Time-series forecasting with decision-making under uncertainty method

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Abstract

Forecasting itself is essentially just a question of how to make the best decisions under incomplete information. The main challenge is of a dual uncertainty; 1) the inherent uncertain external world and 2) the persistent internal uncertainty that lingers in our minds. In this paper we propose a decision-making under uncertainty methodology for forecasting; one that utilizes a quantum-like evolutionary algorithm which incorporates the quantum superposition principle to model the dualistic uncertainty of the external world and internal mind all under unified complex Hilbert Space and by means of genetic programming to evolve the most satisfactory action sequence from the infinite superposed possibilities. By using historical data from the Dow Jones Index, we show that our methodology is able to produce a forecast with 80% odds resulting from the "cooperation" of multiple AI agents.

Keywords: time-series forecasting, machine learning, genetic programming, quantum superposition, natural selection, quantum-like evolutionary algorithm

1. Introduction

Time-series forecasting plays a crucial role in commercial business and academic research. In industries such as; forecasting stock market indexes [1-4], forex [5-6], cryptocurrency [7-10], electricity consumption [11-14], retail demand [15-16], wholesale prices [17], and raw data yield [18]. In applications of research topics such as; biological science [19], medicine [20-22], climate modelling [23-27], precipitation [28], semiconductor anomaly detection [29-32], neural spiking [33-35], neuronal behaviour predictions [36-37], ECG readings [38-41], and earthquake seismic activity [42-45]. Other fields include predicting tidal waves [46-47] and traffic congestion data [48-49].

Of the traditional methods formulated for time-series forecasting [50], the first systematic approach is the Box-Jenkins model [51], which integrated the existing knowledge of the autoregressive and moving average methodologies. There have also been many other mathematical methods formulated such as autoregressive [52], exponential smoothing [53-55], and other structural models [56]. Many attempts to automate time series forecasting have been made [57-60], such as the development of various packages for Python [61-62] and R [63], as well as a plethora of open-source software tools [64]. Various competitions have been hosted with the aim of achieving the highest accuracy for time series forecasting [65-68]. With the increasing availability of data and access to computing power, machine and deep learning has been thrust to the forefront of many next generation and state-of-the-art forecasting methods and models [69-72]. The rising popularity of AI and generative AI tools has also seen the releases of commercial tools such as Amazon SageMaker AI DeepAR [73-74], Facebook Prophet [75], and Nixtla TimeGPT [76] for time series forecasting that all leverage some sort of machine and deep learning.

When it comes to forecasting any time series dataset, it's universally acknowledged that it is impossible to predict the exact absolute future points of the data. Therefore, mainstream traditional methods have broken down the approach into three steps: find a trend, locate an interval cycle, and treat external environment uncertainty as noise or completely ignore it.

Thus, that poses the question: is it possible to forecast the future trend in the context of the data accurately enough to be able to make the corresponding decisions of what is being forecasted?

Essentially forecasting is a form of decision-making under uncertainty [77]; being able to sift out the best possible outcome that's most likely to happen from all the possibilities with the highest degree of confidence, or in plain English find the one that's going to happen and act accordingly [78]. The main challenge for decision-making is that of a dual uncertainty; one of the inherently uncertain external world and the internal uncertainty in our minds. Since no one can predict the future state of the world, this is the first uncertainty, but it's not just how unpredictable mother nature is, we humans and our unpredictable human nature of the decisions that we make leads to another uncertainty. The uncertainty of the world clouds our judgement of exactly what action to take when making a decision, and in certain contexts, our actions influence and affect the ever-changing uncertain world to some degree, thus presenting a significant challenge of modelling both the uncertainty of the objective and the subjective.

This work presents a decision-making under uncertainty model for time-series forecasting, one that utilizes a quantum-like evolutionary algorithm which incorporates the principle of quantum superposition to superpose all the possible forecast outcomes and Darwinian natural selection to optimize the most satisfactory model from many possible models to produce a forecast of a real-world time series dataset. The contributions of this paper are 1) we use our quantum-like evolutionary algorithm to train a single real-world historical dataset to produce a series of action sequences based on training logic decision trees, and 2) by means of majority rules of the 12 produced possible forecast outcomes show that our model is viable enough by producing a final forecast outcome with odds of 80%.

While we endeavour to contribute our methodology to the vast field of time series forecasting in the most effective way possible, and we strive to provide a comprehensive analysis for all the various time series forecasting datasets and review all relevant literature, there are just simply too many and it is not within the scope of one paper to train and produce a forecast for every single time series dataset category and review all relevant literature in the field of time series forecasting that exist. Thus, we note that while this paper only uses one single dataset of real-world historical data, however our methodology can be applied to any other time series dataset; including univariate, multivariate, temporal, and spatiotemporal.

