

行政院國家科學委員會專題研究計畫 成果報告

以雲端系統為基礎之動態物理行為分析於財務交易決策支援系統

研究成果報告(精簡版)

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報告附件：出席國際會議研究心得報告及發表論文

公開資訊：本計畫涉及專利或其他智慧財產權，2年後可公開查詢

中 華 民 國 100 年 10 月 31 日

中文摘要：近年來，有多位學者利用 LCS 或 XCS 對股市及投資人進行預測。MSCI 公布增加、減少甚至是其國家指數的權中會導致相關股票的價格及交易量改變。本研究為了最佳化投資組合配置利用人工智慧中的 XCS 進行動態學習及調適改變組成的股票。即使 MSCI 成份股受到未知及不可測的環境影響價格趨勢，使用 XCS 模型具有探索未來趨勢的模式的能力。針對 MSCI 台指的 121 個成份股 1998 至 2009 年的歷史資料進行測試，發現 XCS 能產生獲利及最佳的投資組合。

英文摘要：In a recent study, Schulenburg and Ross (2001) proposed the LCS for short-term stock forecast. Studley and Bull (2007) proposed the extended classifier system (XCS) agent to model different traders by supplying different input information. Announcement made by Morgan Stanley Capital Investment (MSCI) regarding the additions, removals, and even the weights of the component stocks in its country indices every quarter generally would cause changes to the prices and/or trade volumes of the associated component stocks. This paper takes an XCS in artificial intelligence to dynamically learn and adapt to the changes to the component stocks in order to optimize portfolio allocation of the component stocks. Since these price trends of MSCI component stocks are influenced by unknown and unpredictable surroundings, using XCS to model the fluctuations on financial market allows for the capability to discover the patterns of future trends. This simulation works on the basis of the changes to 121 component stocks in the MSCI Taiwan index between 1998 and 2009 suggests the XCS can produce the great profit and optimize portfolio allocation.

以雲端系統為基礎之動態物理行為分析於財務交易決策支援系統

計畫類別：☒ 個別型計畫 ☐ 整合型計畫

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中 華 民 國 100 年 10 月 21 日

中文摘要

近年來，有多位學者利用 LCS 或 XCS 對股市及投資人進行預測。MSCI 公布增加、減少甚至是其國家指數的權中會導致相關股票的價格及交易量改變。本研究為了最佳化投資組合配置利用人工智慧中的 XCS 進行動態學習及調適改變組成的股票。即使 MSCI 成份股受到未知及不可測的環境影響價格趨勢，使用 XCS 模型具有探索未來趨勢的模式的能力。針對 MSCI 台指的 121 個成份股 1998 至 2009 年的歷史資料進行測試，發現 XCS 能產生獲利及最佳的投資組合。

關鍵字：財務預測，分類元系統，MSCI 台灣加權成份股

Abstract

In a recent study, Schulenburg and Ross (2001) proposed the LCS for short-term stock forecast. Studley and Bull (2007) proposed the extended classifier system (XCS) agent to model different traders by supplying different input information. Announcement made by Morgan Stanley Capital Investment (MSCI) regarding the additions, removals, and even the weights of the component stocks in its country indices every quarter generally would cause changes to the prices and/or trade volumes of the associated component stocks. This paper takes an XCS in artificial intelligence to dynamically learn and adapt to the changes to the component stocks in order to optimize portfolio allocation of the component stocks. Since these price trends of MSCI component stocks are influenced by unknown and unpredictable surroundings, using XCS to model the fluctuations on financial market allows for the capability to discover the patterns of future trends. This simulation works on the basis of the changes to 121 component stocks in the MSCI Taiwan index between 1998 and 2009 suggests the XCS can produce the great profit and optimize portfolio allocation.

