingale; hence, the futures position will not affect the expected return of the portfolio.

The risk of the hedge portfolio is defined by its variance in the mean-variance framework. Therefore, OHR is simply the value of r that minimizes the variance of Equation (8), which is given by

$$\frac{\partial Var(\Delta HP)}{\partial r} = 2r \times Var(\Delta F) - 2Cov(\Delta S, \Delta F) = 0 \tag{9}$$

where $Var(\Delta F)$ is the variance of the futures return and $Cov(\Delta S, \Delta F)$ is the covariance between the spot return and the futures return. OHR is determined by solving Equation (9):

$$r^* = \frac{Cov(\Delta S, \Delta F)}{Var(\Delta F)} \tag{10}$$

The OHR given by Equation (10) can be estimated by regressing the spot return on the futures return using OLS, which corresponds to conventional OHR.

In this study, OHR estimation is improved by replacing the original observations in the estimation period with the collection of observations, which is composed of similar data in the cluster. Their consequent observations in the following hedging horizon have different weights. The traditional OLS method for OHR estimation, expressed by Equation (10), is modified to Equation (11), in which $\Delta\tilde{S}$ and $\Delta\tilde{F}$ refer to the collection of observations derived from spot and futures return series, respectively.

$$r^* = \frac{Cov(\Delta\tilde{S}, \Delta\tilde{F})}{Var(\Delta\tilde{F})} \tag{11}$$

F. Model Evaluating Criteria

1) Hedging Effectiveness: Hedging performance is typically evaluated by hedging effectiveness (HE). The degree of hedging effectiveness is measured by the percentage reduction in the variance of portfolio after hedging (Geppert, 1995). The variance of hedge portfolio with estimated OHR can be expressed as

$$Var_{hedged} = Var(\Delta HP) = Var(\Delta S_t - r \times \Delta F_t) \tag{12}$$

where r is the OHR. Therefore, HE can be expressed as

$$\begin{aligned} HE &= \frac{Var_{un-hedged} - Var_{hedged}}{Var_{unhedged}} \times 100\% \\ &= \frac{Var(\Delta S) - Var(\Delta HP)}{Var(\Delta S)} \times 100\% \\ &= (1 - \frac{Var(\Delta HP)}{Var(\Delta S)}) \times 100\% \end{aligned} \tag{13}$$

The value of HE can be used to evaluate the model of OHR estimation. A higher HE represents better OHR estimation, and vice versa.

2) White's Reality Check: In comparing the different OHR estimation models and to test the statistical significance of variance deduction, we apply White's Reality Check [27], which has been used to compare hedging models [28]. The Reality Check consists of a non-parametric test that checks if any of the numbers in the concurrent methods yield forecasts that are significantly better than a given benchmark method; then, it corrects the data snooping bias. Data snooping bias may occur when a given dataset is reused by one or more researchers for model selection. The null hypothesis that the performance of the proposed hedging model has no predictive superiority over the conventional model is not rejected. The hypotheses are as follows:

H0: No method is better than the benchmark.

H1: At least one method is better than the benchmark.

The detailed process of White's Reality Check can be found in [27] and [28].

IV. Experiments and Results

A. Experimental Design

Fig. 5 shows the framework of the experiments. The feature-extracting process of the proposed model is tested in different settings to achieve the best parameters. The feature vectors that represent the dynamic behaviors of time series for GHSOM similarity measurement are composed of variance, covariance, price spread, and their first and second order differences. We design six combinations of these parameters, which are adopted in the experimental models and denoted by CI_1, CI_2, CI_3, CI_4, CI_5, and CI_6, respectively, to verify