The structure of this paper as follows: Section 2 details the methodology. Section 3 are the results. Section 4 is the discussion. Section 5 is the conclusion.

2. Decision-making under uncertainty model

Essentially, time-series forecasting is predicting future values of a specific target x_k of an entity at any given time t_k. Every entity represents some type of temporal information such as the demand of a retail product or the closing price of a stock. In simplest terms, forecasting is about predicting how point A becomes point B: $A(t_n, x_n) \xrightarrow{m} B(t_{n+1}, x_{n+1})$, where m is all the different possibilities that could happen, essentially all the possibilities that could happen with all the various elements and challenges affecting this transformation.

While the vast spectrum of time series datasets exists and there are an abundant of time series datasets that can be forecasted, one is known for being more volatile than the rest – the equity market. It is widely accepted that it is practically impossible to predict the exact absolute closing prices of the tumultuous equity market; be it stocks, futures, bonds, treasuries, securities, or cryptocurrencies, etc.…

Again, in the context of equity trading the question then arises: is it possible to forecast the future trend of the market accurately enough to be able to make the corresponding decisions of buy or sell?

The answer lies in the challenges faced: 1) the constantly changing state of whether the market will go up or down (external world uncertainty), and the tough time the traders' have in deciding when to buy or sell (internal mind uncertainty), and 2) the interactivity between the market and the traders.

In the scope of this paper, the quantum-like evolutionary algorithm produces action sequences with a set of strategies to guide traders which corresponding actions to take (buy or sell) respective to the trend of the market (up or down).

Our methodology has a few key advantages:

1) We are able to subtly model both the uncertainty of the market state (up or down) and the traders' actions (buy or sell) all together under unified complex Hilbert space, instead of modelling them separately.

2) As the model learns through repetitive iterations, by evolution and natural selection, the quantum-like evolutionary algorithm optimizes strategies (formulated as logic decision trees) that guide traders to take actions with certain degree of beliefs.

3) Our approach does not assume uncertainty is "noise", something that traditional approaches seek to eliminate or reduce. By learning with the mindset that uncertainty is inherent, the quantum-like evolutionary algorithm is able to provide forecasts for data that have little or no regularities, a case where many other forecasting methods might not perform as well.

(a) Main Elements

1. Data: the market can be modelled in the form of a time series, with each recorded closing price represented by a point in the data, described in (1).

$$\{(t_k, s_k)\}\ k = 1, \dots, N \tag{1}$$

where t_k is time and s_k are the observed closing prices.

2. Market trend: at any given time, the trend of the market as reflected by deducing the change from the previous point which can be described as (2).

$$Q = \begin{cases} q_1 | \omega_1 \\ q_2 | \omega_2 \end{cases} \tag{2}$$

where q_1 is when the market is going up, ω_1 is the frequency of the market going up; q_2 is when the market is going down, ω_2 is the frequency of the market going down.

At any given point, in order to deduce whether the market has gone up or down relative to the previous point, if point s_k is greater than s_{k-1} then the market has gone up, and if point s_k is less than s_{k-1} then the market has gone down.

3. Traders' actions: Regardless of what state the market is in, at any given time traders can take the actions of buy or sell, which can be described as (3):

$$A = \begin{cases} a_1 | p_1 \\ a_2 | p_2 \end{cases} \tag{3}$$

where a_1 is the trader will decide to buy, p_1 is the probability of that the trader will buy with degree of beliefs; a_2 is the trader will decide to sell, and p_2 is the probability of that the trader will sell with degree of beliefs.

4. Decision process: The process of taking a single action in correspondence of what state the market is in can be described as (4):

$$D | Q(q_1, q_2) \rightarrow A(a_1, a_2) \tag{4}$$

where D is the decision process under the conditions of the uncertain market Q which is the trend of the market with q_1 and q_2 being whether the market has gone up or down respectively and A are the corresponding actions that the traders can take with a_1 being to buy and a_2 to sell.

5. Evaluation: For every trade made there are four possible outcomes:

1) the market is going up and the trader buys.
2) the market is going up and the trader sells.
3) the market is going down and the trader buys.
4) the market is going down and the trader sells.

For any rational person the trader should expect to profit, thus in the context of equity trading, the maximum expected value is the most reasonable metric to be used for evaluation [79-80]. The trader profits when they buy or sell in correspondence with the trend of the market and will deficit if they buy or sell opposite of the market trend.

(b) Challenges

The main challenges faced to be taken into account are:

(i) How to effectively model the market's inherent volatile nature (whether it will go up or down) plus the hesitation of the traders when deciding what action to take (whether to buy or sell) resulting in a dual uncertainty effect.

