A Brain-Inspired Cerebellar Associative Memory Approach to Option Pricing and Arbitrage Trading

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Abstract. *Option pricing* is a process to obtain the theoretical fair value of an option based on the factors affecting its price. Currently, the nonparametric and computational methods of option valuation are able to construct a model of the pricing formula from historical data. However, these models are generally based on a global learning paradigm, which may not be able to efficiently and accurately capture the dynamics and time-varying characteristics of the option data. This paper proposes a novel brain-inspired cerebellar associative memory model for pricing American-style option on currency futures. The proposed model, called PSECMAC, constitute a local learning model that is inspired by the neurophysiological aspects of the human cerebellum. Subsequently, the PSECMAC-based option pricing model is used in a mis-priced option arbitrage trading system and simulation results demonstrated an encouraging rate of return on investment.

1 Introduction

Options, as a derivative security, provide a means to manage financial risks. They are playing an increasingly important role in modern financial markets [1]. The buyer of an option enters into a contract with the right, but not the obligation, to purchase or sell an underlying asset at a later date at a price agreed upon today. The price of an option is determined by a set of pricing factors such as time to expiry and the intrinsic values of the options. A vital aspect of option trading is to arrive at the theoretical fair value of an option. This process is called *option pricing*.

The conventional approach to option pricing is to construct parametric models that are based on the assumptions of continuous-time finance theory [2]. The pioneering models are the *Black-Scholes formula* [3] and the *Binomial Pricing Model* [4]. However, these models presumed complex and rigid statistical formulations from which the prices are deduced [5].

Nonparametric and computational methods of option pricing based on neural networks [6–9], genetic algorithms [10] and kernel regression [11], on the other hand, are model-free approaches. The pricing model, which is usually represented as a nonlinear functional mapping between the input factors and the theoretical option price, is derived from vast quantities of historical data. However, these methods involve heuristics and therefore suffer from poor interpretability. More recently, neuro-fuzzy approaches [12] are introduced to overcome this problem. With these techniques, a set of comprehensible semantic rules can be extracted from historical trading data for rational pricing of the options.

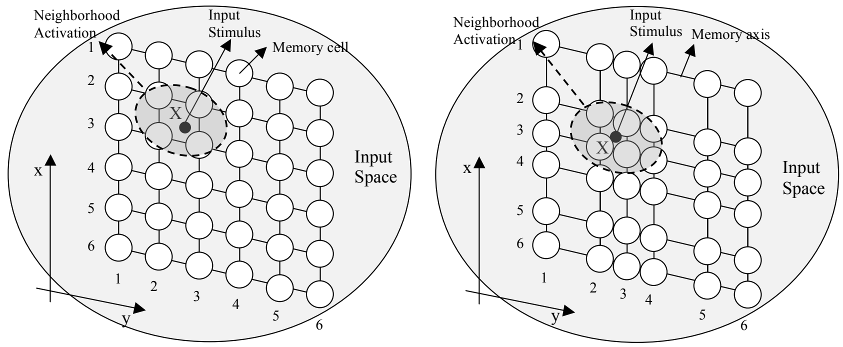
The complex relationship between the valuation of an option and its influencing factors may be modeled as combinatorial associations to be extracted from the historical pricing data. Currently, nonparametric option pricing methods attempts to use a single formulated model to generalize or fit the behaviors/characteristics of the entire set of historical pricing data. Some have argued that it is difficult, if not impossible, to obtain a general and accurate global learning model [13]. Moreover, a financial market is dynamic in nature and thus is characterized by time-varying trading/pricing patterns. Historical option pricing data may contain contradicting time-varying characteristics that make it hard for a single model to accurately approximate the underlying pricing function. This motivates the use of a local associative model as a nonparametric computational method to option pricing. Instead of having a single formulated model, a collection of locally-active models can be used. A local model focuses on modeling the observed data within a given time frame [14] and is obtained from different subset of the training data.

