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Price Jumps: Quantum Theory Aids in Deep Crude Oil Price Forecasting

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Abstract

In this study, a crude oil price prediction model based on quantum leap radius and polynomial fitting is established by building a market atom model, fitting financial funds as "market atoms" with energy, and applying quantum leap theory to describe the leaping behavior of price. The LSTM neural network model is used to learn the price jump paths of financial instruments to improve the prediction effect. After 2000 rounds of iterative training, the RMSE of the model reaches 3.1136, and the correlation coefficient is 0.48084; the model's loss function decreases rapidly, indicating that the training effect is good. The study reveals the potential value of quantum theory in finance, preliminarily verifies the application of quantum leap and LSTM model in crude oil price prediction, and provides new ideas for the in-depth study of quantum finance theory.

Keywords

Machine Learning; Financial Physics; Quantum Finance; Time Series.

1. Introduction

As the intersection of economic physics and quantum mechanics, quantum economics introduces quantum theory into economics, providing a new perspective for understanding complex economic phenomena. Financial physics is rough in the macroeconomic system as a mechanical system but ignores individual differences. In contrast, quantum economics starts from the microscopic level by quantum modeling of personal preferences and behaviors. The theory suggests that individual behavioral interactions can generate quantum statistical laws of economic systems.

This paper aims to explore the application of quantum theory in financial price forecasting. The quantum leap theory can be used to abstractly describe the dynamic changes of funds and price fluctuations in financial markets. On this basis, a crude oil price prediction model based on leap radius and polynomial fitting is proposed. The analysis shows that the model can better capture the quantum fluctuation characteristics of crude oil prices.

In addition, the LSTM neural network shows a powerful financial forecasting ability by learning the long-term dependence of time series. This paper applies the LSTM network to fit and enhance the quantum prediction model. Lower RMSE and loss values are derived through 2000 iterations of training. The results show that combining quantum leap theory and LSTM deep learning is expected to realize more efficient financial price prediction.

The rise of econophysics has laid the theoretical foundation for quantum economics. Econophysics treats the economic system as a macroscopic statistical mechanical system. It analyzes the interactions between economic variables through data models, revealing the complex collective behavior patterns behind individual micro-behaviors. This approach provides a valuable macroscopic perspective but overemphasizes the "mean field" assumption and ignores the variability of economic individuals and the correlation effect of information. Quantum economics draws on the microscopic view of quantum mechanics, starting from the quantum superposition of individual preferences and analyzing in depth how information

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dissemination and decision-making interactions shape individual behaviors and how the interactions of individual behaviors generate the quantum statistical characteristics of economic systems. Many advances have been made in this field, such as using quantum leap theory to model financial asset prices and using LSTM neural networks to predict time series, which have shown strong potential for application. As the idea of quantum economics continues to mature and the further development of scientific and technological means, it will undoubtedly enrich the analytical paradigm of economics and provide new perspectives for modeling the dynamics of economic variables and the operation of financial systems. In general, quantum theory brings new tools and ways of thinking to economics and describing economic behavior in the language of quantum mechanics may open up new horizons. However, the current research is still in the initial stage; with further improvement of the theory and the innovation of technical means, the quantum financial theory will realize a more profound contribution.

2. Literature Review

The Quantum economics, originating from the quantum physics theory, studies economic activity's quantization rules and applications. Planck's revelation of energy discontinuity in 1900 showed that all phenomena, including the economy, have quantization properties. This contrasts traditional economics, which treats economic variables as continuous. In 1960, Schmidt first analyzed the quantum state characteristics of money and debt[1]and suggested that "output is a time-quantized instantaneous event"[2]. In 1978, Qadir introduced the concept of "quantum economics" and hypothesized that individual preferences are revealed after surveys and that infinite factors affect choices[3]. However, progress in this area has been slow over the past 30 years, and innovative research has been scattered.

Russian scholar Ilyinsky applied quantum field theory to explore financial markets, described as "financial fields," to derive equations for the evolution of asset prices and capital flows[4]. American scholar Shubik discovered the inaccuracy of economic dynamics[5]. Singaporean scholar Ba Kui published three monographs on quantum economics, studying futures theory[6], interest rates and coupon bonds[7], and the design of financial instruments[8].

