Innovative Teaching and Learning
http://doi.org/10.4208/itl.20230105

Vol. 5, No. 1, pp. 73-93
June 2023

Innovative Teaching and Learning of Quantum Finance and Intelligent Trading Strategies

Raymond Lee[1,2,*], Sherry Zhou[1], Jefferson Fong[1], Goliath Li[1], Yanyan Ji[1], Jing He[1], and Nuobei Shi[1]
BNU-HKBU United International College

Abstract

Hitherto it has been a real challenge to integrate innovations in advanced quantum computing and AI to supply a practical, intelligent program trading system. Particularly challenging to the financial technology community is quantum finance, which is based on modern technologies that draw upon quantum theory and quantum anharmonic oscillation. There are numerous hybrid economic forecasts with the combination of deep network and various AI technologies recommended with the growth in AI innovation in the past decades. In this paper, we demonstrate how higher education has addressed this critical subject area, namely the development of high-level, cutting-edge AI related, computer technology in the area of financial trading. State of the art AI innovations, including deep networks, fuzzy logic, genetic algorithms and chaos theory are incorporated into MetaTrader platform to design cutting-edge and functional AI-based program trading workshops providing students with hand-on experiences of exactly how to apply such innovation to the real-life economic market and also how to plan for a future career in the growing professional area of AI-fintech.

Keywords: quantum finance, AI-based financial forecast, intelligent trading strategies, innovative teaching and learning method, MetaTrader system

*Corresponding author: Raymond Lee. E-mail: raymondshtlee@uic.edu.cn
[1] Department of Computer Science, Faculty of Science and Technology
[2] Guangdong Provincial Key Laboratory of Interdisciplinary Research and Application for Data Science

Introduction

Quantum Finance (QF) is an interdisciplinary subject applying quantum-theory to economics and finance. Quantitative methods in finance are long established. The most well-known, explicitly mathematical approach used in finance was established by Bachelier (1870–1946) in his PhD thesis. Théorie de la Spéculation (Bachelier, 1900) proposed a mathematical model to financial markets as Brownian-motions. This approach then eventually leads to other quantitative methods (statistical methods, Black-Scholes/PDEs, Econophysics) and more recently in the 1990s to Quantum Finance.

The initial published work on Econophysics—An Introduction to Econophysics: Correlations and Complexity in Finance was written by Mantegna and Stanley (1999). They presented clearly how stochastic dynamics, self-similarity and scaling phenomena can be applied to model financial markets. After that, numerous R&D projects on Econophysics and quantitative finance have been conducted, resulting in various financial applications including derivative pricing (De Spiegeleer et al., 2018), financial forecast (Faria & Verona, 2021), risk management (Cont, 2009), and portfolio analysis (Bauder et al., 2021).

From the very beginning, statistical physics has been a mainstream Econophysics concept and energetic R&D initiatives have been designed to foster quantum theory (now known as Quantum Finance) by applying Feynman-path-integral and quantum-anharmonic-oscillator to analyze financial markets such as stock markets.

The main motivation for the application of quantum physics and quantum field theory into finance is threefold: (a) current research reveals the existence of quantum phenomena such as wave-particle duality (Lee, 2019a) and quantum-wave phenomena in financial markets (Ataullah et al., 2009; Shi, 2006); (b) the feasibility to model various financial phenomena, instruments and markets by the adoption of various quantum physic and related models (Baaquie, 2004); (c) and the feasibility to integrate various AI models and technologies to implement intelligent financial forecast and trading systems (Lee, 2019a, 2020; Qiu et al., 2021).

A recent example of QF R&D is Quantum Finance (Baaquie, 2004) which examined the application of Feynman's path-integral model to US interest rate modeling. Professor Baaquie is also the first scholar to consolidate Quantum Finance into a new academic discipline and offer a well-defined theory to model financial markets based on quantum theory.

Other researchers have been active in Quantum Finance. Schaden (2002) used quantum-field to model financial indices; Piotrowski's team applied a quantum-diffusion model to stock market analysis (Piotrowski & Sładkowski, 2005); Shi (2006) used quantum-wave model to security market analysis; Ye and Huang's (2008) work used a quantum-oscillatory model on forex analysis; Ataullah and his team used a quantum-wave model to analyze security markets (Ataullah et al., 2009); Bagarello (2009) used quantum-analytical tools to model security markets; Nakayama (2009) used Reggeon theory to model quantum financial markets; Zhang's research team adopted a quantum model to study security markets (Zhang & Huang, 2010); Kim's research team used a path-integral model for financial sensitivity analysis (Kim et al., 2011); Cotfas (2013) used a finite-dimensional-quantum model to analyze stock markets; Meng's research team used quantum-harmonic-oscillators to model stock markets (Meng et al., 2015); Gao and Chen's (2017) work used a quantum anharmonic-oscillator for stock prediction; Nasiri's team applied a quantum-well to market reliability analysis (Nasiri et al., 2018). Current related research includes the study of bonds with index-linked stochastic coupons in Quantum Finance (Baaquie, 2018); the study of spontaneous symmetry breaking phenomena in Quantum Finance (Arraut et al., 2020); the study of quantum option pricing in Quantum Finance (Focardi et al., 2020); the study of probability flow in the stock market in Quantum Finance (Arraut et al., 2021); the study of quantum computational finance for derivatives pricing (Gómez et al., 2022); the study of Quantum Finance for intraday trading with the integration of deep reinforcement learning (Qiu et al., 2021) and the investigation of prospects and challenges of Quantum Finance by Bouland et al. (2020).