In this paper, a novel brain-inspired cerebellar associative memory approach to the pricing of American-style option on currency futures of British Pound versus US dollar is investigated. The cerebellar associative memory model, referred to as the Pseudo Self Evolving Cerebellar Model Arithmetic Computer (PSECMAC), constitutes a local learning model to approximate the associative characteristics between the option price and its influencing factors. The structure of the PSECMAC network is inspired by the neurophysiological properties of the human cerebellum [15], and emulates the information processing and knowledge acquisition of the cerebellar memory. The proposed PSECMAC option pricing model is employed to detect any misalignments between the market spot value and the theoretical valuation of an option. Using real-life British Pound Sterling versus US dollar future options trading data, our system is able to obtain a return on investment (ROI) as high as 23.1% which is significant given the risk-free nature of the investment.

This paper is organized as follows. In Section 2, the architecture of the PSECMAC network is briefly described. The cerebellar-inspired memory formation and knowledge acquisition process of the network are also highlighted. Section 3 presents an overview of the proposed cerebellar associative memory based option pricing model and defines the selected input factors considered to have an impact on the pricing of American-style currency future options. An autonomous option trading system that employs the proposed option pricing model is introduced in Section 4. The effectiveness of this system is evaluated on British Pound Sterling versus US dollar future options trading data. Section 4.1 concludes this paper with some suggestions for future work.

2 The PSECMAC Network

The cerebellum constitutes a part of the human brain that is important for motor control and a number of cognitive functions [16], including motor learning and memory. The human cerebellum is postulated to function as a movement calibrator [17], which is involved in the detection of movement error and the subsequent coordination of the appropriate skeletal responses to reduce the error. The human cerebellum functions by



(a) CMAC (b) PSECMAC

Fig. 1. Comparison of CMAC and PSECMAC memory quantization for 2D input problem

performing *associative mappings* between the input sensory information and the cerebellar output required for the production of temporal-dependent precise behaviors [15].

The human cerebellum has been classically modelled by the Cerebellar Model Articulation Controller (CMAC) [18]. As a computational model of the human cerebellum, CMAC manifests as an associative memory network [19], where the memory cells are uniformly quantized to cover the entire input space. The CMAC network operation is characterized by the table lookup access of its memory cells. This allows for localized generalization and rapid algorithmic computation, and subsequently motivates the prevalent use of CMAC for control applications [20, 21].

This paper proposes the use of a brain-inspired cerebellar-based learning memory model named Pseudo Self-Evolving Cerebellar Model Arithmetic Computer (PSECMAC) as a generic functional model of the human cerebellum for solving approximation, modeling, control and classification problems. This architecture differs from the CMAC network in *two* aspects. Firstly, the PSECMAC network employs *one* layer of network cells, but maintained the computational principles of the layered-based CMAC network by adopting a neighborhood activation of its computing cells to facilitate: (1) smoothing of the computed output; (2) distributed learning paradigm; and (3) activation of highly correlated computing cells in the input space. Secondly, instead of uniform partitioning of the memory cells, the PSECMAC network employs the PSEC clustering technique [22] to form an experience-driven adaptive memory quantization mechanism of its network cells. Figure 1 illustrates this fundamental architectural distinction.

The adaptive quantization process of the PSECMAC network is performed in per dimension basis. The non-uniform quantization of the PSECMAC memory structure is inspired by the neurophysiological properties of the brain development, where the precise wiring in the adult brain is a result of experience-dependent refinement of initial architecture through repeated exposures to external stimuli. This experience-dependent plasticity is also observed in the human cerebellum [23], and is incorporated to the PSECMAC network through the PSEC clustering algorithm. Each training data point is a learning episode to the network. In each input dimension, the PSEC clustering algorithm is used to compute clusters of data density, and the memory axes in each dimension are allocated based on the observed density profile of the training data. Thus, more memory cells are allocated to the densely populated regions of the input space. The details on the adaptive quantization algorithm is reported in [24].

