The Fourteenth IEEE International Conference on e-Business Engineering

APPLICATION OF MACHINE LEARNING: AN ANALYSIS OF ASIAN OPTIONS PRICING USING NEURAL NETWORK

Zhou Fang
Department of Electrical Engineering and Computer Science
University of California at Irvine
(217) 819—2454
Zhouf5@uci.edu

K. M. George
Department of Computer Science
Oklahoma State University
Department of Computer Science (405)744-5221
kmg@cs.okstate.edu

Abstract— **Pricing Asian Option is imperative to researchers, analysts, traders and any other related experts involved in the option trading markets and the academic field. Not only trading highly affected by the accuracy of the price of Asian options but also portfolios that involve hedging of commodity. Several attempts have been made to model the Asian option prices with closed-form over the past twenty years such as the Kemna-Vorst Model and Levy Approximation. Although today the two closed-form models are still widely used, their accuracy and reliability are called into question. The reason is simple; the Kemna-Vorst model is derived with an assumption of geometric mean of the stocks. In practice, Average Priced Options are mostly arithmetic and thus always have a volatility high than the volatility of a geometric mean making the Asian options always underpriced. On the other hand, the Levy Approximation using Monte Carlo Simulation as a benchmark, do not perform well when the product of the sigma (volatility) and square root maturity of the underlying is larger than 0.2. When the maturity of the option enlarges, the performance of the Levy Approximation largely deteriorates. If the closed-form models could be improved, higher frequency trading of Asian option will become possible. Moreover, building neural networks for different contracts of Asian Options allows reuse of computed prices and large-scale portfolio management that involves many contracts.**

In this thesis, we use Neural Network to fill the gap between the price of a closed-form model and that of an Asian option. The significance of this method answers two interesting questions. First, could an Asian option trader with a systematic behavior in pricing learned from previous quotes improve his pricing or trading performance in the future? Second, will a training set of previous data help to improve the performance of a financial model? We perform two simulation experiments and show that the performance of the closed-form model is significantly improved. Moreover, we extend the learning process to real data quote. The use of Neural Network highly improves the accuracy of the traditional closed-form model. The model's original price is not so much accurate as what we estimate using Neural network and could not capture the high volatility effectively; still, it provides a relative reasonable fit to the problem (Especially the Levy Model). The analysis shows that the Neural Network Algorithms we used affect the results significantly.

Keywords— Asian Options; Option Pricing; Neural Networks (NNs); Machine Learning; Behavioral Finance

I. INTRODUCTION

For Asian options pricing, we try to use the neural network to set up a parameter for the input of the non-linear model with the change of the volatility. In the thesis, we propose and test a valuation methodology for improving the accuracy of options by using Neural Network integrated with Levy Approximation. Therefore, in our research, we will review the history of the financial derivative and the pricing research, and then study the classical Black-Scholes option model in order to improve the pricing accuracy of the Levy Approximation option pricing formula. Our study also reviews the various numerical methods of Asian pricing options. Based on the literature reviews, a method of Asian option pricing is given based on the filtering of real volatility with the neural network. The parameter of the pricing model is estimated by the neural network B-P algorithm, integrating with Levy Approximation, to construct a new Asian option pricing model. The real market quote of WTI Financial Futures Average Price Options is used to validate the new model, and its performance is compared. Finally, we clarifies the new model will improve the efficiency of valuation and financial decision-making dramatically in the market of Asian Options.

During the last two decades, Asian Options serve as an important financial derivative for investors to control their investment risks in the future markets. Determining the theoretical price for options, especially Asian Options is regarded as one of the most important issues in the financial research. However, many classical and successful pricing models that have been presented, due to these traditional methods that are only simplification to the actual market, the results are less than optimal and the effects are not as good as what people expected.

In our research, we introduced neural network theory and model to analyze Asian Option and price it. Learning capability is a feature of neural networks, which can gain the rule from the sample. The nonlinear neural network is able to approximate any integrated function arbitrarily well. In the application of neural network to Asian Options, a new option-pricing model based on the adjusted Levy Approximation Model is established to improve the pricing performance. First, our new model integrates traditional pricing model–Antithetic Monte Carlo model to obtain a better forecasting result as benchmark of learning in order to cut down the forecasting errors. Second, we modify the implied volatility of the Levy Approximation model using Monte Carlo prices as a benchmark. Third, we build the neural network by mapping the real volatilities to the implied volatilities. After the network is built, we can always use the network to get the right implied volatility and improve the accuracy of Levy Approximation Model. The experiments are divided into simulation experiments and real data experiments. The only difference

978-1-5386-1412-9/17 $31.00 © 2017 IEEE
DOI 10.1109/ICEBE.2017.30

between the two is that in simulations, the Monte Carlo Prices are used as benchmark prices while in real data, the WTI Average Priced Option quotes are used as benchmark prices. The new pricing model improves the performance of Asian option pricing significantly. Compared to the traditional option pricing models, the error of the traditional method will be reduced and our pricing performance will be improved significantly.