Although these approaches and models have enjoyed success in modeling the quantum dynamics of financial markets, it is hard to apply them to real-life scenarios owing to the mathematically complex and computationally extensive structure of these models and the intricacy of economic markets, let alone to apply them to live financial prediction systems. To address such a mathematically complex and computationally intensive problem, we proposed a Quantum Anharmonic Oscillatory Model (QAOH) to simplify the whole quantum price level evaluation scheme.

Based on recent research made available by Lee and later published as Lee (2019a) using the QAOH to model the quantum dynamics of financial markets, a well-developed Quantum Finance Forecast System (QFFS) was created with a Quantum Finance Forecast Center (qffc.org for abroad and qffc.uic.edu.cn for China users). QFFC is a non-profit making AI-Fintech R&D center that focuses on the time series next-day forecast of worldwide financial products to provide an open and intelligent system for individual investors and worldwide traders to obtain complimentary understanding of over 120 financial instruments' forecasts based upon quantum theory, AI, and deep-network technologies. For education and learning purposes, QF was carried out as a high-level computer technology program in a university contributing to an innovative AI-Fintech course for students who are interested to learn how to apply state-of-art QF technology in real-world financial markets, how to create and implement AI-based program trading systems for academic and industrial functions. The next section presents an overview of the Quantum Finance Model (QFM), and later explains how QF is used on finance projection and program trading.

An Overview of the Quantum Finance Model

Basic Concept of Quantum Finance

In QF theory, we model the dynamics of financial instruments—foreign-exchanges and popular worldwide financial indices such as Dow-Jones-Index and Heng-Seng-Index—as quantum-financial-particles (QFP) with both wave and particle phenomena (Ataullah et al., 2009, Baaquie, 2004; Bagarello, 2009). As mentioned in the present author's original work on Quantum Finance (Lee, 2019a), many experienced financial analysts or traders will tell us that financial markets exhibit both particle and wave properties constantly. The two pillars of modern financial analytical tools, the technical analysis (Murphy, 1999) and chart analysis (Bulkowski, 2005) are very good examples of such wave-particle duality. Technical analysis describes the financial markets as physical motion of prices or indices, while for the chart analysis we describe and study financial markets as market patterns, such as the Fibonacci patterns and the famous Elliott wave patterns (Boroden, 2008; Brown 2012).

Based on the Quantum Finance Theory (QFT; Lee, 2019a), the characteristics and movements of these Quantum

Finance Particles (QFP) undergo their inherent quantum-energy-levels (QELs) and reveal as quantum-price-levels (QPLs) in economic markets, that are impacted by the superposition of their very own energy fields and levels similar to subatomic-particles.

From a technological viewpoint, these QPLs represent support-and-resistances (S&R) as we learnt in classical technical analysis. In summary, the objective of QF theory is to establish an effective QF model to help users to locate all the QPLs of global economic markets. This QF model must be practically feasible and make financial sense for worldwide investors and traders.

Quantum Price Levels (QPLs)

Lee (2019a) proposed QPL as an innovative indicator of a market instrument that could be efficiently used in financial market forecasts with the integration of QF theory and a quantum-oscillator-model. Compared with classical technical indicators, QPL has a significant benefit in that it can design the dynamics of financial tools of worldwide finance markets with wave-particle duality in classical quantum phenomena. Given the activity and characteristics of these economic particles (so-called "quantum financial particles," QFP) are subjected to their intrinsic quantum-energy-field, QPL can be used for financial trading as an analogue to S&R-levels in classical technical analysis.

Quantum Financing Schrödinger Equation

In QFT (Lee, 2019a), the characteristics of financial instruments used in worldwide markets are designed as QFP with wave-particle duality features. These QFPs dynamics undergo their intrinsic quantum-energy-fields. Like a physical subatomic particle, a QFP in a financial location has its equilibrium state. If there is an external stimulus able to excite these QFPs, the QFPs will increase or reduce to a greater or lesser energy level. These QPL levels in financial markets are considered as S&R in classical technical analysis. To determine QPLs, we require to resolve the Quantum Finance Schrödinger Equation (QFSE) presented by Lee (2019a):

$$[\frac{-\hbar}{2m}\frac{d^2}{dr^2}+(\frac{\gamma\eta\delta}{2}r^2-\frac{\gamma\eta\upsilon}{4}r^4)]\varphi(r)=E\varphi(r)$$

where:

m is mass of the financial particle such can be considered as the quantity to represent the market capitalization; δ and υ are the damping terms and volatility factors of the financial market; $\hbar$ is the

Planck constant; γ denotes the market depth; r is the price return; $\varphi()$ is the wave-function and E is the energy level.