Keyword: Financial forecasting, XCS, MSCI Taiwan index component stock

1. Introduction

Stocks that are added to major stock indices usually see rises in their trading volumes and prices after the announcements. On the other hand, investors usually sell the stocks after their removals from MSCI indices. This phenomenon has been widely studied in finance Kovalerchuk and Vityaev (2000), Liao and Chen (2001) and Chen and Chen (2006). Most studies to date have focused on US stocks. This paper turns attention to one of the emerging markets. This paper documents and analyzes changes to the returns and the trade volumes in response to additions and removals of the component stocks in MSCI country indices.

Previous works approached the problem in a variety of different ways. They were usually about the institutional investment by means of the traditional statistical analysis and financial engineering. And (McIvor, McCloskey, Humphreys, & Maguire, 2004) they all shared some common characteristics such as technical indicators, quantizing financial series, static prediction rule, and buy or sell prediction signal.

Chen and Chen (2006), Tsai and Chen (2008), Schulenburg and Ross (2001), etc. have applied learning classifier system (LCS) to different financial systems such as the future market, the foreign exchanges market, the derivatives market and the equity market. While their results were promising, it is widely accepted that better

results can be achieved by improving the processes surrounding the main XCS learning components. The following are reasons to use XCS on dynamic and noisy environments:

- XCS is able to evaluate rules that are ideal for modeling problems without retraining all data.
- XCS has been shown to properly learn from noisy, complex, and non-linear environments when the outside information continuously changes.
- XCS is capable of making real-time and accurate learning and responses.
- XCS can discover generally accurate rules to perform on a variety of problem domains (Wilson, 1996).
- XCS can adjust itself to strengthen its inward knowledge step by step.

The stock market traders (Hashemi, Blanc, Rucks, & Rajaratnam, 1998) always look for trading strategies to optimize portfolio allocation and to obtain high returns. This paper presents empirical results for the XCS agents trading system providing trading strategies for the Taiwan MSCI component stocks.

2. Literatures review

2.1. LCS

The classifier systems have been gaining more and more popularity in the artificial intelligence (AI) domain. Holland (1975) and Holland and Reitman (1978) introduced the concept the mechanism of learning classifier systems (LCS) in the 1980s, and a series of researches has focused on the problem derived from LCS, such as generalization, the classifier syntax, the credit allocation procedure, the discovery component, and the internal messages list in Holmes (1996). The schematic overview of LCS in Fig. 1 shows three major functional components of LCS:

- The detecting function which allow the machine to interact with its environment.
- Reward mechanism allows separating successful rules from unsuccessful or meaningless rules.
- Genetic algorithm (Glodberg, 1989; Yuan & Shaw, 1995; Yuan and Zhung, 1996) used to generate more optimal rules for the rule set.

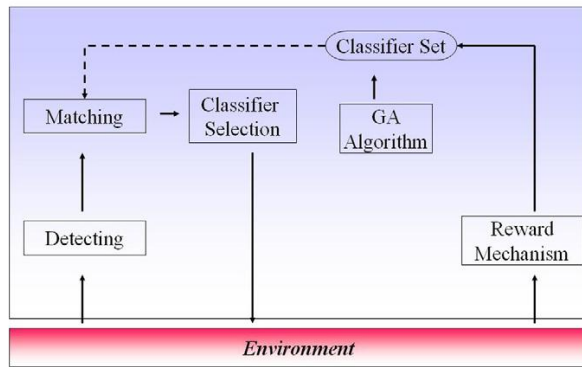


Fig. 1. System architecture of LCS.

2.2. XCS

Recently, the extended classifier systems (XCS) have been becoming the primary research topic in AI, especially in the financial domain (Chen & Chen, 2006; Studley & Bull, 2007; Tsai & Chen, 2008). The schematic overview of XCS in Fig. 2 provides three major functional phases of XCS:

- Transaction data encoding phase decodes and normalizes the different stocks.
- Knowledge extraction phase allows separating successful rules from unsuccessful or meaningless rules.
- Knowledge integration phase generates more optimal rules including the single stock perdition rule and portfolio allocation rule.