As stated above, for the Levy Approximation Model, when the value of $\sigma\sqrt{\tau}$ (volatility multiply by square root maturity) is larger than 0.2 its performance deteriorates [1]. In extreme cases in my experiment, when the option have a high volatility and is deep in the money, the mean square error of the value using Levy Approximation could be larger than 10 making the model completely useless. The question of this thesis is with the aid of neural network, could the performance of the Levy Approximation be improved and the deteriorating of the performance be fixed. Moreover, we perceive neural network as a tool for simulating human mind to answer the question if an experienced Asian Option trader realized that there is a gap between the model and the real quotes. Could he fill the pricing gap according to his previous trading experience? At last, we want to see that if a model proposed decades ago could better applied with new tools and techniques.

Asian options trading are a significant component of committing money or capital in derivatives markets. They perform a role of controlling risks and creating income. Trading in options unlike other derivatives provides unparalleled set of merits as follows; they offer inexpensive and productive ways of hedging one's portfolio against unfavorable and unforeseen price variations, and they provide a speculative method to trading among others. Trading on either call or put options are all the time inexpensive than the underlying stock. Majority of traders would rather trade on options than stocks in order to; conserve transaction costs, circumvent tax exposures, and circumvent stock market restrictions among others [2].

Several attempts have been made to model the Asian option prices with closed-form over the past twenty years such as the Kemna-Vorst Model and Levy Approximation Model. Although today the two closed-form models are still widely used, their accuracy and reliability are called into question. The reason is simple, the Kemna-Vorst is derived with an assumption of geometric mean of the stocks. In practice Average Priced Options are mostly arithmetic and thus always have a volatility high than the volatility of a geometric mean making the Asian options always underpriced. On the other hand, the Levy Approximation using Monte Carlo Simulation as a benchmark, do not perform well when the value of $\sigma\sqrt{\tau}$ (volatility multiply by square root maturity) is larger than 0.2. And when the maturity of the option enlarges, the performance of the Levy Approximation largely deteriorates. Although in practice a long maturity does not often exist, there is still requirements for Asian Style FLEX options with long Maturity. Monte Carlo Simulation or numerical methods are the existing best method for pricing Asian Options. However, numerical methods required long running time to achieve a reasonable price. In such a case, a fast and reliably closed-form pricing model is still preferable for adapting to the actively trading of underlying contract and the dynamic change of the volatility. If the closed-form model could be improved, not only the higher frequency trading of Asian option will become possible but also the large-scale Asian option portfolio management becomes achievable.

In this paper, we use Neural Network to fill the gap between the price of a closed-form model and that of an Asian option. The significance of this method answers two interesting questions. First, could an Asian option trader with a systematic behavior in pricing learned from previous quotes improved his pricing or trading performance in the future? Second, will a training set of previous data help to improve the performance of a financial model? We perform a simulation experiment and a real data experiment to show that the performance of the closed-form model is significantly improved. The accuracy of the Levy Approximation Model with Neural Networks id higher than that of the other traditional models. The analysis shows that after learning and testing, the pricing of Asian Options on simulation or on the real data test, all have a significant effect on the results. Moreover, the neural network algorithms used in study impact the results significantly.

II. Literature Review

Robert R. Trippi and EfraimTurban [3] said, neural networks are revolutionizing virtually every aspect of financial and investment decision making. Financial firms worldwide are employing neural networks to tackle difficult tasks involving intuitive judgement or requiring the detection of data patterns, which elude conventional analytic techniques. Many observers believe neural networks will eventually outperform even the best traders and investors. Neural networks have already being used to trade the securities markets, to forecast the economy and to analyze credit risk.

In order to avoid the shortage of these traditional parametric models, neural network model has been widely applied and studied in the option pricing model. Huchison [4] first used RBF and BP neural network models for pricing European options, His research demonstrated that the model is better than the Black-Scholes model. Huchison proposed a nonparametric method for estimating the pricing formula of a derivative asset using neural networks. Huchison pointed out that although not a substitute for the more traditional arbitrage-based pricing formulas, network-pricing formulas may be more accurate and computationally more efficient alternatives when the underlying asset's price dynamics are unknown, or when the pricing equation associated with the no-arbitrage condition cannot be solved analytically.