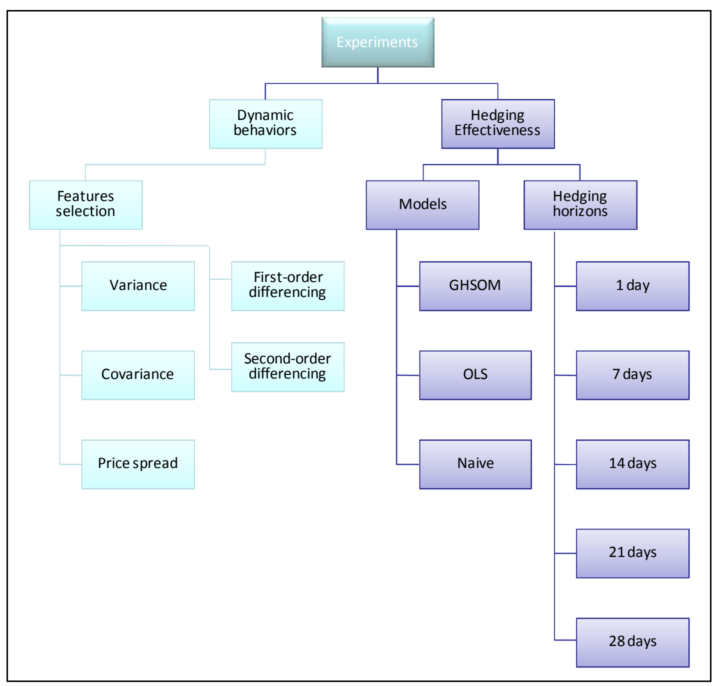

Figure 5. Experiment framework

TABLE II. PARAMETER SETTINGS FOR TESTING DYNAMIC BEHAVIORS

Model	Parameter setting: Variance	Covariance	Price spread
CI_1	$Var(\Delta S)$, $Var(\Delta F)$		
CI_2	$Var(\Delta S)$, $Var(\Delta F)$ $Var'(\Delta S)$, $Var'(\Delta F)$ $Var''(\Delta S)$, $Var''(\Delta F)$		
CI_3	$Var(\Delta S)$, $Var(\Delta F)$	$Cov(\Delta S, \Delta F)$	$Spread(S, F)$
CI_4	$Var(\Delta S)$, $Var(\Delta F)$ $Var'(\Delta S)$, $Var'(\Delta F)$ $Var''(\Delta S)$, $Var''(\Delta F)$	$Cov(\Delta S, \Delta F)$	$Spread(S, F)$
CI_5	$Var(\Delta S)$, $Var(\Delta F)$	$Cov(\Delta S, \Delta F)$ $Cov'(\Delta S, \Delta F)$ $Cov''(\Delta S, \Delta F)$	$Spread(S, F)$ $Spread'(S, F)$ $Spread''(S, F)$
CI_6	$Var(\Delta S)$, $Var(\Delta F)$ $Var'(\Delta S)$, $Var'(\Delta F)$ $Var''(\Delta S)$, $Var''(\Delta F)$	$Cov(\Delta S, \Delta F)$ $Cov'(\Delta S, \Delta F)$ $Cov''(\Delta S, \Delta F)$	$Spread(S, F)$ $Spread'(S, F)$ $Spread''(S, F)$

TABLE III. EXPERIMENT DATA

Index (Spot)	Exchange (Futures)	Observations
Taiwan Weighted Index (TWI)	Taiwan Futures Exchange (TAIFEX)	2217

Note: Data period is from July 21, 1999 to July 18, 2008.

the performance over various hedging horizons. Table II presents the parameter settings of these models.

Moreover, the optimal hedge ratio is estimated by the proposed model concerned with the hedging horizon, and the performances are compared with conventional models. For each hedging horizon in the testing period, the hedged portfolio is adjusted once according to the latest OHR at the beginning of a hedge horizon and lasts until the beginning of the next hedging horizon. At the end of the testing period, hedging effectiveness is calculated based on the variance of the hedging portfolio in each hedging horizon. Hedge horizons in the experiments are set at 1, 7, 14, 21, and 28 days, which cover the intervals from short-term to long-term. The superiority of the proposed model is verified using two conventional models, the OLS and naïve models, both of which are widely used in OHR research on different hedging horizons [29] [30].

B. Experiment Data

This study obtained empirical trading data of the daily closing price from Taiwan stock and futures markets. Table III lists the stock market index and exchange of their correlative futures contracts trade. All data were obtained from the Thomson Datastream database in the same period from July 21, 1999 to July 18, 2008. The futures prices series was gathered from the nearest month contracts and rolled over to the next nearest contracts on the maturity day due to the consideration of liquidity and price spread risk. Among the total observations, the first 90% is considered the estimation period, and the remaining 10% is considered the testing period.