Certain key characteristics can be found in the QFSE:

1. The time independent Schrödinger Equation of Quantum Finance contains both KE (the first term) and PE (the second term). As in our Quantum Finance modelling, we will focus on the overall energy level (corresponding to the quantum price level), we will focus on the PE (second term) of the QFSE for the evaluation of QPL.
2. Unlike the classical quantum harmonic oscillator, the Quantum Finance oscillator is an anharmonic quantum oscillator which consists of two high-order PE terms to represent (a) damping (trading restoration and market absorption) potential and (b) volatility (risk control) potential.
3. Although the market is visualized (observed) as the price, the quantum dynamics are constrained by the price return ($r = dp/dt$), which is consistent with classical financial theory.

Significance of QFSE in Quantum Finance

The significant characteristics of QFSE in Quantum Finance include:

1. Once the QFSE is fully formulated, it provides a feasible and practical solution to evaluate all the Quantum Finance energy levels, or so-called Quantum Finance price levels (QPLs).
2. Such QPLs provide a new way for us to study and model the support and resistance (S&R) levels found in various financial markets.
3. In terms of AI and Data Mining, the integration of these QPLs provides us with a new way to build a new generation of financial prediction models featuring the integration of Quantum Finance QPL technology with contemporary deep networks such as the Long Short Term Memory model model and chaotic neural networks.

Basic Components of Quantum Finance and Applications of Quantum Finance

QF and AI can be used to model international financial markets. Such models explore how modern AI technology such Deep Networks, Fuzzy Systems, Genetic Programming and Chaos Systems can be integrated with a QF model to develop financial prediction, intelligent financial trading and hedging applications.

Figure 1

Basic Component of Quantum Finance (Lee, 2019a)

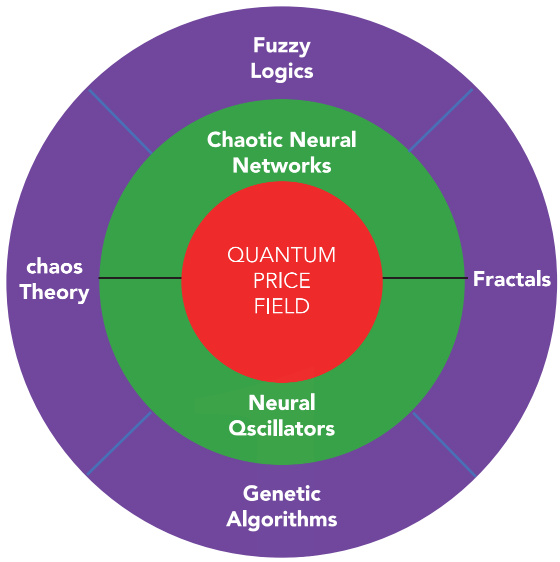


Figure 1 shows a basic framework of a QF model. The first tier is the QF-Core which consists of QPLs. The second tier is the QF-Network-Layer, which provides the neural characteristics in QF. The third tier is the QF-AI-Layer, which provides QF enabled AI technology including Fuzzy Systems, Genetic Programming, Chaos Systems and related AI tools and technology. The fourth tier is the QF AI-fintech Layer, which offers the support and execution tools/technology for the growth of different QF based fintech applications such as the QPL of worldwide financial instruments, interest rate prediction, trading systems.

In terms of application of the Quantum Finance, current and potential applications include:

1. The implementation of QPLs for worldwide financial products.
2. Time series chaotic oscillatory networks for financial prediction.
3. Intelligent Quantum Financial Forecast and Intelligent Trading System.

Quantum Finance Forecast Center (QFFC)

The Quantum Finance Forecast Center (QFFC; official website: qffc.uic.edu.cn for users in China, qffc.org for overseas users) was developed in early 2017 to provide an innovative financial forecast solution for global financial markets. QFFC is a non-profit making, worldwide financial research and forecast center focusing on AI-Fintech R&D to provide a scientific open system for independent traders and worldwide investors to acquire complimentary knowledge of 120+ financial product predictions worldwide consisting of international financial indices (17); major foreign exchanges (84); major commodities such as gold, silver and crude oil (19). Figure 2 reveals a snapshot of QFFC's main site.

Figure 2

Official Site of Quantum Finance Forecast Center (qffc.uic.edu.cn)

From students' perspective, QFFC provides both workshops for the students to practice the concepts learned in the course and a live demonstration of how Quantum Finance is applied to global financial product prediction in international financial markets such as the Dow Jones Indices and Forex prediction.

Regarding the popularity of the QFFC, since its launch in 2017 to date, a total of around 15,000 members have registered with the QFFC official website to receive Quantum Finance's 120 global financial product daily forecasts. These QFFC members include: local and overseas finance analysts, financial traders, data scientists, research students and investors.