Jingtao Yao at el. [5] Conducted forecasting of the option prices of Nikkei 225 index futures by using back propagation neural networks. Different results in terms of accuracy are achieved by grouping the data differently. The results suggest that for volatile markets a neural network integrated option-pricing model outperforms the traditional Black–Scholes model. In the neural network model, data partition according to moneyness is applied, and those who prefer high risk and high return may choose to use the neural network model results.

In 2004, Marco J. Morelli at el. [6] applied neural network algorithms to the problem of option pricing and adopted it to simulate the nonlinear behavior of such financial derivatives. Two different kinds of neural networks, i.e. multi-layer perceptions and radial basis functions, are used and their performances compared in detail. The analysis was carried out both for standard European options and American ones, including evaluation of the Greek letters, necessary for hedging purposes. Marco J. Morelli at el. 's detailed numerical investigation show that, after a careful phase of training, neural networks are able to predict the value of options and Greek letters with high accuracy and competitive computational time.

Gradojevic et al. [7] proposed a nonparametric modular neural network (MNN) model to price the S&P-500 European call options. The modules are based on time to maturity and moneyness of the options. The option price function of interest is homogeneous of degree one with respect to the underlying index price and the strike price. When compared to an array of parametric and nonparametric models, the MNN method consistently exerts superior out-of-sample pricing performance. In their study they found out that, modularity improves the generalization properties of standard feedforward neural network option pricing models.

Yi-Hsien Wang [8] integrated new hybrid asymmetric volatility approach into artificial neural networks option-pricing model to improve forecasting ability of derivative securities price. Owing to combines, the new hybrid asymmetric volatility method can be reduced the stochastic and nonlinearity of the error term sequence and captured the asymmetric volatility simultaneously. In Wang's ANNS option-pricing model, the results demonstrated that Grey-GJR–GARCH volatility provides higher predictability than other volatility approaches.

Zhang Hongyan, at el. [9] proposed a model of hybrid wavelet neural network based on the Black-Scholes model, and built some hybrid forecasting models combining the hybrid Wavelet neural network and genetic algorithm for test. In such an approach, options are classified according to their moneyness, and the weighted implied volatility rates are regarded as the input of the neural network. Zhang used a genetic algorithm to determine the optimal weights of the implied volatility rates of different kinds of options. Case study on Hong Kong derivative market shows that these hybrid models are better than the conventional Black-Scholes model and the other neural network models.

S. Shakya, at el. [10], described how neural networks and evolutionary algorithms can be combined together to optimize pricing policies in their study. Particularly, they built a neural network based demand model and use evolutionary algorithms to optimize policy over build model. There are two key benefits in their approach. Use of neural network made it flexible enough to model a range of different demand scenarios occurring within different products and services, and the use of evolutionary algorithm made it versatile enough to solve very complex models. Shakya also evaluated the pricing policies found by neural network based model to that found by other widely used demand models. The results showed that proposed model is more consistent, adapts well in a range of different scenarios, and in general, finds more accurate pricing policy than other three compared models.

Mitra [11] pointed out, the Black and Scholes formula for theoretical pricing of options exhibits certain systematic biases, as observed prices in the market differs from the formula. A number of studies attempted to reduce these biases by incorporating a correction mechanism in the input data. Amongst non-parametric approaches used to improve accuracy of the model, Artificial Neural Networks are found as a promising alternative. Mitra's study made an attempt to improve accuracy of option price estimation using Artificial Neural Networks where all input parameters are adjusted by suitable multipliers. The values of these multipliers were determined using known data that minimizes errors in valuation.

Fei Chen and Charles Sutcliffe [12] compared the performance of artificial neural networks (ANNs) with that of the modified Black model in both pricing and hedging short sterling options. Using high-frequency data, standard and hybrid ANNs are trained to generate option prices. Chen's study testified that the hybrid ANN is significantly superior to both the modified Black model and the standard ANN in pricing call and put options. Hedge ratios for hedging short sterling options positions using short sterling futures are produced using the standard and hybrid ANN pricing models, the modified Black model, and also standard and hybrid ANNs trained directly on the hedge ratios. The performance of hedge ratios from ANNs directly trained on actual hedge ratios is significantly superior to those based on a pricing model, and to the modified Black model.

III. PROBLEM STATEMENTS

In our research, we use the Asian Option's Analytic Pricing Formula as the basic equation to price the Asian Options first. If Save is defined as the geometric average of stock prices, since the product of log normally distributed random variables also follows the lognormal distribution, Save is log normally distributed. In the risk-neutral world, the process of S_{ave} over a certain period T is with the expected continuously compounding growth rate [13].