3. System architecture

The key quantity the trading system

predicts is the percentage of current total investment in MSCI component stocks. This is closely related to the expected changes to the prices in the subsequent trading days Wang (2003). Three major phases in Fig. 2 allow XCS agents to predict future price movements based on different sets of historical financial data.

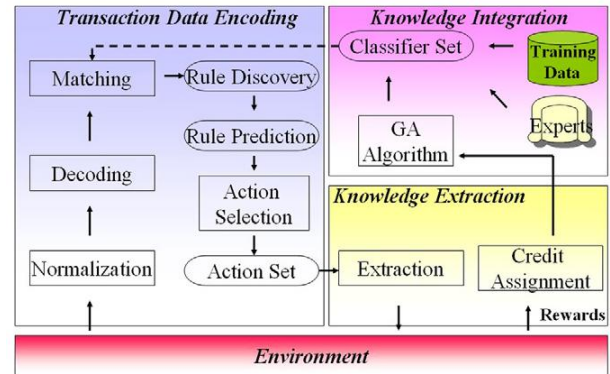


Fig. 2. System architecture of XCS.

3.1. Algorithm

The XCS algorithm is shown in Table 1. The XCS algorithm describes how to forecast from the input to result.

Table 1
Algorithm of XCS.

```

1: XCS Algorithm
2: Input RS ← q rule sets(RS) from different knowledge sources
3: Output one integrated rule set
4: procedure XCS
5:   Initialize classifier set
6:   While (termination condition of XCS is false)
7:     Get environment state
8:     Normalized the state
9:     Decode the state
10:    Generate match set
11:    Generate prediction rule
12:    Selection action
13:    Generate action set
14:    do winner action
15:      Get rewards
16:      Update attribute-values of relevant classifiers
17:      trigger Genetic Algorithm
18:      Selection
19:      Crossover
20:      Mutation
21:    end trigger
22:  end do
23: end while
24: Report the execution and learning performances
25: Store the learned classifier set
26: end procedure

```

3.2. Transaction and encoding phase

This phase generally normalizes the MSCI component stock prices and trading volumes to the status such as up, down or ignored. The decoding sample is given in Table 2.

Table 2
Decoding.

Date	Symbol	High	Low	Price	Volume	Change	Decode
31-March-09	2330.tw	0	0	0	0	0	00000
30-March-09	2330.tw	1	1	#	1	#	11#1#
27-March-09	2330.tw	1	1	1	1	1	11111
26-March-09	2330.tw	0	1	1	0	1	01101
25-March-09	2330.tw	1	#	#	1	1	1##11

3.3. Knowledge extraction phase

During this phase, the XCS trading system follows the action set to adjust the portfolio such as increasing the percentages of 2303.tw and 2408.tw while reducing the percentages of 2330.tw and 2345.tw. The action set table is given in Table 3.

Table 3
Action set.

Company ID	Name	Action	As-Is (%)	To-Be (%)
2330.tw	TSMC	Sell	23	20
2303.tw	UMC	Buy	9	10
2408.tw	...	Buy	3	5
...	...	...	...	...
2345.tw	Accton	Sell	3	0

3.4. Knowledge integration phase

In this phase, the XCS trading generates more optimal rules including the single stock perdition rule and portfolio allocation rule. The rule set is shown in Table 4.

Table 4
Action set.

Factor code	Action	Currency (%)
11#110001#10	Sell	82
01111#0#0110	Buy	81
01#101#10001	Sell	79
01011#0#1101	Buy	79
01#111#10000	Sell	73
...	...	...
101##0011101	Buy	53

4. Simulation

4.1. Simulation

Experiment is performed on the MSCI Taiwan index component stock data, which is derived from Securities & Futures Institute (SFI). The trading period for this experiment is from January 1998 to March 2009. Since the simulation corresponds to the foreign capital, the stocks which below to the MSCI Taiwan index component. The condition part of the

classifiers is within 5 days; while the action part is the trend of the next 3 days. There are some preprocess to be completed before having the data placed into XCS.