Performance of Quantum Finance Forecast System (QFFS)

From the system performance perspective, the Quantum Finance Forecast System (QFFS) is compared with four contemporary forecast models, they are: (a) Feedforward Backpropagation Network (FFBPN); (b) Support Vector Machine (SVM); (c) Deep Neural Network (DNN) with PCA (Principal Component Analysis) model (Singh & Srivastava, 2017); (d) Chaotic Neural Oscillatory Network without QPL (CNON) (Lee, 2019b). Table 1 depicts the performance comparison chart.

Certain interesting findings are revealed in Table 1:

1. For Case 1 simulation (RMSE 1x10-4), QFFS outperforms FFBPN (447.25), SVM (294.41), DNN-PCA (224.05), CNON (1.37) times in terms of speed. Similar findings can be found in Case II simulation results. It clearly reflects the improvement of network learning rate achieved by the QFFS system.
2. Across the 3 Cases with decreasing RMSE from 1x10-4(Case 1), 1x10-5 (Case 2), 1x10-6 (Case 3) to 1x10-7 (Case 4). All forecast systems can achieve the target RMSE in Case 1 and Case 2. However, for the Case 3 and 4 simulations using target RMSE 1x10-6 and 1x10-7, FFBPN (which is using sigmoid-based FFBPN for machine learning) encounters deadlock problems during the network training of Cryptocurrency and Forex products; while QFFS can still finish the network training with promising training speeds.
3. Comparing QFFS against CNON across the four cases, it is interested to reveal that QFFS outperforms its counterpart by 1.37–1.39 times respectively. It clearly reflects the merits for the integration of QPL as additional input vectors with chaotic neural oscillator technology for network training and deep learning.

In terms of system performance across different financial products, the simulation results clearly show that both cryptocurrency and forex are more chaotic and difficult for network training than other financial products as expected, which will be further explored in our future research on QFFS.

Table 1

System Performance Comparison Chart

Product Category	FFBPN Total STT	FFBPN Av. STT	SVM Total STT	SVM Av. STT	DNN-PCA Total STT	DNN-PCA Av. STT	CNON Total STT	CNON Av. STT	QFFS Total STT	QFFS Av. STT
Case 1 (RMSE = 1x10-4)										
Crypto-currency	5572511	61916.78	3722444	41360.41	244633	27181.47	1401	155.67	1078	119.78
Forex	508453	6053.01	331511	3946.56	291344	3468.38	1454	17.31	1031	12.27
Financial Index	41120	2164.21	26152	1376.44	19738	1038.82	242	12.74	169	8.89
Com-modity	46641	2743.59	29384	1728.46	22108	1300.46	427	25.12	301	17.71
Overall	1153465	8941.59	759291	5885.98	577823	4479.25	3524	27.32	2579	19.99
Case 2 (RMSE = 1x10-5)										
Crypto-currency	1460000	162222.22	937320	104146.67	823440	91493.33	3934	437.11	2980	331.11
Forex	1235543	14708.85	841405	10016.72	720322	8575.26	4524	53.86	3142	37.40
Financial Index	111024	5843.37	68391	3599.51	50627	2664.58	774	40.74	549	28.89
Com-modity	109142	6420.12	71925	4230.86	44967	2645.09	1065	62.65	761	44.76
Overall	2915709	22602.40	1919041	14876.29	1639356	12708.19	10297	79.82	7432	57.61
Case 3 (RMSE = 1x10-6)										
Crypto-currency	DL	-	6102255	678028.38	3601307	400145.17	15155	1683.89	12321	1369.00
Forex	DL	-	5477816	65212.10	4184833	49819.44	20831	247.99	14567	173.42
Financial Index	577324	30385.47	373529	19659.40	318683	16772.78	1932	101.68	1342	70.63
Com-modity	687595	40446.76	468252	27544.25	385741	22690.64	2887	169.82	2019	118.76

Overall	-	-	12421852	96293.43	8490564	65818.33	40805	316.32	30249	234.49
Case 4 (RMSE = 1x10-7)										
Crypto-currency	DL	-	25141291	2793476.73	14405228	1600580.89	55426	6158.44	42310	4701.11
Forex	DL	-	26896077	320191.39	17785540	211732.62	90435	1076.61	63241	752.87
Financial Index	DL	-	1714498	90236.74	1446821	76148.46	9068	477.26	6431	338.47
Com-modity	DL	-	2088404	122847.29	1917133	112772.52	11414	671.41	7872	463.06
Overall	-	-	55840269	432870.30	35554721.84	275618.00	166343	1289.48	119854	929.10