A. *The Levy Model*

The Levy Model [14] can be used to price and calculate prices and sensitivities of European geometric Asian options as well in the financial practice:

$$dS(t) = \alpha S(t)dt + \sigma S(t)dW(t) \tag{1}$$

A (t) is the running average: For 0≤m≤N,

$$A(t) = \frac{1}{m+1}\sum_{i=0}^{m} S(t_i) \tag{2}$$

Undetermined component of the final average:

$$M(t) = [A(t_N) - \frac{A(t)(m+1)}{N+1}] \tag{3}$$

Where M(t) is a sum of correlated log normal random variables and follows a lognormal distribution.

$$\Psi_x(k) = E^*[M(t)^k] = e^{k\alpha(t)+\frac{1}{2}k^2 v(t)^2} \tag{4}$$

where,

$$\alpha(t) = 2lnE^*[M(t)] - \frac{1}{2}E^*[M(t)^2] \tag{5}$$

and,

$$v(t) = \sqrt{lnE^*[M(t)^2] - 2lnE^*[M(t)]} \tag{6}$$

The final option prices will be:

$$C[S(t), A(t), t] = e^{-r(T-t)}\{E^*[M(t)]N(d_1)$$

$$-[K - A(t)(m+1)/(N+1)]N(d_2)\} \tag{7}$$

where,

$$d_1 = \frac{\frac{1}{2}lnE^*[M(t)^2] - \ln[K - A(t)(m+1)/(N+1)]}{v(t)} \tag{8}$$

and,

$$d_2 = d_1 - v(t) \tag{9}$$

B. *Neural Networks (NN) Models*

Asian Option pricing is important as it helps to have a better picture of the market in the future and enables us to monitor the factors that might affect the price movement. There are several techniques to model and predict Asian Option pricing trend. Since the Asian Option price change is random, NN models could explain the nature of this oscillation. In addition, the periodic fluctuations of the Asian Option price introduce some other variables which can describe these vacillations. Another method that could explain this random trend is the time series techniques. The price could be modeled based on various pricing models and methods. Neural network came into the picture when computers became much faster tools. Using Matlab enables us to run and train a neural network with high speed and accuracy.

C. *Methodologies of Neural Network Analysis and Asian Option Pricing*

In our study, the two methodologies to improve option pricing accuracy we focus attention on here are using simulation data from Antithetic Monte Carlo and real data for Asian options price. The difference between the two methodologies is that in real data experiments, the real data are used for benchmark to derive the implied volatility while in the simulation experiments, the simulated option price from Antithetic Monte Carlo is used.

In our study, the first step is to calculate the benchmark price by Antithetic Monte Carlo Model. The results from the closed form model with integrated neural network will be compared with the closed form without neural network. The built neural network could be used as a filter for the real volatility and provide a reliable way of mapping the real volatility to the implied volatility.

Firstly, calculate the benchmark option prices by Antithetic Monte Carlo Model. Firstly, create one set of option prices with volatility ranging from 0.1 to 0.9 with interval of 0.05. This set of data is used to build the neural network. Then two set of option prices are generated to form the test set. The two sets are generated using the same method with the volatilities increased by 20% and decreased by 20%. (We increased the volatility by 20% from 0.1 to 0.9 by 20% to get one set and decrease the volatility by 20% from to 0.9 by 20% to get the other set. Option price with volatility (0.1 ~ 0.9), Option price with volatility increased by 20%, Option price with volatility decreased by 20%).

Secondly, extract the implied Volatility Using the Levy Model. Note that the implied volatility is not the real volatility of the underlying asset but the volatility that serve as the response variable within the neural networks. The algorithm used is also the Levenberg–Marquardt algorithm.

Thirdly, we take the Volatility ranging from 0.1 to 0.9 as input and the corresponding implied volatility as response variable to build the neural network. The data set is divided into training, validation and test set while building the neural network.

Fourthly, we then take the set of option price with volatility that increased by 20% and decreased by 20% as test sets. The option price of the Levy model and the integrated model is calculated and compared. This will give straightforward view how the price would change after the neural network is applied.

The experiment is designed to primarily test the error of the closed-form model and to see that if there is any improvement made when implied volatility is computed using neural network. Firstly, 9 panels of synthetic data are generated. These simulated prices have a stock price to strike price ratio of 1.2, 1.0, and 0.8. Within each set of the Stock price to strike price ratio, we have different maturity of 1, 2 and 4-year contract prices. So, there will be nine panels in total. Within each panel, we first generate a series of prices with volatility ranging from 0.1 to 0.9 with an interval of 0.05. This set of data is used to build the network. We then generate two other sets of option prices with the same parameter except that the volatility is increased by 20% for one set and decreased by 20% for the other. These two sets are used as test sets for the trained neural network. We want to see that if the volatility changes, how well neural network is able to deal with the change of the error. The 0.1 to 0.9 set will be considered as the minimum number of data required to build a convincing neural network for adjusting the error. We also try to use part of the increased 20% and decreased 20% set as data sets to build the neural network. The result of the neural network is expected to be better since more data points are incorporated.