(ii) How to accurately describe the interactivity between the market's volatility and the traders' hesitant actions, as the two are intertwined because the market's unpredictability hampers the traders decisive decision-making ability and in turn the collective actions taken by all the traders influences and eventually determines the closing prices of the market.

The entire process of modelling this dual uncertainty is that the market is constantly in a state where there are infinite possibilities that could happen in a split second, but at any given time it is impossible to know whether the market will go up or down. Therefore, the inherent uncertainty of the market has no significant meaning without any traders' involvement, and it is only with the participation of traders' that brings the infinite possibilities of whether to take the action of buy and sell, each with a certain degree of beliefs in doing so. The uncertainty of the market, coupled with the uncertainty of the actions that can be taken by the traders results in this infinite superposed spectrum of subjective and objective possibilities.

(i) Quantum Superposition

Thus, to effectively model the first challenge of the dualistic overlapping uncertainty is to utilize the quantum principle of superposition. The first postulate of quantum mechanics is "the state of an isolated physical system is represented, at a fixed time t, by a state vector $|\psi\rangle$ belonging to a Hilbert space $\mathcal{H}$ called the state space [81]." Thus, when something is in a superposed state, all the possible states can be expressed by a state $|\psi\rangle$, which can be represented as a linear combination of the states of the observable as (5). Essentially a superposed state is where all the possible states are simultaneously existent until it is observed [82], just like how Schrodinger's Cat can be dead and alive before the box is opened [83] or a qubit can be in a state of 0 and 1 until it is actually observed [84].

$$|\psi\rangle = c_1|\psi_1\rangle + c_2|\psi_2\rangle + \cdots + c_n|\psi_n\rangle \tag{5}$$

There are corresponding observed values of $o_1, o_2, \ldots, o_n$, and once the measurement happens [85] only one of these values on can be observed with a probability of $|c_n|^2$, as in (6).

$$|\psi\rangle \rightarrow |\psi_n\rangle \tag{6}$$

By superposing all the possible states of the market (either going up or down) and all the possible actions that the traders can take (either buy or sell) together according to the principle of quantum superposition we are able to postulate an effective model of both the potential states of the market and the collective possible actions taken by all the traders as in (7) and (8).

$$|Q\rangle = c_1|q_1\rangle + c_2|q_2\rangle \tag{7}$$

where $|q_1\rangle$ denoting the market trending upwards; $|q_2\rangle$ denoting the market trending downwards. $\omega_1 = |c_1|^2$ is the objective frequency of the increase; $\omega_2 = |c_2|^2$ is the objective frequency of the decrease.

$$|A\rangle = \mu_1|a_1\rangle + \mu_2|a_2\rangle \tag{8}$$

where $|a_1\rangle$ denotes the buy action; $|a_2\rangle$ denotes the sell action. $p_1 = |\mu_1|^2$ are the degree of beliefs to buy; $p_2 = |\mu_2|^2$ are the degree of beliefs to sell.

(8) represents the decision-maker's potential actions that can be taken (buy or sell) in a superposed state with infinite possibilities of buy or sell with varying degree of beliefs. Given this, the question then becomes how does the trader decide which action to take: buy or sell?

The second postulate of quantum mechanics is "all measurable quantities (observables) are described by Hermitian Linear operators" [81-85]. In this case, the observable for traders' actions is represented by an operator (matrix) ρ as in (9a), and the matrix just means the operation of transferring a state to another state. ρ in this context is just a 2x2 matrix and serves as a projection operator, one that projects the traders' undecided mind of whether to buy or sell to a final action taken of either buy or sell. Pure state in (9a) is a state with "quantum interference" which means that the trader can't decide yet whether to buy or sell as $\mu_1\mu_2^*|a_1\rangle\langle a_2| + \mu_1^*\mu_2|a_2\rangle\langle a_1|$ in (9a). Mixed state in (9b) is the state without "quantum interference" which means that the trader either buys with degree of beliefs p_1 or sells with degree of beliefs p_2. The role of the projection operation is that it projects a result (buy or sell) with a probability p_1 or p_2, and for equity trading it just projects whether to buy (a_1) or sell (a_2) with subjective probability as in (9c). In other words, the projection operator projects the traders' mind to an action that the trader will take, or as how Aristotle put it "from potentiality to actuality."

$$\text{Pure state:} \quad \rho = |A\rangle\langle A| = p_1|a_1\rangle\langle a_1| + p_2|a_2\rangle\langle a_2| + \mu_1\mu_2^*|a_1\rangle\langle a_2| + \mu_1^*\mu_2|a_2\rangle\langle a_1| \tag{9a}$$

$$\text{Mixed state:}\ \rho' = p_1|a_1\rangle\langle a_1| + p_2|a_2\rangle\langle a_2| \tag{9b}$$

$$\text{Decision process D:} \quad \rho \xrightarrow{\text{decision}} \rho' \tag{9c}$$

From ρ to ρ' is the projection operation highlighted, it projects the pre-action superposed mindset (buy and sell) to the actual decision the trader made (either buy or sell) with degree of beliefs. We also call the projection operator ρ the logic decision tree, and this entire projection of the decision process can be seen as a transformation from pure state to mixed state as in (9c).