The PSECMAC network employs a *Weighted Gaussian Neighborhood Output* or WGNO computational process, where a set of neighborhood-bounded computing cells is activated to derive an output response to the input stimulus. For each input stimulus $\mathbf{X}$, the computed output is derived as follows:

Step 1: Determine the region of activation
Each input stimulus $\mathbf{X}$ activates a neighborhood of PSECMAC computing cells. The neighborhood size is governed by the neighborhood constant parameter N, and the activated neighborhood is centered at the input stimulus (see Fig 1(b)).
Step 2: Compute the Gaussian weighting factors
Each activated cell has a varied degree of activation that is inversely proportional to its distance from the input stimulus. These degrees of activation functioned as weighting factors to the memory contents of the active cells.
Step 3: Retrieve the PSECMAC output
The output is the weighted sum of the memory contents of the active cells.

Following this, the PSECMAC network adopts a modified *Widrow-Hoff learning rule* [25] to implement a *Weighted Gaussian Neighborhood Update* (WGNU) learning process. The network update process is briefly described as follows:

Step 1: Computation of the network output
The output of the network corresponding to the input stimulus $\mathbf{X}$ is computed based on the WGNO process.
Step 2: Computation of learning error
The learning error is defined as the difference between the expected output and the current output of the network.
Step 3: Update of active cells
The learning error is subsequently distributed to all of the activated cells based on their respective weighting factors.

3 A PSECMAC based Option Pricing Model

The PSECMAC network is used to construct a pricing model to predict the correct valuations for American call options on the British pound (GBP) and US dollar (USD) exchange rate futures contract. In this study, the option pricing formula is represented as a function of the following inputs: S_0, X, T, and σ_{30}; where S_0 is the current GBP vs. USD exchange rate futures value; X is the strike price of the option on the GBP vs. USD exchange rate futures; T is time to maturity of the option in years; and σ_{30} is the historical price volatility for the last 30 trading days. We introduce the notion of *moneyness* (or intrinsic value) of the futures option, which is computed as the difference between the current futures value S_0 and the options strike price X (i.e. $S_0 - X$). Thus, the pricing function f to be approximated by the PSECMAC network is:

$$C_0 = f(S_0 - X, T, \sigma_{30}) \tag{1}$$

Table 1. Simulation set-ups based on permutations of the three sub-groups A, B and C to define the training and testing sets of the proposed PSECMAC option pricing model

Configuration	Simulation	Training set	Testing set
$1/3$ training and $2/3$ testing	I	Sub-group A	Sub-groups B and C
	II	Sub-group B	Sub-groups A and C
	III	Sub-group C	Sub-groups A and B
$2/3$ training and $1/3$ testing	IV	Sub-groups A and B	Sub-group C
	V	Sub-groups B and C	Sub-group A
	VI	Sub-groups A and C	Sub-group B

where C_0 is current option price; and $(S_0 - X)$ reflects the moneyness of the options.

The data used in this study consists of the daily closing quotes of the GBP versus USD currency futures and the daily closing bid and ask prices of American style options on such futures in the Chicago Mercantile Exchange (CME) [26] during the period of Sept 2002 to Aug 2003. In total, 792 data samples are available in the selected futures option data set, which contains the historic pricing data for five different strike prices: $\$158$, $\$160$, $\$162$, $\$166$ and $\$168$, with 159, 158, 173, 137 and 165 data samples respectively. The presentation order of the 792 data samples is randomized and subsequently partitioned into three evenly distributed sub-groups denoted as A, B and C, each containing 264 data tuples. A total of six different cross-validation sets are constructed based on the permutations of the sub-groups, as outlined in Table 1.

A PSECMAC network with a memory size of 12 cells per dimension is constructed. A neighborhood size of 0.2 and Gaussian weighting factor of 0.5 is employed. Table 2 tabulates the *recall* (training) and *generalization* (testing) performances of the PSECMAC option pricing model under the various cross-validation sets. *RMSE* denotes the root-mean-square-error between the predicted and desired option prices, and *Correlation* is the Pearson correlation coefficient, a statistical measure reflecting the goodness-of-fit between the predicted and desired pricing functions. The performances of the PSECMAC option pricing model are generally good, with an average RMSE of around 0.13 and 0.23 for the recall and generalization process respectively. An average correlation of 0.98 is achieved in the generalization process, indicating a very low performance degradation as the evaluation emphasis is shifted from the recall to the generalization capability of the system. From Table 2, one can also observe that a larger training data set improves the generalization performance of the option pricing model.