The range of the set has to cover the whole range of the volatility to be priced. If this is achievable, more reasonable fitting for large portfolio management will become available.

The real data experiment will be similar to that of the previous simulation experiment. The real data experiment will be simpler than the simulation experiment. Since the Asian option contracts of WTI all are one month maturity. We build the neural network by mapping the real volatility to the implied volatility using data of one month period. Then we use the neural network to map the real volatility to the estimated implied volatility for the data of one week long. The error of the estimated option price is then measured by the real price of the option. The errors of Asian option prices with and without the learning process are compared using the real data quote as a benchmark.

Firstly, retrieve the Real data from Chicago Mercantile exchange. We will use one-month real data to build the neural network and take the whole week after the real data as the test set.

Secondly, extract the implied Volatility Using the Levy Model. Note that the implied volatility is not the real volatility of the underlying asset but the volatility that serve as the response variable within the neural networks. The algorithm used is also the Levenberg–Marquardt algorithm. Also, note that the maturity, rate, and the underlying price will be the real data retrieved each day. (These parameters follow the same assumption across time).

Thirdly, we calculate the real Volatility from the underlying asset as input for the neural network and the implied volatility as the response variable. We build neural networks and record the mean square error and R-value.

Fourthly, we then use the neural network to fit the real volatility in the test set to the target volatility. Then the error of pricing with real volatility and the target volatility is compared using the real data as benchmark.

To summarize, this proposal is to augment the accuracy of the Levy Model for option pricing [14] by integrating the model with a neural network to fit the real volatilities to the implied volatilities. The objective is to obtain an improved Levy Model to better price Asian options. We propose to evaluate the augmented model by two approaches namely, Antithetic Monte Carlo Model and real options price data.

IV. RESULTS

A. The Result of the Simulation Experiment

Three sets of data with an S/K ratio of 1.2, 1, and 0.8 is tested. We also extended the experiment to option with three different maturities of one year, two year and three year. First, we run the Monte Carlo simulation to retrieve an option price with volatility ranging from 0.1 to 0.9 with an interval of 0.05 within the each set. Using these prices as benchmark, we extract corresponding volatility using the closed forms of Levy Approximation. These implied volatilities are used as outputs for building the network (We divide the data points randomly) and we matched the training set using neural network. Within the same set, we change the volatility within the set by ±20 percentage. The changed volatilities are the test sets and we used neural network to examine the test sets and achieved a learned volatility. We also try to use different proportion of data for training set, validation set and test set. The more data available for building the network, the more accurate the neural network will be in terms of predicting. In this experiment, we will use the least possible data for building the neural network. We rework 5 different networks in and see how its average performance will be. We compared the error of Levy Model with and without the learning phase against the Antithetic Monte Carlo benchmark.

As an example, we take the experiment when S/K=1.2, τ=4. The statistics for the Asian option is as Table 1.

TABLE I. NEURAL NETWORK STATISTICS FOR OPTIONS OF S/K=1.2 τ=4

Neural Network Number	Sets	
	Training Set	*Test Set*
No.1	MSE: 1.32955e-7	MSE: 4.90016e-6
	R: 9.99986e-1	R: 9.99830e-1
No.2	MSE:1.35725e-6	MSE: 2.26924e-6
	R: 9.99985e-1	R: 9.99998e-1
No.3	MSE: 1.36251e-6	MSE: 3.89050e-6
	R: 9.99986e-1	R: 9.99966e-1
No.4	MSE: 9.64506e-7	MSE:5.34932e-6
	R: 9.99989e-1	R:9.99967e-1
No.5	MSE:.1.51718e-6	MSE: 7.48646e-6
	R:9.99981e-1	R: 9.99995e-1

After that we calculate the Average pricing error for the model with and without the aid of the neural networks.