C. Results of the Dynamic Behavior Prediction

Table IV presents the hedging effectiveness for all models. Results indicate that based on the same experiment data, the

TABLE IV. COMPARISONS OF DYNAMIC BEHAVIORS

Market/model		Hedging effectiveness: Hedging horizon (days) 1	7	14	21	28
TWI						
CI	1	93.3309% *	97.1661% **	99.2656%	99.3811%	99.3131%
	2	93.3905% **	97.1534% *	99.2480%	99.3942%	99.3556% *
	3	93.2715%	96.9289%	99.2751%	99.3947%	99.3160%
	4	93.0998%	96.8809%	99.2879% *	99.4342% *	99.3802% **
	5	93.1081%	97.0102%	99.3111% **	99.4327%	99.3431%
	6	93.1798%	96.9169%	99.2047%	99.4666% **	99.3470%
OLS		93.3055%	97.0244%	99.1612%	99.3860%	99.3089%
Naïve		90.6982%	96.0278%	98.5331%	99.0888%	98.8415%

Note: ** and * represent the best and second best HE among eight models at the same hedging horizon, respectively.

CI-based model can obtain the best performance compared with the traditional OLS and naïve models. A comparison of the six experiment models indicates that the best CI-based model is different over different hedging horizons. The results imply that the ability to capture fluctuation under various timescales is different for CI-based models. Short-term dynamic behavior may be captured by variance and its first and second differences. Long-term tendency may need more variables for its description than short-term tendency by adding covariance and price spread.

D. Results of the Hedging Performance

For a comparison of hedging performance, we list the best CI-based model from the six experiments models, and the two conventional models (naïve and OLS) in Table V. The hedging performance of the model is evaluated using hedging effectiveness and statistic testing for significance of superiority. The hedging effectiveness of the model is calculated using the variance reduction of the hedged portfolio (Table IV). Table V presents the variance of unhedged and hedged portfolios employed in White's reality check to verify the significance of superiority.

Table V shows that increasing the hedging horizon will increase the variance of unhedged portfolio but will be effectively reduced by the hedging model. The percentage of variance reduction, shown as hedging effectiveness in Table IV, is higher in a long hedging horizon than in a short one.

The value of hedging effectiveness is slightly different in these models. To test the significance of these models' performance improvements, we perform White's reality check. When OLS is treated as the benchmark, the null hypothesis of no improvement of CI-based model over benchmark is rejected for 28 days hedging in TWI at the significance level of 1%. Results of the reality check provide evidence that the proposed CI-model can improve the OLS model, especially in long-term hedging.

TABLE V. VARIANCE OF THE PORTFOLIO

Market/models	Variance				
	Hedging horizon				
	1	7	14	21	28
TWI					
Unhedged	2.7527	20.5443	41.8060	35.5709	39.9629
Naïve	0.2561	0.8161	0.6132	0.1840	0.1698
OLS	0.1843	0.6113	0.3507	0.1454	0.1546
CI-based	0.1819 ***	0.5822 ***	0.2880 ***	0.1148 ***	0.1056 ***
Reality check p value	0.134	0.026 *	0.015 *	0.085	0.000 **

Note: (1) The benchmark model for White's reality check is the OLS model. (2) * and ** represent significance at the 5% and 1% levels, respectively. (3) *** represents the minimum variance among the naïve, OLS, and CI-based hedged portfolios.

V. CONCLUSION AND FUTURE WORK

In this study, we propose a novel computational intelligence approach to estimate the time-varying minimum variance hedge ratio. Clustering time series are employed to recognize the observations with similar time series patterns. Observations with a high possibility of occurrence in the future are selected when hedging. These observations are used to modify the distribution probability of time series data using a resampling process with different weights given based on cluster result. The empirical findings in this study are consistent with the following notations. First, hedging horizon will increase hedging effectiveness. When hedge horizon is increased, hedging effectiveness is also increased. Second, the proposed CI-based model can improve the typical OLS model, especially in long-term hedging.

This study evidences that the proposed model is superior to the conventional OLS model in hedging effectiveness, but the usability of this computational approach is worse than conventional OLS model. Many factors, such as the breadth and depth parameters of GHSOM, the period of data for feature extraction, which may influence the performance of the proposed model, should to be determined appropriately in practical use. Further, most non-parametric models based on computational intelligence are challenged that the experiment results of non-parametric model are more unstable than parametric model when repeating the experiments.