As benchmarks, the set of option pricing simulations is repeated using two global nonparametric approximators: the multi-layered perceptron (MLP) and the GenSoFNN-TVR [12] networks; as well as the CMAC network, which is a well-established local learning model. Table 3 summarizes the benchmarking results. The network structure of the MLP, which consists of three input, eight hidden and one output nodes respectively, has been empirically determined, while the GenSoFNN-TVR network is a self evolving structure. Also, for a fair comparison, the size of the CMAC network is set as 12 cells per dimension. From Table 3, one can observe that the MLP network possesses the most accurate pricing decisions as compared to the other benchmarked systems. However, it is a black-box model as its complex synaptic weight structure is hardly human

Table 2. Performances of the proposed PSECMAC option pricing model

Configuration	Simulation	Recall RMSE	Recall Correlation	Generalization RMSE	Generalization Correlation
$1/3$ training and $2/3$ testing	I	0.1299	0.9956	0.2386	0.9858
	II	0.1376	0.9954	0.2727	0.9816
	III	0.1178	0.9964	0.2638	0.9847
$2/3$ training and $1/3$ testing	IV	0.1382	0.9952	0.2103	0.9889
	V	0.1404	0.9949	0.2210	0.9885
	VI	0.1353	0.9954	0.2007	0.9902
	Average	0.1332	0.9955	0.2345	0.9866

Table 3. Benchmarking results for various global and local option pricing model

System	Type	Recall RMSE	Recall Correlation	Generalization RMSE	Generalization Correlation
MLP(3-8-1)	global	0.0384	0.9997	0.0982	0.9963
PSECMAC	local	0.1332	0.9955	0.2345	0.9866
CMAC	local	0.0605	0.9990	0.2738	0.9813
GenSoFNN-TVR	global	0.1808	0.9946	0.2576	0.9873

interpretable. There is no mechanism to explain the logical steps that the MLP network employs for its pricing decisions. Moreover, the empirical determination of the network structure often renders the MLP network hard to use. In contrast, the global learning-based GenSoFNN-TVR network offers interpretable semantic rules, at the expense of lower pricing accuracy. The performances of both the CMAC and PSECMAC local models, on the other hand, exceed those of the global GenSoFNN-TVR model. Furthermore, the pricing decisions of the proposed PSECMAC option pricing model outperform those of the CMAC model. The associative structure of the PSECMAC model also enables discrete pricing rules to be extracted. For example, "IF the *time-to-maturity* is between 0 - 0.04 years and the *volatility* is between 5.08 - 5.28 and the *moneyness* is between $\$5.03$ - $\$7.98$ THEN the Option-Price (on average) is $\$9.4$" is a representative discrete rule extracted from the PSECMAC model that expresses the knowledge induced from the training data.

4 Cerebellar Associative Memory Approach to Arbitrage Trading

This section introduces a mis-priced option *arbitrage* trading system, where the PSECMAC option pricing model is employed to detect any misalignments between the market spot value and the theoretical valuation of an option. When such mis-pricing occur, potential arbitrage trading opportunities on that option are created and investors can exploit these opportunities to derive risk-free profits.

An arbitrage opportunity arises when the *Law of One Price* [1] is violated, making it possible for an investor to make a *risk-less* profit. In this paper, an arbitrage trading strategy known as the *Delta Hedge Trading Strategy* (DHTS) [1] is employed in the proposed PSECMAC-based trading system. In the DHTS, a delta hedge ratio h is computed to determine the quantity of the underlying asset (e.g. stock) required to cover the risk of taking a naked position on the call option. Hence, the selling of one call option is hedged by the buying of h quantity of the underlying asset and vice versa. The hedge ratio h is computed as:

$$h_t = \frac{\Delta C}{\Delta S} = \frac{(\hat{C}_{u,t+1} - \hat{C}_{d,t+1})}{(S_{u,t+1} - S_{d,t+1})} \in [0, 1] \tag{2}$$

where h_t is the hedge ratio at current time t (i.e. this trading opportunity) employed to build up a risk-free portfolio with proper ratio of call option and the underlying asset; $S_{u,t+1}$ is the price of the underlying asset at time $t+1$ (i.e. the next trading opportunity) if the price goes up; $S_{d,t+1}$ is the price of the underlying asset at time $t+1$ (i.e. the next trading opportunity) if the price goes down; ΔS is the change in value of the underlying asset due to the projected change in price S_t at time $t+1$; ΔC is the change in value of the call option due to the projected change in price of the underlying asset at time $t+1$; $\hat{C}_{u,t+1}$ is the predicted price of the call option if the value of the underlying asset is $S_{u,t+1}$ at time $t+1$; and $\hat{C}_{d,t+1}$ is the predicted price of the call option if the value of the underlying asset is $S_{d,t+1}$ at time $t+1$.

However in this study, for simplicity, the price of the underlying asset is assumed to either go up by 0.5 unit price or go down by 0.5 unit price (i.e. $S_{u,t+1} = S_t + 0.5$ and $S_{d,t+1} = S_t - 0.5$) such that the variable ΔS in equation (2) evaluates to unity. That is, there is only a unit change in the price of the underlying asset from time t to time $t+1$. Hence, equation (2) can be reduced to:

$$h_t = \frac{(\hat{C}_{u,t+1} - \hat{C}_{d,t+1})}{(S_{u,t+1} - S_{d,t+1})} = \frac{(\hat{C}_{u,t+1} - \hat{C}_{d,t+1})}{(S_t + 0.5 - (S_t - 0.5))} = (\hat{C}_{u,t+1} - \hat{C}_{d,t+1}) \tag{3}$$

Thus, the hedge ratio of the portfolio at current time t is simply computed as the difference in the predicted and current prices of the call option at times $t+1$ and t respectively.

4.1 Trading Strategy

Based on the DHTS discussed in the last section, the PSECMAC-based option trading system is implemented. The general framework of the trading system proposed in this paper is a modified version of the generic trading decision model found in [27], and is illustrated in Figure 2.

The format of the training set is as described in Section 3. Historic data of options with strike prices of $158, $160, $162, $166 and $168 respectively from Sept 2002 to Feb 2003 is used to train the PSECMAC-based option pricing model. The test set contains out-of-sample data consisting of the intra-day bid and ask prices of options with strike prices of $158, $159, $160, $164 and $170 respectively from Mar 2003 to Aug 2003. The trading algorithm is summarized as follows:

1. The proposed trading system takes in the theoretical option value C_t computed by the PSECMAC-based option pricing model and subsequently compares it to the spot bid-ask prices of this option.

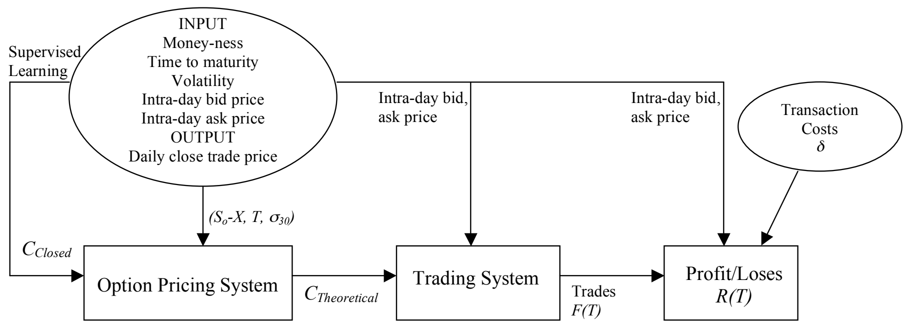


Fig. 2. General framework of the proposed mis-priced option arbitrage system

2. If the predicted theoretical option value C_t falls out of the bid-ask spread range, the trading system assumes a mis-priced arbitrage opportunity as being detected.
3. The trading system would take up trading positions according to the following trading strategy:
   (a) Evaluate if the call option is overpriced or under-priced using equation (4).