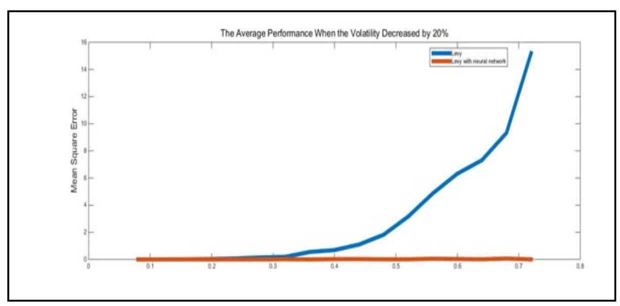

Fig. 1. The average performance when the volatility is decreased by 20%

For figure 1, when the options is in the money, the result for mapping in the money will be better. Neural network seems to have a more stable prediction compared to at the money and out of the money options. We can get a similar performance when the volatility is increased by 20%.

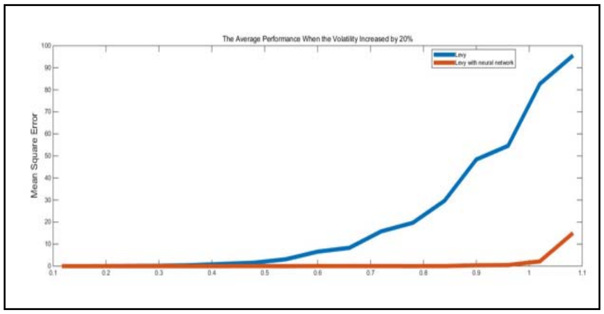

Fig. 2. The average performance when the volatility is Increased by 20%

For figure 2, we can conclude that as the deepness of in the money increases, the method could achieve a better result by adjusting the volatility using the neural network and could improve the degree of accuracy of Asian option pricing.

In conclusion, all of the nine experiments, neural network could successfully adjust the volatility and reduce the error of the Asian options. All of them work similarly like the example above. Also, note that the neural networks has a very high value and a very low mean square error for fitting, meaning that the volatility can be fitted using algorithms and neural network. More experiments will be performed with the real data in the next section.

B. The Result of the Real Data Experiment

For real data, we chose several different contracts of different maturity and underlying asset price to validate our method on real data. We test five contracts in total. Some of the contracts are already expired while some are still trading. We attempt to cover different types of contracts as well. For convenience proposes, the prices we display are prices of option that have a strike price of 30. The reasons are as follows. Firstly, with a strike price of 30, the premium will not be too low or too high. If the premium is too low or the option is out of the money, then the price not be obvious enough to show the pattern of the errors across a wide range of volatilities between the levy model and the adjusted model with neural network. (When the option premium is less than 0.01 theoretically, it will be sold at a price of 0.01 in the exchange.) The author also applied the same method for different strike prices and they show the same result. As the premium is higher, the improvement is more obvious while the premium of the option is lower, the improvement will be less. The experiment also shows that the error of the Levy Model is proportional to the premium. (This also reflects in the maturity and the strike price of the option since they affect the premium of an option). For testing purpose, data of one month period is used as the dataset to build the neural network. Then we use the neural network with the levy approximation model to price the option for the next one-week period. Other parameters use corresponding data on that specific date. The risk free rate uses treasury bills as a reference.

The contract CSM 2018 (Jun 2018) is tested with or without the neural network. The data ranging from 2016-Aug-02 to 2016-Sept-15 (One month period) is used as the data set to build the neural network. We then use the built neural network with levy approximation to price the option of future one-week time. We found that the there is still room for improvement for the levy approximation according to the real data. After the learning process is applied, the accuracy of the pricing model is improved. The results are shown in figure 3.

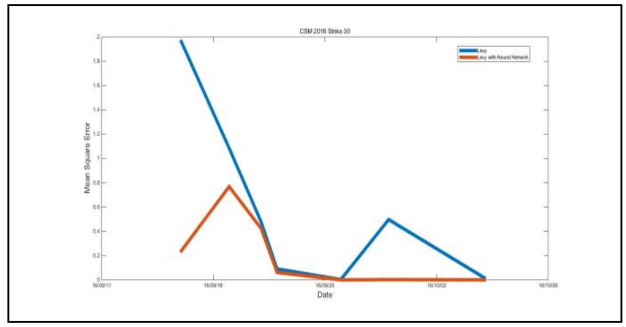

Fig. 3. Contract CSM 2018 Average Pricing Accuracy Comparison

As shown in table 2, the mean square error is not as ideal as the previous simulation experiments. The reason is that the difference between the real volatility and implied volatility within real option prices is even larger. In such a case, the mean square error will seem less desirable. However, the result shows that the mapping could improve the option pricing accuracy. Also, note that these networks are not the optimized networks, and if carefully filtered the selection of the networks, we can even get a better result.

On the other hand, the R-value is not as good as that of the simulation experiment. The most possible explanation is that the real data might have more noises. For research purposes, the author also tests a few groups of assumed parameters but traders in the market bear different expectation of the parameters. Still there is a large improvement after the neural network is applied involving the noise. Other contracts of different maturities are also tested and all of them show significant improvement.