Although this research still have some restriction of model parameters selection, this novel approach based on computational intelligence can improve the performance of traditional approach without too many inappropriate assumptions and restrictions. Consequently, the proposed model can also be considered as a powerful tool to investigate any financial market, in which the probability distribution of data is unrestricted and not necessary to fit any type of probability distribution.

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國科會補助計畫衍生研發成果推廣資料表

日期:2012/10/12

國科會補助計畫	計畫名稱: 以雲端服務為基礎之期貨避險交易決策支援系統
	計畫主持人: 許育嘉
	計畫編號: 100-2410-H-028-005- 學門領域: 資訊管理
無研發成果推廣資料	

100 年度專題研究計畫研究成果彙整表

計畫主持人：許育嘉	計畫編號：100-2410-H-028-005-
計畫名稱：以雲端服務為基礎之期貨避險交易決策支援系統	

成果項目			量化			單位	備註（質化說明：如數個計畫共同成果、成果列為該期刊之封面故事...等）
			實際已達成數（被接受或已發表）	預期總達成數(含實際已達成數)	本計畫實際貢獻百分比		
國內	論文著作	期刊論文	0	0	100%	篇	
		研究報告/技術報告	0	0	100%		
		研討會論文	0	0	100%		
		專書	0	0	100%		
	專利	申請中件數	0	0	100%	件	
		已獲得件數	0	0	100%		
	技術移轉	件數	0	0	100%	件	
		權利金	0	0	100%	千元	
	參與計畫人力（本國籍）	碩士生	1	1	100%	人次	
		博士生	0	0	100%		
		博士後研究員	0	0	100%		
		專任助理	0	0	100%		
國外	論文著作	期刊論文	0	0	100%	篇	
		研究報告/技術報告	0	0	100%		
		研討會論文	1	1	100%		
		專書	0	0	100%	章/本	
	專利	申請中件數	0	0	100%	件	
		已獲得件數	0	0	100%		
	技術移轉	件數	0	0	100%	件	
		權利金	0	0	100%	千元	
	參與計畫人力（外國籍）	碩士生	0	0	100%	人次	
		博士生	0	0	100%		
		博士後研究員	0	0	100%		
		專任助理	0	0	100%		

其他成果 (無法以量化表達之成果如辦理學術活動、獲得獎項、重要國際合作、研究成果國際影響力及其他協助產業技術發展之具體效益事項等，請以文字敘述填列。)	無

	成果項目	量化	名稱或內容性質簡述
科教處計畫加填項目	測驗工具(含質性與量性)	0	
	課程/模組	0	
	電腦及網路系統或工具	0	
	教材	0	
	舉辦之活動/競賽	0	
	研討會/工作坊	0	
	電子報、網站	0	
	計畫成果推廣之參與（閱聽）人數	0	

國科會補助專題研究計畫成果報告自評表

請就研究內容與原計畫相符程度、達成預期目標情況、研究成果之學術或應用價值（簡要敘述成果所代表之意義、價值、影響或進一步發展之可能性）、是否適合在學術期刊發表或申請專利、主要發現或其他有關價值等，作一綜合評估。

1. 請就研究內容與原計畫相符程度、達成預期目標情況作一綜合評估

■達成目標

□未達成目標（請說明，以 100 字為限）

□實驗失敗

□因故實驗中斷

□其他原因

說明：

2. 研究成果在學術期刊發表或申請專利等情形：

論文：□已發表 □未發表之文稿 ■撰寫中 □無

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技轉：□已技轉 □洽談中 ■無

其他：（以 100 字為限）

3. 請依學術成就、技術創新、社會影響等方面，評估研究成果之學術或應用價值（簡要敘述成果所代表之意義、價值、影響或進一步發展之可能性）（以 500 字為限）

在發展雲端化的財務避險決策服務上，一個自動化參照過去市場行為估算出的避險比例模型是需要的，而傳統的最小變異數避險比例之估算太過簡單，不容易達到輔助決策的效果。雲端化的優點包括了可以讓多人同時使用(Service as a Service，SaaS)、節省運算資源(Infrastructure as a Service，IaaS)、節省儲存空間(Database as a Service，DaaS)。因此本研究以大量歷史交易資料為基礎，發展出計算智慧模型來找尋出相似行為的模型，研究中經過實證可提高期貨避險之效能，將來進行雲端化後可達到 SaaS 及 IaaS 之效益。