The entire decision-making process can also be expressed in matrix form as in (10-11):

$$\rho = \begin{bmatrix} \rho_{11} & \rho_{12} \\ \rho_{21} & \rho_{22} \end{bmatrix} \xrightarrow{\text{diagonalization}} \begin{bmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{bmatrix} \xrightarrow{\text{normalization}} \rho' = \begin{bmatrix} p_1 & 0 \\ 0 & p_2 \end{bmatrix} = p_1|a_1\rangle\langle a_1| + p_2|a_2\rangle\langle a_2| \tag{10}$$

$$|a_1\rangle = \begin{bmatrix} 1 \\ 0 \end{bmatrix}, |a_2\rangle = \begin{bmatrix} 0 \\ 1 \end{bmatrix}; \ |a_1\rangle\langle a_1| = \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix}, |a_2\rangle\langle a_2| = \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix} \tag{11}$$

During the entire decision process, the trader has to take into account the state of the market, if they want to maximize their profit they can't just go in blindly and make a decision, thus the probability of the market (up or down) can be described by the objective frequency ω_1 and ω_2, essentially the market up-down ratio is approximately 50-50 (hence the market is in a random walk). Now the question becomes how can the traders' subjective probability of p_1 and p_2 in (9) be formulated?

Sometimes traders' will 100% firmly believe that the market will go up, other times they'll only have a 60% belief that the market will go up, but every time no matter what final action the traders' decide to take they will always have a degree of beliefs ranging from 0-100% to buy or 0-100% to sell, though that doesn't necessarily mean that they will always do so believing 50-50 buy/sell, it could be 60-40, 30-70, 80-20, etc.

Just having degree of beliefs to decide whether to buy or sell is not enough, therefore we need to optimize a dynamic degree of beliefs that are a group of strategies which will guide the traders' actions in the form of an action sequence to maximize their expected value, which is in line with the rational economic agent hypothesis that would be to make the most profit on every trade conducted.

Essentially this action sequence is the traders' actions taken at any given time coupled with their degree of beliefs. If the trader believes that the market will go up with 100% degree of beliefs and the market does indeed went up and the trader bought with that 100% degree of beliefs then that is the best-case scenario that the trader should be aiming for every time. Other times it could be that the trader bought with having an 80% degree of beliefs that the market will go up and 20% that the market will go down and the market did go up, then that is a satisfactory strategy, which is also what the trader should aim for.

Basically, the so-called trading strategies produced by the action sequence is to aid the trader in buying or selling in line with the trend of the market with the greatest corresponding degree of beliefs, i.e. to buy with 95% degree of beliefs that the market will go up when the market is trending upwards. Now the remaining problem is how to find, or balance the ability to find the most satisfactory strategy that allows the trader to buy or sell with the greatest degree of beliefs when the market is going up or down respectively to make the most profit every time.

For example, if the trader is able to buy with 100% of belief that the market will go up and does so when the market indeed goes up then this is the pinnacle of the action sequence strategies, the remaining job is to attempt to get to this level of excellence every time, or as close as possible. But this is easier said than done, the market's myriads of kaleidoscopic changes significantly hampers the ability to do so, essentially the best we can do is to find the most satisfactory ones to play our hand in this "game" of strategy, to "deal" with the cunning interactivity between the traders and the market, we turn to evolution and Genetic Programming (GP). From these satisfactory strategies formulated by GP is what constantly pushes us to construct the most accurate action sequences to forecast the market's trend.

(ii) Genetic Programming

This brings us to how we model the second challenge of the interactivity between the market and the traders by using GP, an algorithm that draws on the principles of Darwinian natural selection and evolution [86]. GP uses random crossover, selection, and mutation to formulate an executable program that solves problems accordingly [87-88]. First by randomly generating a certain number of individuals that comprise of a population, the algorithm obtains the fitness of each individual in the group and then by utilizing the principles of natural evolution for a number of generations it will optimize a most "satisfactory" solution to be used. The fittest ones that survive are the ones utilized, in line with the theory of natural evolution that states life has evolved through generations of selection, mutation, and crossover, the ones most adapted to the environment survive long enough to pass their genes off to the next generation [89]. The GP algorithm is shown in Algorithm 1.