TABLE II. NEURAL NETWORK STATISTICS FOR CSM 2018

Neural Network Number	Sets	
	Training Set	***Test Set***
No.1	MSE: 9.48765e-3	MSE: 2.49870e-2
	R: 9.33968e-1	R:9.94202e-1
No.2	MSE: 1.54002e-2	MSE: 1.54002e-2
	R: 8.75441e-1	R: 9.89976e-1

In figure 4, the data ranging from 2017-Mar-22 to 2017-Apr-26 (One month period) is used as the data set to build the neural network.

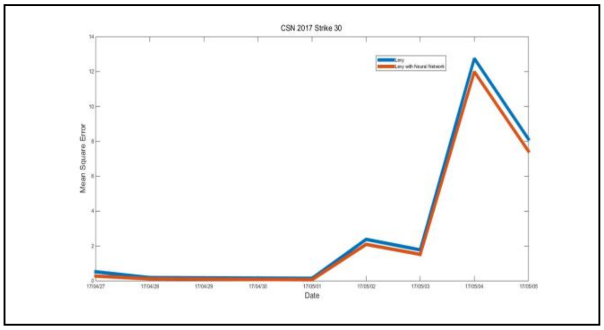

Fig. 4. Contract CSN 2017 Average Pricing Accuracy Comparison

From figure 4, we can see that at the some of the data point, the error is as high as the original model. The reason might be that the implied volatility of the Asian option is very close to the volatility of the Asian option. In that case, the neural network might give a very close solution. Still, on average, as shown in in figure 4 the neural network gives a more accurate result and we can argue that it is at least as good as the original pricing model. On the other hand, if the implied volatility (not unique) is chosen more carefully, we can even get a more precise result.

TABLE III. NEURAL NETWORK STATISTICS FOR CSN 2017

Neural Network Number	**Sets**	
	Training Set	***Test Set***
No.1	MSE: 9.19668e-2	MSE: 2.72365e-2
	R: 7.20562e-1	R: 9.34908e-1
No.2	MSE: 1.06288e-2	MSE: 4.27134e-3
	R: 8.05127e-1	R: 9.96222e-1

The R-value of the neural networks on average in table 3 is not as good as that of table 3 since the maturity of the option is shorter. Due to the noise from the option price, the volatility will not show a strong correlation.

In figure 5, the data ranging from 2017-Feb-14 to 2017-Mar-21 (One month period) is used as the data set to build the neural network.

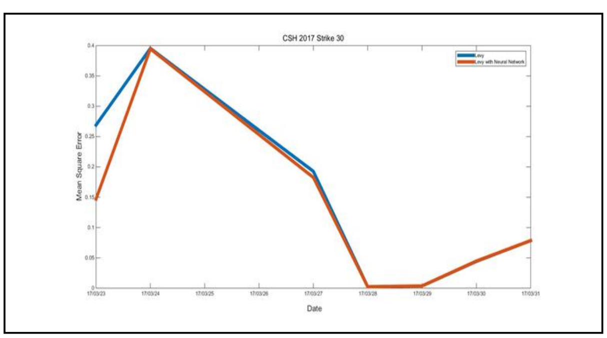

Fig. 5. Contract CSH 2017 Average Pricing Accuracy Comparison

For contracts that have a short maturity, the mean square error that measures the deviation from the real data quote is smaller since the premium is lower. We also achieve a better improvement after the neural network is applied. The mean square as shown in table 4 is similar to that of table 3. Since the mean square error is not low enough, the pricing accuracy of the option in figure 5 showed that when the maturity is short, the volatilities are more difficult to map and the pricing accuracy are more difficult to improve.

TABLE IV. NEURAL NETWORK STATISTICS FOR CSH 2017

Neural Network Number	**Sets**	
	Training Set	***Test Set***
No.1	MSE: 5.53375e-1	MSE: 8.88603e-1
	R: 8.80796e-1	R: 8.36442e-1
No.2	MSE: 6.82120e-1	MSE: 7.64490e-1
	R: 7.85836e-1	R: 9.39447e-1

The R-value shows that the volatilities have a stronger positive correlation due to the long maturity of the option meaning that levy model option prices with longer maturity result in larger deviation from the market option prices.

By using Neural Networks, the levy model should exhibit improvements after the learning process. These improvements should exist across options of all spot price, all volatility and all maturity. For the Levy model, in the original paper (Levy, 1992), the author showed that when the product of volatility and square root of maturity is lower than 0.2, the closed-form price approximates the Monte Carlo price accurately. (Note that an underlying asset with a volatility lower than 0.2 is a rare case in practice.) In such a circumstance, the prices of options with volatility higher larger than 0.2 or higher required correction because premiums are very far from the real premium.