After 2010, quantum finance developed rapidly. Serbian scholar Vukotik predicted that quantum economics would be the foundation of global economic theory[9]. Portuguese scholar Goncalves studied chaos theory and quantum game theory[10], and quantum financial approaches to finite strategy games[11]. British scholar Haven and Swiss scholar Khrennikov discuss quantum probability effects in economics[12], finance[13], and the application of quantum information in the social sciences[14]. American scholar Wendt considers consciousness a macroscopic quantum mechanical phenomenon[15].

Prof. Amit Goswami builds a bridge between physics and economics, charting the path from neoclassical to quantum economics[16]. Arijit predicts GDP changes using quantum economics formulas[17]. The research of quantum economics has covered various subfields, showing the trend of systematization.

In recent years, Long Short-Term Memory (LSTM) neural networks have shown great potential for application in predicting financial time series data. Early studies have demonstrated that LSTM can capture the long-term dependence of time series and outperform traditional methods in stock price forecasting[18]. Follow-up studies further confirm that LSTM can learn the nonlinear patterns of time series, and its accuracy in stock price prediction significantly outperforms that of ARIMA and other methods[19]. Y. Liu[20]examined the effectiveness of LSTM in predicting financial market indices and demonstrated that it can provide more accurate market predictions, especially in volatile markets, to maintain model stability. C. Szegedy et al.[21]applied LSTM to anomaly detection of time series to predict fraudulent

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behavior in financial markets. In addition,K. He et al[22]designed a hybrid model based on LSTM and convolutional neural network (CNN), showing that this fusion method can further improve the accuracy of stock price prediction.

Research in recent years also supports the broad application of LSTM in financial forecasting. G. Huang et al[23]proposed an integrated learning method combining LSTM, CNN, and random forest algorithms to improve the effectiveness of stock price prediction. J. Hu et al[24]used the LSTM network and attention mechanism to predict foreign exchange prices and proved that the attention mechanism could help the model to focus on more important input information. The current study shows that LSTM can learn the long-term dependence and nonlinear changes of time series, which shows great advantages and application prospects in financial market forecasting.

Quantum economics reveals the uncertainty and volatility of economic variables by studying the quantization law of economic activities. We can apply quantum game theory and quantum probability theory to build a quantum model to describe the crude oil market and analyze the quantum fluctuation characteristics of crude oil prices. On the other hand, LSTM networks are excellent in dealing with financial time series forecasting by learning the long-term dependence of time series. Therefore, this study proposes to build a hybrid quantum finance-LSTM prediction model:

1) A quantum model describing the crude oil market is constructed based on the principles of quantum economics to reveal the quantum laws of the crude oil price.

2) An LSTM network is used to learn the time series of crude oil price output from the quantum model, and LSTM networks are trained to capture the long-term dependence of the time series.

3) A hybrid model that integrates the principles of quantum economics and deep learning is built up.

This research proposes an integration of quantum econometrics and long short-term memory deep learning for enhanced predictive modeling of crude oil price dynamics. By synthesizing the theoretical underpinnings of quantum economics with the pattern recognition capacities of recurrent neural networks, this novel framework aims to advance the efficacy of forecasting for this complex financial time series. The fusion of these multidisciplinary techniques offers new perspectives and endeavors to improve petroleum price prediction through a hybrid quantitative approach. Overall, this study contributes novel concepts and methodologies for amalgamating quantum economic theory with machine learning algorithms to better comprehend and anticipate the behavior of global commodity markets.

3. Theory and Algorithm

The objective world of energy, frequency reaction cycle characteristics, based on these two main factors to build a financial physical model to describe the energy in the time series as a way to predict the price.