Input:

- Historical dataset $\{(t_k, s_k), k = 0, \cdots, N\}$ (each sample consists of an equity's time and closing price);
- Setting:
  (1) Operation set F;
  (2) Dataset T;
  (3) Crossover Probability = 70%; Mutation probability = 5%.

Initialization:

- Population: randomly create 300 individuals.

Evolution:

- Loop: for i = 0 to 80 generations.
  a) Calculate fitness for each individual based on the historical dataset;

b) According to the quality of fitness:

i. Selection: selecting parents.

ii. Crossover: generate a new offspring using the roulette algorithm based on crossover probability.

iii. Mutation: randomly modify the parent based on mutation probability.

Output:

- An individual of the best fitness.

Algorithm 1. GP Algorithm

The pure state (2x2 density matrix) ρ can be approximately constructed from eight basic quantum gates as (12).

$$\begin{Bmatrix} H = \frac{1}{\sqrt{2}}\begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix} X = \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix} Y = \begin{bmatrix} 0 & -i \\ i & 0 \end{bmatrix} Z = \begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix} \\ S = \begin{bmatrix} 1 & 0 \\ 0 & i \end{bmatrix} D = \begin{bmatrix} 0 & 1 \\ -1 & 0 \end{bmatrix} T = \begin{bmatrix} 1 & 0 \\ 0 & e^{i\pi/4} \end{bmatrix} I = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \end{Bmatrix} \tag{12}$$

The operation set and the dataset for GP are as:

(1) Operation set $F = \{+, *, //\}$;

(2) Dataset $T = \{H, X, Y, Z, S, D, T, I\}$.

In order to find the most satisfactory set of strategies the quantum-like evolutionary algorithm optimizes the best actions by using logic trees (pure state ρ). The logic tree is essentially a decision tree that guides which strategies to take with corresponding actions. At any given time, the expected value under the current environment and the corresponding actions can be represented as (13c).

$$\rho_{market} = \omega_1|q_1\rangle\langle q_1| + \omega_2|q_2\rangle\langle q_2| \tag{13a}$$

$$\rho_{action} = p_1|a_1\rangle\langle a_1| + p_2|a_2\rangle\langle a_2| \tag{13b}$$

$$\rho_{market} \otimes \rho_{action} = \omega_1 p_1|\langle q_1||a_1\rangle|^2 + \omega_1 p_2|\langle q_1||a_2\rangle|^2 + \omega_2 p_1|\langle q_2||a_1\rangle|^2 + \omega_2 p_2|\langle q_2||a_2\rangle|^2 \tag{13c}$$

where (13a) is the market observable operator; (13b) is the traders' actions observable operator; and (13c) is the composite system of the market and the traders' actions. In (13c), the first term means that the market is going up and the trader buys (this is a reward), the second term means that the market is going up and the trader sells (this is a punishment), the third term means that the market is going down and the trader buys (punishment), and the fourth term is that the market is going down and the trader sells (reward). Again, according to economic theory, anytime someone makes a "decision", whether acting in their own self-interest or by other considerations of strategy there is always an expected value [90-92]. The expected value of each individual one is the possible scenarios of what the outcome could be paired with the state of what is being observed, as in (14):

$$EV_t = \begin{cases} \omega_1 p_1 s_{t,t-1}, \text{trend is up and trader believes so with probability } p_1 \\ -\omega_1 p_2 s_{t,t-1}, \text{trend is up and trader doesn't so with probability } p_2 \\ -\omega_2 p_1 s_{t,t-1}, \text{trend is down and trader doesn't with probability } p_1 \\ \omega_2 p_2 s_{t,t-1}, \text{trend is down and trader believes with probability } p_2 \end{cases} \tag{14}$$

where $s_{t,t-1}$ is the absolute difference between the closing price of the current point and the previous point.

The fitness function of the logic tree is the sum of all the expected value of all the individual actions as (15):

$$fitness_{logicTree} = \sum_{t=1}^{n} EV_t \tag{15}$$

The purpose the fitness function is essentially an incentive system of reward and punishment. Before a decision is made and an action is chosen, there are the four potential outcomes that exist. Of course, only one can happen, basically one out of the four scenarios of the expected value in (14). Therefore, if the market is trending upwards and the belief is that it's trending upwards, that results in a reward. But if the market is trending downwards and the belief is that it's trending upwards, then a punishment is concurred. Vice versa with the other two scenarios. By learning historical data, the more rewards that are reaped then the more accurate chance there is of predicting the next trend. This also allows for no presumptions of the trend, the more times the right trend is "guessed" correctly the best strategies and actions are effectively evolved as a result. Generation after generation of evolution, the best strategy naturally arises, which is the ultimate goal of the fitness function. The best strategy that has evolved by natural selection is the one that can be utilized for future forecasting.