We anticipated that after applying neural network, the error of the options with high underlying asset volatility would be lower than that of the original closed-form. Another finding for the closed-form is that, it has part of error incurred by assumption of the model. The same thing happens to the Levy model. When the maturity and the volatility are large, the errors that incurred by the assumption will magnify, making the model meaningless. That is also why these models perform better for out of the money options since the premium for an out-of-the-money option is smaller than that of an in-the-money option. The biases incurred by the assumption of the closed form model are somehow alleviated when the premium is low. One of our major goals is to fix such biases and improve the pricing accuracy. As shown in the previous section, after the neural network is applied and the volatility is adjusted, the pricing accuracy is significantly improved and the biases are fixed.

V. CONCLUSION

The method proposed in this paper can significantly improve the efficiency of pricing and financial decision. The use of Neural Network highly improves the accuracy of the traditional closed-form model. The analysis shows that after learning and testing, the pricing of Asian Options on simulation or on the real data, all have a significant effect on the results. On the other hand, the Neural Network Algorithms we used affect the results significantly.

It is well known that the study of the volatility surface is one of the most difficult problem in option pricing. This paper also provides an intuition that rather than fitting the volatility surface with some unreliable mathematical model, as an alternative we can remember the whole volatility surface with Neural Networks or other machine-learning algorithm. The methodology could also be applied to deal with the term structure of fixed income securities. This behavior resembles the human behavior that when we encounter a difficult problem we do not understand; we first start to remember it. Although the Method required certain amount of computation, once the neural network finished training, the neural network can be used for a long-time and output accurate result instantaneously.

ACKNOWLEDGMENT

I would like to convey my gratefulness to professors of the department of computer science at OSU and the department of finance of University of Illinois at Urbana Champaign for the knowledge in finance and computer science within this paper that the author was taught. The author also owe a deep of gratitude to their rigorous attitude of scholarship which serves as a model for my study and research.

REFERENCES

[1] Levy, E. ,*Pricing European Average Rate Currency Options,* Journal of International Money and Finance (1992), 11, 474-491.

[2] Robert Kolb,Understanding Options 2, Wiley & Sons,1995

[3] RR Trippi, and E Turban. Neural networks in finance and investing: Using artificial intelligence to improve real world performance, 1992.

[4] James M. Hutchinson; Andrew Lo and Tomaso Poggio, (1994), A Nonparametric Approach to Pricing and Hedging Derivative Securities Via Learning Networks, No 4718, NBER Working Papers, National Bureau of Economic Research, Inc

[5] Yao, J., Li, Y., & Tan, C.L. (2000). Option price forecasting using neural networks. OMEGA: International Journal of Management Science, 28, 455-466.

[6] Marco J. Morelli, Guido Montagna, Oreste Nicrosini; C, Michele Treccani, Marco Farina, Paolo Amato, Pricing Financial Derivatives with Neural Networks, Physica A, 338 , 2004,pp. 160 – 165.

[7] Gradojevic N., Gencay R., Kukolj D., (2009), Option Pricing with Modular Neural Networks, IEEE Transactions on Neural Networks, 20(4), pp. 626-637

[8] Wang, YH. & Lin, CT. Qual Quant (2009) 43: 237. doi:10.1007/s11135-007-9102-6

[9] Zhang Hong-yan, Lin Hui, and Jiang Cai-lou, Study on Option Pricing by Applying Hybrid Wavelet Networks and Genetic Algorithm, Journal of Systems Engineering, Vol.25 No.1, 2010: 43-49.

[10] S. Shakya, M. Kern, G. Owusu, C.M. Chin, Neural Network Demand Models and Evolutionary Optimisers for Dynamic Pricing, Knowledge-Based Systems, 2012, 29,pp.44–53

[11] Mitra, S. K., An Option Pricing Model that Combines Neural Network Approach and Black Scholes Formula, Global Journal of Computer Science and Technology, Vol. 12, No. 4, 2012, pp. 6-16.

[12] Fei Chen and Charles Sutcliffe, Pricing And Hedging Short Sterling Options Using Neural Networks, Intelligent Systems in Accounting, Finance And Management, , 2012, 19, pp.128–149.

[13] Kemna and Vorst, A Pricing Method for Option Based on Average Asset Values,Journal of Banking & Finance 1990, 14, pp. 113–129.

[14] Levy, E. ,Pricing European Average Rate Currency Options, Journal of International Money and Finance (1992), 11, 474-491.