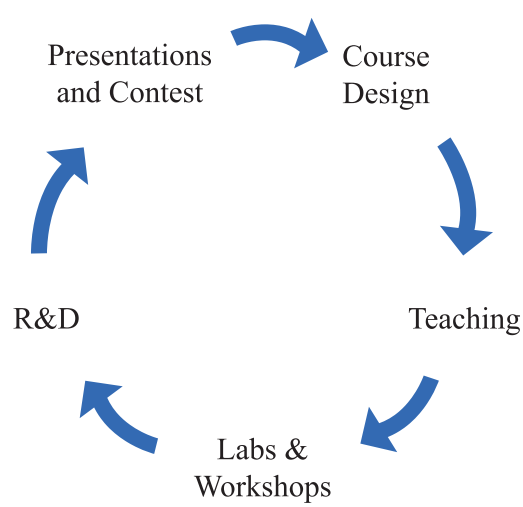
Note. [a] Results are generated by 500 simulations of each neural network system (measured in msec). [b] "Total STT" denotes the total average system training time for 500 simulations of network training. [c] "Av. STT" denotes the average system training time for a single financial product. d "DL" denotes deadlock during system training.

Innovative Teaching and Learning Philosophy of Quantum Finance Course

Since early 2019, QF has been adopted as a high-level AI-fintech Major Elective course for Year 3 & 4 undergraduate students in BNU-HKBU United International College across various disciplines including Computer Science and Technology, AI, Data Science, Financial Mathematics, Statistics, etc. With respect to this course's teaching and learning (T&L) philosophy, we realize that the constituent parts of teaching (especially in IT and AI) that Teaching, Course Design, R&D and Workshop all closely related as shown in Figure 3.

Figure 3

Five Major Components of Innovative T&L in Quantum Finance Course



Computer Technology, especially AI, is constantly changing in the sense that new technology emerges every year (or even week) as is not necessarily the case in other disciplines. It is our task as educators to adapt to change and even lead the technology by designing new courses and syllabuses to cope with the state-of-art IT and AI technology development.

Figure 4

Quantum Finance Interactive Workshops in QFFC Official Site

"Teaching", in fact, is not just about how to conduct lectures, but rather it involves delivering a kind of experiential training that develops students' "comprehensive perspective" via:

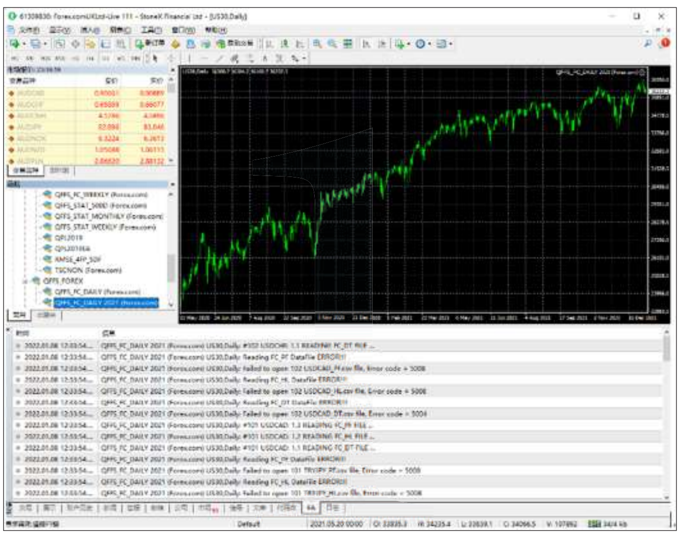
1. Labs/workshops—in which students demonstrate how to apply QF knowledge they learnt from the course into something truly functional, which can be accessed via MetaTrader workshops in the official QFFC site (Figure 4). MetaTrader is de facto industrial software for financial traders and analysts to implement program trading systems that have real-time access to worldwide financial markets. In labs and workshops, students can attain hand-on experience on how to apply QF

Theory to real-world financial markets. Figure 5 shows a snapshot of the MetaTrader platform for the daily Quantum Finance forecast of the Dow Jones Index (DJI).

2. R&D—if students truly want to do (or invent) something different, they must have to complete a thorough literature review and several case studies, even as undergraduate students.

Figure 5

Quantum Finance Interactive Workshops in the Official QFFC Site



3. Presentation and Contest – conference presentation for example, is an ideal way to provide more opportunities for the best performance. Final Year Project (FYP) team(s) can submit their papers to international conferences and presentations, which not only provide presentation skills practice but can also enhance self-confidence, which are beneficial for future study and development. Through participating in local and national contests such as program trading competitions, students' ability is enriched, and they gain solid experience of applying QF knowledge to real-world financial engineering and trading scenarios.

Although the Quantum Finance course conducted at UIC is the first of its kind to be taught in the university, there was a similar Quantum Finance course conducted a number of years ago at the National University of Singapore (NUS) by Prof. Baaquie that adopted his textbook *Quantum Finance: Path Integrals and Hamiltonians for Options and Interest Rates* published by Cambridge University Press in 2004. Unlike the Quantum Finance conducted in NUS which is a theoretically and mathematically oriented course without practical labs and computer workshops, the Quantum Finance course conducted at UIC not only focuses on the basic concept and theory of Quantum Finance, but also focuses on the integration of the Quantum Price Levels (QPL) with a contemporary Deep Network model for real-time multiagent based financial prediction and intelligent program trading. As a result, the students can learn the fundamentals of Quantum Finance, and at the same time attain the technical know-how and capability to apply this knowledge for industrial use as well.