- Missing values will be deleted due to the concept of data cleaning.
- The five attributes, which are buy/sell of QFII, buy/sell of securities investment trust, balance of margin purchasing, balance of short selling, and volume, are the most important factors when it comes to the institutional analysis. Thus, they are taken into account in the simulation. Each condition will be considered into four parts on the basis of discretion technique.
- The action part will also be described into four regions corresponding to levels of the upward or downward trends for the next trading day. The format of classifiers is shown in Table 4, and the simulation procedures are shown in Fig. 3.

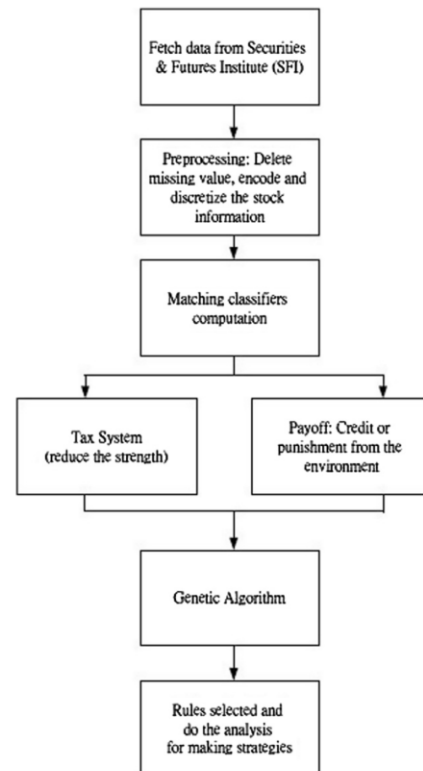


Fig. 3. Simulation procedure.

4.2. Implementation

Due to the historical data of MSCI, United Microelectronics Corporation (UMC), Advanced Semiconductor Engineering Inc. (ASE), Compal Electronics (COMPAL), Taiwan Semiconductor Manufacturing (TSMC), AU Optronics (AUO) and so on are more favored by institutional and individual investors. Hence, the experiment selects 121 stocks. The processes are summarized as follows.

In XCS system, the condition part of the classifiers is considered into 4 parts in accordance with each of the discrete and normalized attributes. The detector will encode the inputted information into 12-bit strings. All classifiers will be matched. If the condition matches the current state, the rule will be activated, and then put into classifier list.

In XCS, the bucket brigade algorithm (Oh, Kim, & Min, 2005) is implemented for credit apportionment. In apportionment of credit system, matching classifiers are available for bidding. The fitness of the classifiers will be reflected through adjusting the strength. In Eq. (1), $B_{i,t}$ is the bid of classifier X_i at time t , where r is the learning rate, S_i is the strength of the classifier, and $u_{i,t}$ is the number of non-wildcard symbols

$$B_{i,t} = \gamma \cdot S_i \cdot u_{i,t} \quad (1)$$

The probability that a classifier wins will be proportional to its bid value is shown in Eq. (2)

$$P(X_i \text{ wins}) = \frac{B_{i,t}}{\sum B_{j,t}} \quad (2)$$

4.3. Simulation result

In Fig. 4, the profit of using XCS to allocate the MSCI component stocks during the

training interval is remarkably increasing.