3. Facilitating decision support with quantum-like evolutionary algorithm

Although most model builders themselves are more concerned about the accuracy of the forecasts they produce, end-users typically are more concerned about gaining valuable information from predictions to guide their future decision making and which corresponding actions to take. For instance, sales associates can make use of demand forecasts to know when to stock up and how much to avoid supply shortages or surpluses, or traders can benefit greatly from forecasts to help them decide when to buy or sell when the market might go up or down. Thus, while time-series forecasting itself is a crucial step, it is not the only factor and the sole objective shouldn't be to forecast the exact absolute future data points of a time series dataset but seeking to understand the principles and motivations of why and how the model formulated the given forecast outcome. The more valuable information an end user can grasp from forecasts, the more they can significantly increase the success of their actions.

For the purposes of equity trading illustrated in this paper, the quantum-like evolutionary algorithm attempts to provide the best information to traders when making future trades by providing an action sequence to help decide whether to buy or sell in response to if the market might go up or down in the future. In a sense, the quantum-like evolutionary algorithm acts as the trader's AI trading assistant, helping it to make the best decisions but not actually doing so itself, by providing important information and metrics to assist the human trader in making the best decisions possible. In this section, we detail the specific way the quantum-like evolutionary algorithm generates 12 possible outcomes for the following week of trading and then by majority rules "chooses" the most satisfactory one to provide the trader as a reference metric when deciding whether to buy or sell.

(a) Dataset

Four weeks of data from October 4th, 2024 to November 1st, 2024 were downloaded on November 2nd, 2024 and was used as training data. The data was trained consecutively on November 2nd, 2024 and November 3rd, 2024 and produced a forecast outcome for the week of November 4th, 2024 to November 8th, 2024. This ensures that the quantum-like evolutionary algorithm is able to produce its outcomes before actual trading data is recorded. After the forecasted trading week ends, the predicted results can then be compared to the actual recorded results at the end of the week, therefore guaranteeing a 100% real-world forecast with no possibility of knowing what has happened already beforehand. Following this strict procedure, the quantum-like evolutionary algorithm assisting decision-making abilities are fully reflected.

(b) Trainings and Forecasts

On both days, the training parameters were set the same, with 3 agents and a training frequency of 1000 repetitions. Once training concludes the quantum-like evolutionary algorithm obtains an optimized logic decision tree to produce forecasts. Both trainings produced 6 different possible outcomes each (total 12), which were all taken together and provided as reference metrics to make the final forecast "decision". Figure 1 shows the training results on November 2nd and Figure 2 shows the training results on November 3rd.

In both figures, the blue line is the recorded historical data, the closing prices of the Dow Jones Index from October 4th to November 1st, 2024. The yellow line are the most optimal calculated prices comprising of the fitted line of the data as produced by the quantum-like evolutionary algorithm through machine learning the historical data according to the logic tree utilized.

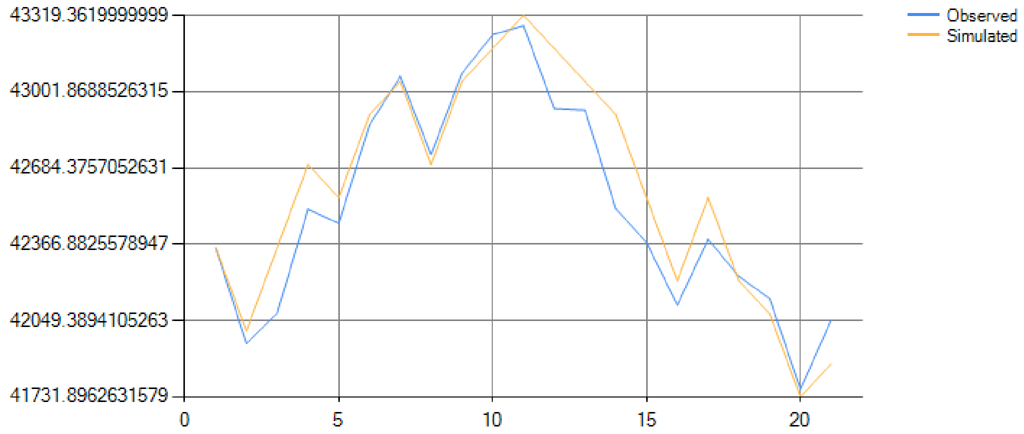

Figure 1: Results of first training on November 2nd, 2024.