$$\text{Call option} = \begin{cases} \text{Overpriced}, & \text{if } C_t < \text{Option bid-price at time } t \\ \text{Underpriced}, & \text{if } C_t > \text{Option ask-price at time } t \end{cases} \tag{4}$$

   (b) If the call option is overpriced, short sell the call option and hedge the risk by buying in h_t quantity of the underlying asset, i.e. the GBP vs. USD exchange rate futures. The hedge ratio h_t is computed using equation (3). Else, if the call option is under-priced, buy in the call option and short sell h_t quantity of the GBP vs. USD exchange rate futures to hedge the risk.
4. If the trading system has already possessed a portfolio (i.e. has either a long or short open position on the call option and with the appropriate ratio of hedged futures), it would continuously check whether the mis-priced option has been pulled back into the option bid-ask spread range. If it is the case, the trading system closes all the outstanding position immediately; and if it is not, it continues to hedge the portfolio by computing a new hedge ratio h_{t+1} and adjusting the portfolio composition.

4.2 Results and Analysis

The proposed PSECMAC-based trading system is evaluated by observing its arbitrage performances using real-life GBP vs. USD currency exchange rate futures options with various strike prices. To simplify the simulation setup, the costs of the trading transactions are omitted here. The results are tabulated in Table 4. The ”total capital outlay” refers to the overall amount of investment made on the sales and purchases of the respective options and futures in the hedging exercises, while ”return on investment” (ROI) denotes the profit earned from the trading endeavors. As tabulated in Table 4, the PSECMAC-based trading system has demonstrated fairly high returns for investment, with ROI of as high as 23.1% for the option strike price of $\$164$ and an average ROI of

Table 4. Arbitrage performances of the proposed PSECMAC-based opntion trading system. (Note: UO is option under-priced arbitrage opportunity; OO is option over-priced arbitrage opportunity; and ROI denotes the return on investment)

Option Strike Price X ($)	**Sim Period** (days)	**Num of UO transaction**	**Num of OO transaction**	**Total Capital Outlay** ($)	**Absolute ROI** ($)	**Percentage ROI** (%)
158	156	26	19	143300	7964.80	5.56
159	61	7	15	50940	4228.60	8.3
160	65	0	17	30820	1809.30	5.87
164	97	17	10	20560	4759.60	23.15
170	94	10	12	5560	1175.20	21.14
					Average ROI (%)	12.80

around 12.8% percent for all of the five options. Such an average rate of return is considered encouraging given the risk-free nature of the investment portfolio constructed and when compared against other interest rates of risk-free investments at this moment. For example, according to the Federal Reserve Board, the 3-months compounding interest rate of US Treasury Bill is 0.93% on 30th September 2003, and the 3-month fixed deposit interest rate in Singapore is only 0.25% on 3rd October 2003 according to data provided by the Development Bank of Singapore (DBS).

5 Conclusions

This paper proposes the use of a brain-inspired cerebellar associative learning memory structure named PSECMAC to perform nonparametric option pricing of American style call options on the British pound (GBP) versus US dollar (USD) currency futures. The PSECMAC-based option pricing system constitutes a local learning approach to the approximation of the associative characteristics between the option price and its influencing factors. Evaluation results have demonstrated that the modeling capabilities of the proposed pricing system exceed those of the global learning-based GenSoFNN-TVR model, as well as the well established local learning-based CMAC network. The associative structure of the PSECMAC model also enables discrete pricing rules to be extracted from the pricing system. Subsequently, the PSECMAC-based option pricing model is employed in a mis-priced option arbitrage trading system. Simulation results on various options with different strike prices showed that such a mis-priced arbitrage trading system is able to construct risk-free investment portfolios with a satisfactory rate of return on investment. Future studies will attempt to incorporate other external factors such as transaction costs, as well as to extend the PSECMAC-based option pricing system to a fuzzy associative model to enable the extraction of fuzzy rules.

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