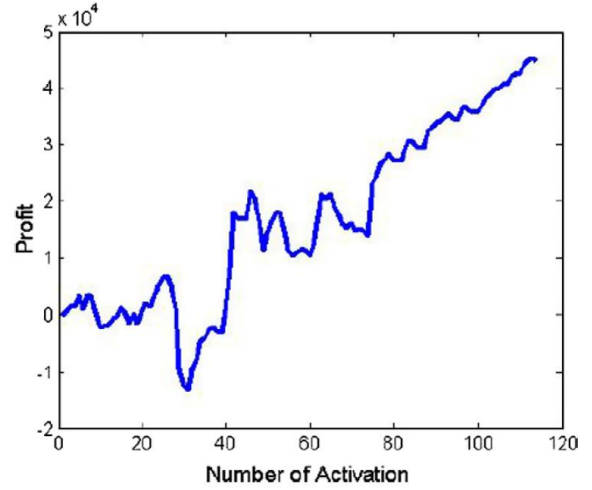


Fig. 4. Training period, the result is not good in the initial period, but the final profit can be achieved to 50 thousand dollars or so.

In Fig. 5, the profit of using XCS to allocate the MSCI component stocks during the experimental report shows that we will gain a lot in the noisy stock market using XCS.

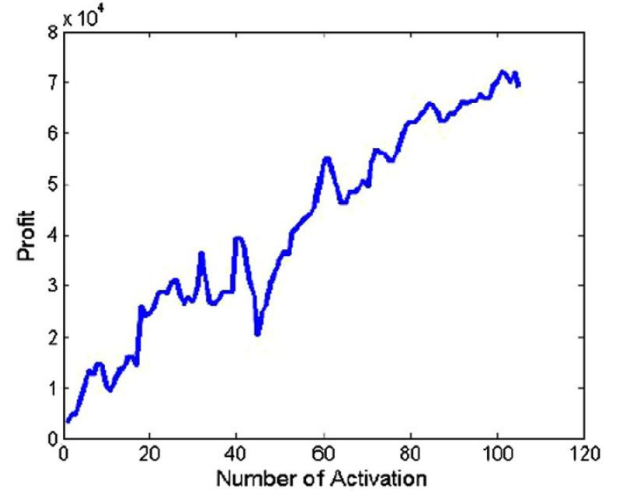


Fig. 5. Simulation period, the profit can be achieved to 71.3 thousand dollars or so.

5. Conclusion

According to the simulation, the proposed model is the combination of XCS and stock market data to demonstrate that XCS can learn well from the complex, dynamic and noisy environment. XCS model possesses a strong advantage over traditional statistical analysis. The XCS provides guidance to stock market traders about how to adjust the weight of the

MSCI component stocks. The profit according to the simulation is also satisfactory. Since the stock market is sensitive, using artificial intelligence is more appropriate because of continuous learning from the environment. So far, XCS works so adaptively that it is a good tool for further research of fundamental, technical, industrial, and news analysis on stock market. The simulation result shows that the accumulated return can be much higher than the original investment capital. Therefore, applying the mechanism proposed by this paper to stock data seems to be capable of profiting.

The profit gained through applying XCS to the financial markets is remarkable, because XCS is capable of adapting to the complex environment. Some works are still in the process of implementation for obtaining much better profit. First of all, the method of credit apportionment will be the focus of future researches. Recurrent reinforcement learning (RRL) and direct reinforcement (DR) will be replaced by bucket brigade algorithm to see whether the profit will be better. If the results are as much as desirable, the bucket brigade algorithm will be a brand new idea of implementing RRL or DR into classifier systems. In addition, Q-learning will also be compared with bucket brigade algorithm. Secondly, anticipatory classifier system (ACS) will also be applicable to continuous simulation (Stolzmann, 2000). The comparison of using different classifier systems will be discussed in future researches as well.

Last but not least, other attributes, such as ratio of margin purchasing and short selling (Oh et al., 2005; Trippi & Desieno, 1992), buy/sell of security dealers, TSE stock index,

and volume of TAIEX, will be also considered to check whether the factors are affecting the financial market significantly.