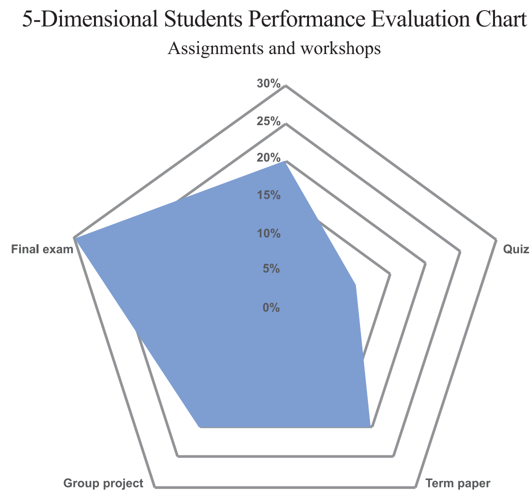
Evaluation Scheme and Teaching and Learning Outcomes

A five-dimensional scheme has been adopted to provide a multi-perspective training and performance evaluation. It covers not only the QF concept and theories but also the hands-on experiences of applying what has been learnt to real-world situations. This evaluation scheme consists of (a) assignments and workshops, (b) quizzes, (c) term paper, (d) group project, and (e) final exam as shown in Figure 6.

Figure 6

5D Multi-perspective Quantum Finance Course Students Performance Evaluation Chart

Assignments and Workshops



Assignments include both written and lab assignments. The main purpose is to evaluate students' capability in both basic concepts and practical skills in QF. After the students have attained basic knowledge and skills in QF, they will form project teams and start QF Workshops, which provide hands-on experience of mini QF projects, to prepare for their QF group projects.

Weekly 10-min MC Quiz

Every week, a ten-minute multiple-choice (MC) based quiz is conducted by using the iSpace platform (a Moodle-based virtual learning management system) during the lab period. The main purpose of these 10-min weekly MC quizzes is to evaluate the students' understanding progress of concepts and knowledge during the 14-week lectures. More importantly, the lecture contents can be modified in case students encounter any common problems, uncertainty and misunderstanding of concepts and knowledge presented.

QF Term Paper

The term paper is an important component in a high-level technical subject such as QF because in addition to concepts and knowledge learnt, the students are required to explore further knowledge to enrich their understanding of the course content. It serves as an excellent starting point to train students on their R&D. In the QF course, we established a Reference Paper Library as shown in Figure 7 which addresses 10 QF and AI related topics for students to further expand and investigate, which include: Quantum Finance theory, Chaos Theory, Fractals, Fuzzy Logic, Genetic Algorithms, Neural Networks and Deep Networks, Neural Oscillators, Quantum Field Theory, Support Vector Machine and Intelligent Trading systems.

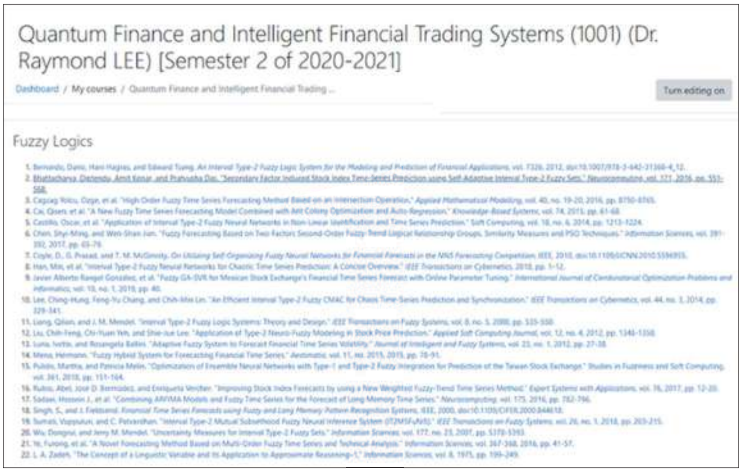
Figure 7

Reference Paper Library for Literature Review

There are overall a total of 200 journal and conference papers selected for these 10 QF related research areas. Students are also encouraged to explore other related papers in the group literature review. Figure 8 shows a snapshot of the Reference Paper Library on the AI Topics of Fuzzy Logics.

Figure 8

Reference Paper Library for AI Topic—Fuzzy Logics



QF Group Project

The QF group project is another important component of the whole course evaluation scheme. The main purpose of the QF group project is two-fold: (a) to provide a real-world scenario in finance for students to apply concepts and knowledge learnt in the course and to design and implement practical financial applications; (b) to provide an opportunity to train students in group collaboration to design and implement a practical AI-Fintech project, which is an important factor for future R&D and a career in the industry after graduation. In the QF course, we allow students to select any AI tool such as Fuzzy Logic and integrate it with a QF model to build an AI-based QF forecast and intelligent financial trading system. Students who contribute to the best team projects will be selected to develop their work in their FYP and compete for a project award and program trading competitions.