3.1. Price Leap Theory

Quantum leap, as the name suggests, is a description of the movement of electrons outside the atomic nucleus. In the microscopic world, the electrons outside the nucleus of an atom rotate around the nucleus in different orbital jumps, and different orbitals correspond to different energy states. The energy states of the various orbits are intermittent and discontinuous. Its electrons can only jump one energy from one energy level up or down. If irradiated by a very strong photon from outside, the electron absorbs the photon's very strong energy and will cross several levels and reach a very high energy level. The intervals between energy levels can be calculated according to the formulae of quantum theory. Similarly, money in the market absorbs or releases energy to produce price increases or decreases, which produces

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movements similar to price jumps in the microscopic world. The movement of electrons in the atom is discontinuous, and its energy is also intermittent, the study found that through the long-term observation of the law of price movement in the market found that the movement of price characteristics are also discontinuous, discrete.

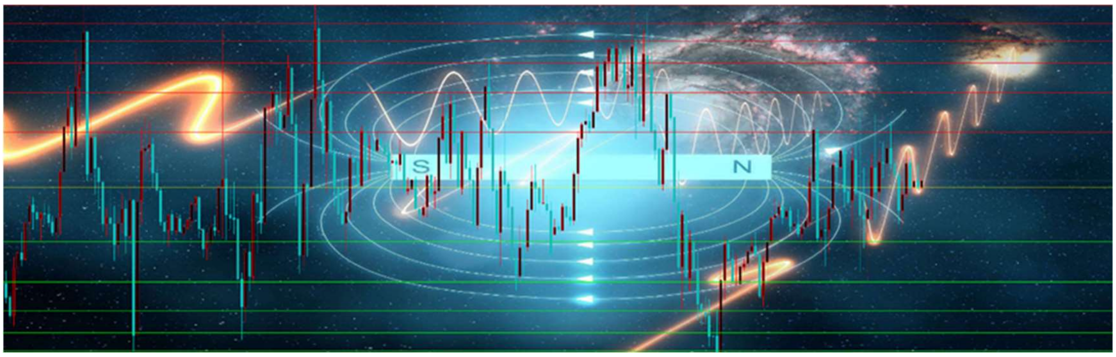

Figure 1. Schematic diagram of price jump fluctuation

As shown in Figure 1, the chart of the up and down fluctuations in the financial market is the candle line, the horizontal line in the figure is the price jumping "track", the price in the movement of the process is also made from a track jump to another track of the leaping movement.

In this paper, the financial market operation in the interrelationships abstract a financial market atomic model, in this model, the basic elements of the financial market is the "market atoms", securities is the core of the value, analogous to the nucleus in the atom, in the actual process, the price around the value of the similar to the micro-world of electrons around the nucleus of the atom fluctuations.