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計畫成果自評

本研究中心在連續的計畫支持下，逐漸將金融工程物理學的輪廓描繪成形。金融工程物理學的基本原理在於市場是具有行為影響，市場的供給與需求構成了不同程度及力量的賣方及買方。而傳統財務工程根據套利的機會進行價格範圍的推論雖能估計約略範圍，但對於實務預測上卻仍顯得不足，最大的原因在於市場是由人類所參與。由於人類具有各種理性及不理性的行為，因此市場往往無法照著理性的財務工程模型進行價格的預測，金融工程物理學認為人類的行為在過去歷史上不斷的重現，因此若能從大量過去歷史中找到異常現象的發生，便能更有效的對金融商品的定價。

本研究針對金融商品的投資組合進行動態模型的建構，將金融工程物理學與人工智慧進行整合，而實驗結果也顯示透過人工智慧建構的動態模型能夠有效的進行資產配置。近年來由於政府積極推動雲端運算，也由於科技進步，使得我們能夠獲得更強大的運算資源，本研究除了研究人工智慧外，更積極探討雲端運算對計算的幫助。因此本計畫之相關著作除了運用人工智慧及金融工程物理學理論外，另外也探討了雲端運算的相關應用。根據上述的研究而論，本計畫之相關著作包含兩篇期刊論文及四篇研討會論文，並於研究中心建構了私有雲的虛擬平台，提供相關計畫的運算服務使用。

本人也曾多次在國內多所大學及中國大陸進行課程教學，並將此知識進行深度的探討與傳授給學子，課程結束後也獲得學子們的熱烈歡迎，並進而實作了相當多的應用，使本領域的知識逐漸擴散。

相關著作發表

【期刊】

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【研討會論文】

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4. Mao-Ping Wen, Hsio-Yi Lin, An-Pin Chen, Chyan Yang, "An Integrated Home Financial Investment Learning Environment Applying Cloud Computing in Social Network Analysis." Advances in Social Networks Analysis and Mining (ASONAM), July 2011, Pages 751 - 754.

**國立交通大學博士班研究生
出席國際會議報告**

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發表論文題目	(中文) 建構專家決策策略提升面板業品質 (英文) Establishing the Expert Decision-making Strategy to Improve the TFT-LCD Quality		

報告內容包括下列各項：

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- 二、 與會心得
- 三、 建議
- 四、 攜回資料名稱與內容
- 五、 其他

心得報告

2011 資訊技術國際研討會包含了決策分析、資訊科學、互動科學等相關領域，一年一度。我今年非常榮幸能有這個機會參加該場研討會並且進行口頭報告，這次的研討會有許多不同的主題。我的論文是被安排在 Hilton Hotel Gyeongju 中發表。因此，這幾天除了參加自己有興趣的 Sessions 之外，亦很早就到了會場準備論文口頭發表，因此，在開始之前有充裕的時間布置所需的設備。有了萬全的準備，當有人諮詢問題時，自然就較不緊張，順利地將論文的重點做了一個簡單的解釋報告給有興趣的人。

感謝我的指導教授－陳安斌教授的鼓勵與支持，讓我有這個機會來參加這次盛大的國際研討會，不但增廣了我的視野，也認識了許多來自不同國家與不同領域的人士，同時更讓我在這次的旅程當中學習到許許多多寶貴經驗。這些經驗是我自己在許多地方都學習不到的，因此我將參加本次的心得以下列幾個重點來敘述：

1. 參加會議經過

- 06 月 21 日（台灣時間）： 上午七點，從台灣桃園國際機場搭乘中華航空之班機至韓國首爾仁川機場。
- 06 月 21 日（韓國時間）： 晚上查詢 ICNIT 2011 會場位置。
- 06 月 22 日（韓國時間）： 參加 ICNIT 2011 註冊與研討會活動。
- 06 月 22 日（韓國時間）： 上午，參加 Section 2 研討會。
下午，研究論文口頭發表報告。
- 06 月 23 日（韓國時間）： 上午，參加 Section 11 研討會。
中午，參加閉幕式。
- 06 月 24 日（韓國時間）： 下午八點半，從韓國首爾仁川機場搭乘中華航空之班機回台灣。
- 06 月 24 日（台灣時間）： 下午十一點，抵達台灣桃園國際機場。