In addition, students need to present their QF projects in Week 14 which provides a good opportunity to practice their presentation skills.

Final Exam

The final exam provides an overall evaluation in terms of understanding the basic concepts and knowledge learnt by practical workshops, group projects and presentation as a whole since there are many high-level courses that focus more on outcomes and train students to apply what they have learned in real-world situations.

Between 2019 and 2021, over three iterations of this semester-long course, participating students published related research papers in 3 international journals, and contributed 3 papers to international conferences, namely the Symposium on Automation, Information and Computing (ISAIC 2020), IEEE Symposium Series on Computational Intelligence (IEEE SSCI 2019) and the International Conference on Artificial Intelligence Applications and Technologies (AIAAT 2019). In addition, three QF and AI project teams were awarded prizes in various local and national competitions, winning the national computational project award, the best paper award, and the FYP award.

Discussion and Conclusion

In this paper, we introduced Quantum Finance–an innovative AI-fintech technology and we have demonstrated how such technology can be applied to financial engineering and program trading; and more importantly, we have shown how such state-of-art technology can be integrated into an AI-fintech course. As mentioned, Quantum Finance is not an isolated discipline, but is rather an interdisciplinary field which involves (a) Computational Finance; (b) Quantum Theory; and (c) various AI-related technologies such as deep networks, fuzzy logic, genetic algorithms and chaos theory. We also consider ways of teaching and learning a technical course such as Quantum Finance. Its focus should not only be on concepts and theories. Rather a contemporary course should involve multi-disciplinary learning from multiple perspectives, hands-on training, and, most importantly, the application of the concepts, theories and technology to real-world situations.

Acknowledgment

This paper was supported in part by the Guangdong Provincial Key Laboratory IRADS (2022B1212010006, R0400001-22), Key Laboratory for Artificial Intelligence and Multi-Model Data Processing of Department of Education of Guangdong Province and Guangdong Province F1 project grant UICR0400050-21CTL on Curriculum Development and Teaching Enhancement.

References

Arraut, I., Au, A., & Tse, A. C. (2020). Spontaneous symmetry breaking in quantum finance. *Europhysics Letters, 131*(6), Article 68003. https://doi.org/10.1209/0295-5075/131/68003

Arraut, I., Lobo Marques, J. A., & Gomes, S. (2021). The probability flow in the stock market and spontaneous symmetry breaking in quantum finance. *Mathematics, 9*(21), Article 2777. https://doi.org/10.3390/math9212777

Ataullah, A., Davidson, I., & Tippett, M. (2009). A wave function for stock market returns. *Physica A: Statistical Mechanics and its Applications, 388*(4), 455–461. https://doi.org/10.1016/j.physa.2008.10.035

Baaquie, B. E. (2004). *Quantum finance: Path integrals and Hamiltonians for options and interest rates.* Cambridge University Press. https://doi.org/10.1017/CBO9780511617577

Baaquie, B. E. (2018). Bonds with index-linked stochastic coupons in quantum finance. *Physica A, 499*, 148–169. https://doi.org/10.1016/j.physa.2018.02.003

Bachelier, L. (1900). Théorie de la Spéculation. *Annales Scientifiques de l'École Normale Supérieure, 3*(17), 21–86. http://doi.org/10.24033/asens.476

Bagarello, F. (2009). A quantum statistical approach to simplified stock markets. *Physica A: Statistical Mechanics and its Applications, 388*(20), 4397–4406. https://doi.org/10.1016/j.physa.2009.07.006

Bauder, D., Bodnar, T., Parolya, N., & Schmid, W. (2021). Bayesian mean-variance analysis: Optimal portfolio selection under parameter uncertainty. *Quantitative Finance, 21*(2), 221–242. https://doi.org/10.1080/14697688.2020.1748214

Boroden, C. (2008). *Fibonacci trading: How to master the time and price advantage.* McGraw-Hill.

Bouland, A., Dam, W. V., Joorati, H., Kerenidis, I., & Prakash, A. (2020). Prospects andchallenges of quantum finance. *Computational Finance*. Advance online publication. https://doi.org/10.48550/arXiv.2011.06492

Brown, C. (2012). *Mastering Elliot wave principle: Elementary concepts, wave patterns, and practice exercises.* Bloomberg Press.

Bulkowski, T. N. (2005). *Encyclopedia of chart patterns* (2nd ed.). John Wiley & Sons.

Cont, R. (Ed.). (2009). *Frontiers in quantitative finance: Volatility and credit risk modeling.* John Wiley & Sons.