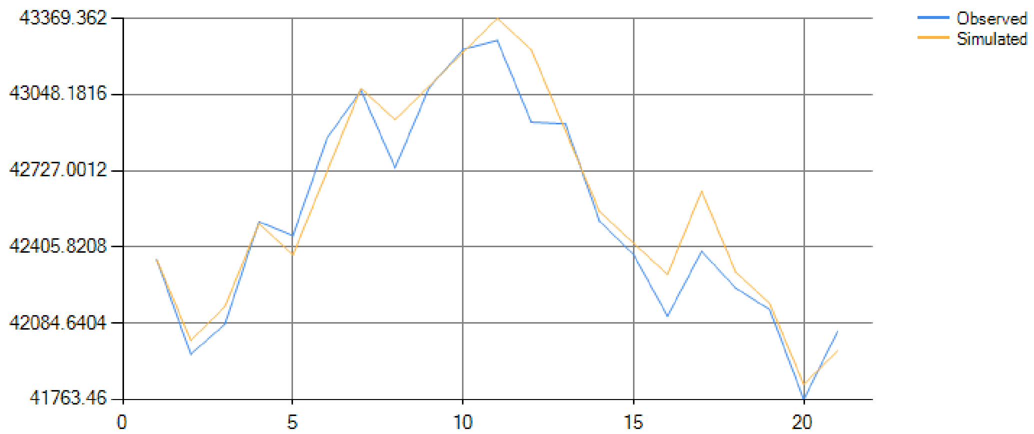

Figure 2: Results of second training on November 3rd, 2024.

Table 1 shows the 12 total possible forecast outcomes from the trainings on November 2nd, 2024 and November 3rd, 2024.

Date	**Trend**	**Train 1 (Nov 2)**						**Train 2 (Nov 3)**					
11/04/2024	Down	1	1	0	0	0	1	1	0	0	0	1	1
11/05/2024	Up	0	0	0	1	0	0	1	0	0	0	0	0
11/06/2024	Up	0	0	0	0	0	0	0	0	0	0	0	0
11/07/2024	Down	1	0	0	1	0	1	1	1	0	0	1	0
11/08/2024	Up	0	0	1	0	0	0	0	0	1	0	0	1

Table 1 12 possible forecast outcomes training table

The actual observed trend of the market is displayed in the trend column, while the Train 1 and Train 2 columns show the predicted outcomes (whether the market will go up or down) from the days the data was trained on November 2nd and 3rd respectively. 0 represents the logic decision tree "believes" that the market will go up and 1 represents the logic decision tree "believes" that the market will go down, together they represent the action sequence calculated by the quantum-like evolutionary algorithm's logic trees; for example, 1 0 0 1 0 from the first possible forecast from training one represents the logic decision tree "believes" the future market will be Down, Up, Up, Down, Up.

(c) Analysis

The two groups of 6 forecasts produced from the two separate trainings are analysed according to majority rules. Taking all 12 forecast outcomes into account, the one that is decided by majority rules is chosen as one action sequence to guide the final decision whether to buy or sell for each coming day from 11/04/2024 to 11/08/2024, as shown in Table 2.

Date	Trend of DJIA	Action sequence produced
11/04/2024	Down	Buy
11/05/2024	Up	Buy
11/06/2024	Up	Buy
11/07/2024	Down	Sell
11/08/2024	Up	Buy

Table 2 Final action sequenced provided by logic tree table

For the action sequences produced for the days of November 5th, 6th, and 8th, the majority are that the trend will go up, thus following majority rules the corresponding action to take is naturally to buy. For example, 10 out of the 12 outcomes produced by the quantum-like evolutionary algorithm for November 5th are that it believes that the market will go up and only 2 that it will go down. Therefore, it is most reasonable for the quantum-like evolutionary algorithm to believe that the market will go up, leading it to decide to buy on November 5th. The same applies for November 6th and 8th to buy, as the majority of the outcomes points to buy, leading the quantum-like evolutionary algorithm to do so.

However, for November 4th and 7th, the 12 trainings produced over the course of two days each produced 6 each, resulting in a tie of up and down, therefore there is no majority rule to decide whether to buy or sell. In this case, the quantum-like evolutionary algorithm will then have to randomly chose one or the other, here it chose to buy on the 4th and to sell on the 7th.

By taking a look at the actual results that were recorded for the following week of November 4th, 2024 to November 8th, 2024 and comparing it with the forecast results, the quantum-like evolutionary algorithm got 4 out of the 5 actions right, therefore its odds are 80%. If the quantum-like evolutionary algorithm chose to sell for both the 4th and 7th then it would have gotten them all right and the odds would've been 100%. If the quantum-like evolutionary algorithm chose opposite of what it ended up choosing this time, then the odds would've still been 80%. And if the quantum-like evolutionary algorithm had chosen the worst-case scenario of buy for both the 4th and 7th, the odds still would've been 60%. Thus, no matter what, whatever outcome the quantum-like evolutionary algorithm ends up with, best case 100%, worst case 60%, and an equal split of 80% odds, making the average of the possible odds still 80%.