2. 發表論文

本篇論文參加的是 Section 8 的場次，主席為 **Feng-Hsu Wang** 教授。論文以口頭發表，內容主要是運用灰色系統方法來分析建構專家決策策略提升面板業品質。

3. 參加國際研討會

此次赴韓國慶州參與 ICNIT 2011 之國際學術會議是一個相當特別的經驗，參加會議後發現不論是在資訊科學、互動科學，或是決策分析的領域上，其發展與應用皆非常的豐富與廣泛。此外，藉由參加本次研討會的機會，除了提昇視野，攫取不同研究領域的新知與精華外，也與來自不同國家的優秀學者進行溝通與交流，使得個人的研究經驗可以於國外學者研究經驗作結合，產生許多創新研究的能量。本次出席此國際學術性研討會可以說是收穫滿載。

4. 語文能力

英語文能力乃生活、學習、工作之必要且重要的配備。英語文的能力並非一觸可及，需要持續的練習與努力，不斷的累自己的實力。在參與這次國際研討會的過程中，不論是進出海關或是在研討會上，都聽不到中文，在會場上更是一場國際交流的舞台，若英文不通要如何與他人溝通。我十分榮幸有此次的機會讓我走出台灣，有更多的機會練習已學習多年的英文，這也是出席國際會議的另外一項收穫。

5. 建議

本次研討會吸引了來自世界各地的學者共襄盛舉參與，根據大會統計，本年度投稿論文經過審查通過在會議中發表之論文共有來自世界不同國家近百篇口頭報告與海報，全文摘要收錄於大會發行之論文集。此外，每天會議從上午 9:30 開始安排到下午 6:10 左右，總共分為三個時段，每一時段同時有不同的主題分別在兩個會議廳進行發表。藉由場次主題的明顯區分，得以讓該領域的研究者有機會相互交換心得，除對於理論的最新進展有更深層的認識，也促進台灣在國際間的能見度。這樣盛大的安排，讓論文發表的流程更為快速及流暢，未來在國內舉行學術研討會時，是可以參考的方式之一。

6. 結論

國際性學術研討會議不但可促進學術的交流，更可讓國際專家學者更進一步瞭解台灣。本人能恭逢其盛，並唯一台灣人得獎，實在是感到無比的榮耀，也獲益良多。另外，感謝貴單位的補助，提供我這次去參加這個研討會的經濟來源，期盼教育部與國科會能多加鼓勵國內研究生參與此類國際性研討會，以提昇我國之學術國際化的能力。也建議博士生要多主動參與，讓台灣的研究可以繼續在國際舞台上發光發熱。

7. 攜回資料名稱與內容

(1)會議議程

(2)研討會相關書面報告資料

出席國際學術會議照片

研討會名稱	(中文) 2011 年資訊技術國際研討會 (英文) The 2 nd International Conference on Next Generation Information Technology		
時間	June 21-23, 2011	地點	Hilton Hotel Gyeongju Gyeongju, Korea

照片一說明

大會報到處之景象。



照片二說明

口頭發表會議室之景象。



照片三說明

口頭發表會議室之景象。



發表論文全文：

Paper presented at conference: “The 2nd International Conference on Next Generation Information Technology”, Gyeongju, Korea, June 22, 2011

**Establishing the Expert Decision-making Strategy
to Improve the TFT-LCD Quality**

國科會補助計畫衍生研發成果推廣資料表

日期:2011/10/20

國科會補助計畫	計畫名稱：以雲端系統為基礎之動態物理行為分析於財務交易決策支援系統	
	計畫主持人：陳安斌	
	計畫編號：99-2410-H-009-044-	學門領域：資訊管理
無研發成果推廣資料		