Cotfas, L. (2013). A finite-dimensional quantum model for the stock market. *Physica A: Statistical Mechanics and its Applications, 392*(2), 371–380. https://doi.org/10.1016/j.physa.2012.09.010

De Spiegeleer, J., Madan, D. B., Reyners, S., & Schoutens, W. (2018). Machine learning for quantitative finance: Fast derivative pricing, hedging and fitting. *Quantitative Finance, 18*(10), 1635–1643. http://doi.org/10.1080/14697688.2018.1495335

Faria, G., & Verona, F. (2021). Time-frequency forecast of the equity premium. *Quantitative Finance, 21*(12), 2119–2135. https://doi.org/10.1080/14697688.2020.1820071

Focardi, S., Fabozzi, F. J., & Mazza, D. (2020). Quantum option pricing and quantum finance. *The Journal of Derivatives, 28*(1), 79–98. http://doi.org/10.3905/jod.2020.1.111

Gao, T., & Chen, Y. (2017). A quantum anharmonic oscillator model for the stock market. P*hysica A: Statistical Mechanics and its Applications*, *468*, 307–314. https://doi.org/10.1016/j.physa.2016.10.094

Gómez, A., Leitao, Á., Manzano, A., Musso, D., Nogueiras, M. R., Ordóñez, G., & Vázquez, C. (2022). A survey on quantum computational finance for derivatives pricing and VaR. *Archives of Computational Methods in Engineering, 29,* 4137–4163. https://doi.org/10.1007/s11831-022-09732-9

Kim, M. J., Hwang, D. I., Lee, S. Y., & Kim, S. Y. (2011). The sensitivity analysis of propagator for path independent quantum finance model. *Physica A: Statistical Mechanics and its Applications, 390(*5), 847–863. https://doi.org/10.1016/j.physa.2010.11.016

Lee, R. S. T. (2019a). *Quantum finance: Intelligent financial forecast and program trading systems.* Springer Singapore. http://doi.org/10.1007/978-981-32-9796-8

Lee, R. S. T. (2019b). COSMOS trader—Chaotic Neuro-oscillatory multiagent financial prediction and trading system. *The Journal of Finance and Data Science, 5*(2), 61–82. https://doi.org/10.1016/j.jfds.2019.01.001

Lee, R. S. T. (2020). Chaotic type-2 transient-fuzzy deep neuro-oscillatory network (CT2TFDNN) for worldwide financial prediction. *IEEE Transactions on Fuzzy Systems, 28*(4), 731–745. http://doi.org/10.1109/TFUZZ.2019.2914642

Mantegna, R. M., & Stanley, H. E. (1999). *Introduction to econophysics: Correlations and complexity in Finance.* Cambridge University Press. https://assets.cambridge.org/052162/0082/sample/0521620082WS.pdf

Meng, X., Zhang, J., Xu, J., & Guo, H. (2015). Quantum spatial-periodic harmonic model for daily price-limited stock markets. *Physica A: Statistical Mechanics and its Applications, 438,* 154–160. https://doi.org/10.1016/j.physa.2015.06.041

Murphy, J. J. (1999). *Technical analysis of the financial markets: A comprehensive guide to trading methods and application.* New York Institute of Finance.

Nakayama, Y. (2009). Gravity dual for Reggeon field theory and nonlinear quantum finance. *International Journal of Modern Physics A, 24*(32), 6197–6222. https://doi.org/10.1142/S0217751X09047594

Nasiri, S., Bektas, E., & Jafari, G. R. (2018). The impact of trading volume on the stock market credibility: Bohmian quantum potential approach. *Physica A: Statistical Mechanics and its Applications, 512*, 1104–1112. https://doi.org/10.1016/j.physa.2018.08.026

Piotrowski, E. W., & Sładkowski, J. (2005). Quantum diffusion of prices and profits. *Physica A: Statistical Mechanics and its Applications, 345*(1–2), 185–195. https://doi.org/10.1016/j.physa.2004.07.002

Qiu, Y., Qiu, Y., Yuan, Y., Chen, Z., & Lee, R. (2021). QF-TraderNet: Intraday trading via deep reinforcement with quantum price levels based profit-and-loss control. *Frontiers in Artificial Intelligence, 4,* Article 749878. https://doi.org/10.3389/frai.2021.749878

Schaden, M. (2002). Quantum finance. *Physica A: Statistical Mechanics and its Applications, 316*(1–4), 511–538. https://doi.org/10.1016/S0378-4371(02)01200-1

Shi, L. (2006). Does security transaction volume-price behavior resemble a probability wave? *Physica A: Statistical Mechanics and its Applications, 366,* 419–436. https://doi.org/10.1016/j.physa.2005.10.016

Singh, R., & Srivastava, S. (2017). Stock prediction using deep learning. *Multimedia Tools and Applications, 76,* 18569–18584. https://doi.org/10.1007/s11042-016-4159-7

Ye, C., & Huang, J. P. (2008). Non-classical oscillator model for persistent fluctuations in stock markets. *Physica A: Statistical Mechanics and its Applications, 387*(5), 1255–1263. https://doi.org/10.1016/j.physa.2007.10.050

Zhang, C., & Huang, L. (2010). A quantum model for the stock market. *Physica A: Statistical Mechanics and Its Applications, 389*(24), 5769–5775. https://doi.org/10.1016/j.physa.2010.09.008

Received January 11, 2023
Accepted August 28, 2023