4. Discussion

Majority of traditional methods tend to focus on breaking down forecasting into three steps: 1) find a trend, 2) apply an interval cycle, and 3) eliminate external noise (uncertainty) as much as possible. If the said dataset can't be broken down into these three parts, then that dataset is treated as an unpredictable data series filled with random external noise that can't be reduced. Basically, traditional methods strive to reduce or completely eliminate external noise (uncertainty) by treating it as a bad thing to find a certain possible trend.

Compared to traditional methods, our methodology doesn't treat external noise (uncertainty) necessarily as a bad thing, we don't strive to reduce or eliminate noise and uncertainty but quite the contrary, we attempt to utilize uncertainty to find valuable information from the constantly changing environment to formulate a trend. Thus, we don't set out with the mindset of attempting to break up the data into trend, interval cycle, and noise, instead we seek to embrace uncertainty as a factor to help us find possible outcomes.

The main challenge is still how to deal with the dual uncertainty of the environment and possible actions that can be taken as well as the interactivity between them. Our quantum-like evolutionary algorithm applies quantum superposition to superpose all the possibilities of the external world and internal mind in terms of a unified complex Hilbert Space to model the dual uncertainty while utilizing GP to find the most satisfactory model from all the possibilities by using the maximum expected value as the fitness function.

While uncertainty is an intrinsic part of the world and life, overly emphasizing trying to eliminate the noise that uncertainty brings by all means overlooks the fact that it is because of uncertainty that makes life the ever more plentiful. In some means in the words of Claude Shannon, "information is the resolution of uncertainty”, for forecasting it’s not just any information that will propel you to make the best forecast decisions but its valuable information that is key. It is the inherent uncertainty that brings the excitement of making those tough decisions, because by doing so, our actions affect the states of the constantly changing world but this in turn then clouds our judgement and hampers our decision-making ability, resulting in a game of wits and strategy between us human nature and mother nature and it becomes more exciting and fruitful when we reap the rewards associated with it. It’s just like if your entire life was played out for you in a movie would you still find it meaningful to live it? Yes, the inherent uncertainty of the world brings frustration and chaos at times, but it is because of it brings out the excitement and makes life more wonderful and exciting.

5. Conclusion

With the exponential growth of methods formulated for time series forecasting and the expanding collection of tools that can be used, there has been much success achieved in the field of forecasting. In this paper, we put forth a quantum-like evolutionary algorithm for time series forecasting – highlighting the dual uncertainty challenge and the corresponding methodology used. We briefly outline the traditional methods developed for time-series forecasting and the different approaches they take. Furthermore, we described the dualistic uncertainty challenge and used a complex Hilbert space to describe both the inherent uncertain external world and internal mind and then used GP to optimize a set of satisfactory strategies in the form of an action sequence to model the interactivity between them. Finally, by using equity trading as a medium, we have shown by training four weeks of stock market data and then producing two groups of 6 possible forecast outcomes for the next week on the preceding weekend, the quantum-like evolutionary algorithm can produce a forecast with odds of 80%.

Although many models across various domains have been developed for time series forecasting, limitations still exist. In the words of George Box, “remember that all models are wrong the practical question is how wrong do they have to be to not be useful”, many models for time series forecasting still face significant challenges, such as overfitting, black box operation, and requiring vast amounts of data to provide meaningful forecasts.

Thus, we note that our model is not by any means all-encompassing or universally omnipotent either, it is no crystal ball that one can peer into and gain oracle like powers. However, for this specific dataset, the quantum-like evolutionary algorithm shows that it was able to produce a forecast with 80% odds, but had the market somehow encountered a black swan event during the week forecasted, then in that case the forecast produced by quantum-like evolutionary algorithm’s would be hampered significantly. To limit the chance of this from happening, the training parameters of the quantum-like evolutionary algorithm can be adjusted accordingly, thus if the number of agents trained and the frequency of training repetitions are increased, the quantum-like evolutionary algorithm may avoid a situation like that from happening.

Lastly, further research will include increasing the number of agents trained and increasing the frequency of the training repetitions to see if more stable and accurate results can be produced for more datasets of the Dow Jones Index. Hypothetically the longer training time is, i.e. more agents are used and the frequency of training repetitions are set, then the results produced should be more stable and accurate to some degree. Other research will be conducted on the vast amounts of other time series datasets that can be forecasted, we will see if our algorithm can be put up to the test for those other datasets. Given the flexibility of our methodology, our algorithm can find valuable information from raw data by producing action sequences to assist in the forecasting decision-making process, and we’re confident that further research will show that using our quantum-like evolutionary algorithm in the same way for any discrete time series to be a “AI machine assistant decision-maker”.

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