99 年度專題研究計畫研究成果彙整表

計畫主持人：陳安斌			計畫編號：99-2410-H-009-044-				
計畫名稱：以雲端系統為基礎之動態物理行為分析於財務交易決策支援系統							
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	5	2	250%	人次	
		博士生	2	1	200%		
		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	2	1	200%	篇	
		研究報告/技術報告	0	0	100%		
		研討會論文	4	2	200%		
		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%		

<p>其他成果</p> <p>(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。)</p>	<p>本研究中心在連續的計畫支持下，逐漸將金融工程物理學的輪廓描繪成形。金融工程物理學的基本原理在於市場是具有行為影響，市場的供給與需求構成了不同程度及力量的賣方及買方。而傳統財務工程根據套利的機會進行價格範圍的推論雖能估計約略範圍，但對於實務預測上卻仍顯得不足，最大的原因在於市場是由人類所參與。由於人類具有各種理性及不理性的行為，因此市場往往無法照著理性的財務工程模型進行價格的預測，金融工程物理學認為人類的行為在過去歷史上不斷的重現，因此若能從大量過去歷史中找到異常現象的發生，便能更有效的對金融商品的定價。</p> <p>本研究針對金融商品的投資組合進行動態模型的建構，將金融工程物理學與人工智慧進行整合，而實驗結果也顯示透過人工智慧建構的動態模型能夠有效的進行資產配置。近年來由於政府積極推動雲端運算，也由於科技進步，使得我們能夠獲得更強大的運算資源，本研究除了研究人工智慧外，更積極探討雲端運算對計算的幫助。因此本計畫之相關著作除了運用人工智慧及金融工程物理學理論外，另外也探討了雲端運算的相關應用。根據上述的研究而論，本計畫之相關著作包含兩篇期刊論文及四篇研討會論文，並於研究中心建構了私有雲的虛擬平台，提供相關計畫的運算服務使用。</p> <p>本人也曾多次在國內多所大學及中國大陸進行課程教學，並將此知識進行深度的探討與傳授給學子，課程結束後也獲得學子們的熱烈歡迎，並進而實作了相當多的應用，使本領域的知識逐漸擴散。</p>
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	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

專利：☐已獲得 ☐申請中 ☒無

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）

本研究中心在連續的計畫支持下，逐漸將金融工程物理學的輪廓描繪成形。金融工程物理學的基本原理在於市場是具有行為影響，市場的供給與需求構成了不同程度及力量的賣方及買方。而傳統財務工程根據套利的機會進行價格範圍的推論雖能估計約略範圍，但對於實務預測上卻仍顯得不足，最大的原因在於市場是由人類所參與。由於人類具有各種理性及不理性的行為，因此市場往往無法照著理性的財務工程模型進行價格的預測，金融工程物理學認為人類的行為在過去歷史上不斷的重現，因此若能從大量過去歷史中找到異常現象的發生，便能更有效的對金融商品的定價。

本研究針對金融商品的投資組合進行動態模型的建構，將金融工程物理學與人工智慧進行整合，而實驗結果也顯示透過人工智慧建構的動態模型能夠有效的進行資產配置。近年來由於政府積極推動雲端運算，也由於科技進步，使得我們能夠獲得更強大的運算資源，並且由於雲端的高度彈性及穩定性，使得我們能夠進行更完整的運算。本研究除了研究人工智慧外，更積極探討雲端運算對計算的幫助。因此本計畫之相關著作除了運用人工智慧及金融工程物理學理論外，另外也探討了雲端運算的相關應用。本計畫之相關著作包含兩篇期刊論文及四篇研討會論文，並於研究中心建構了私有雲的虛擬平台，提供相關計畫的運算服務使用。

本人也曾多次在國內多所大學及中國大陸進行課程教學，並將此知識進行深度的探討與傳授給學子，課程結束後也獲得學子們的熱烈歡迎，並進而實作了相當多的應用，使本領域的知識逐漸擴散。