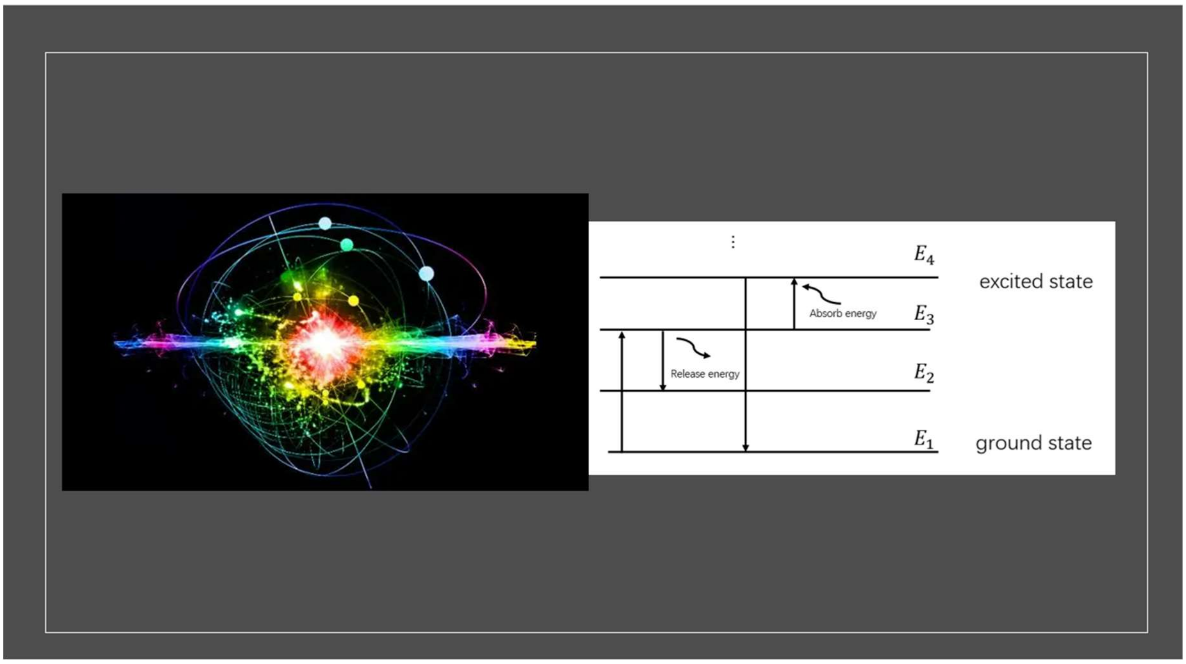

Figure 2. Absorption or release of energy to generate jumps

In the atomic model of the market, energy is the driver of price, analogous to the energy absorbed or released by electrons in the microcosm. In the natural sciences, visible matter and invisible energy are the two most basic elements, and in economics and finance, visible data

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and invisible information are also two basic elements. This leads to the basic assumptions of this paper: the money in the financial market is energy, the market absorbs energy prices will rise, the release of energy prices will fall.

3.2. Leapfrog Algorithm

The behavior of financial markets is often described as difficult to predict and understand. However, by applying the theories of quantum mechanics to financial markets, it may provide a completely new way of understanding and predicting market behavior. Here, leapfrog radius combined with quantum modeling is used to understand financial markets. The radius of the jump can be thought of as the "distance" over which the price moves, or the strength of the price jump.

In this model, a basic quantum mechanical concept, the wave function, is involved. The wave function describes the state of a quantum system in quantum mechanics. In this case, the wave function is used to describe the state of a financial market. The wave function can be written as:

$$|\Psi\rangle = \sum_{i=1}^{n} a_i |P_i, r_i\rangle$$

Here, $|P_i, r_i\rangle$ represents a state where P_i is the price, r_i is the radius of the jump, and a_i is the amplitude of this state. What this formula indicates is that the state of the system is a superposition of all possible states, each with a corresponding amplitude.

The next thing to consider is the dynamics of the system, that is, how to describe the evolution of the system over time. This requires the use of the Hamiltonian, which in quantum mechanics describes the total energy of the system. In this model, the Hamiltonian can be described as:

$$H = \sum_{i,j=1}^{2n} H_{ij} |P_i, r_i\rangle\langle P_j, r_j|$$

Here, H_{ij} represents the $\langle P_j, r_j|$ probability of jumping from state $|P_i, r_i\rangle$ to state.For the time evolution of the system, the Schrödinger equation can be used to describe it. In this model, it can be simplified as:

$$\Psi(\Delta t)\rangle = e^{-iH\Delta\ /\hbar}|\Psi(0)\rangle$$
$$P(P_i, r_i) = |a_i|^2$$

In this equation, $\Psi(0)\rangle$ denotes the initial state of the system, while $\Psi(\Delta t)\rangle$ denotes the state after time Δt. In short, this equation describes how the state of the system changes over time.

Alternatively, we can measure the state of the system by calculating the square of the amplitude. In this model, when the price is P_i and the radius of the leap is r_i, the corresponding probability will be $|a_i|^2$, which provides a new way of understanding and predicting the behavior of the market, including changes in the price and the leap of intensity.

3.3. Price Leap Distance

In the quantum mechanical model, electrons move in a circular motion around the nucleus of an atom, and their energy consists of kinetic energy and potential energy. potential energy and the principal quantum number n satisfy $\Delta E = \frac{\beta \Delta r}{r_n r_m}$ relationship, the radius of the atomic nucleus r also with n meet the $n^2 = \frac{r_n}{\alpha_1}$. $\Delta E = \frac{\beta \Delta r}{r_n r_m}$ between the energy difference between the two energy levels ΔE and the corresponding radius difference Δr, where β is a parameter, $\Delta E = E_n - E_m$, $\Delta r = r_n - r_m$.

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Sinceis not independent ofr_n,r_m,Δrcan be expressed as the$r$function, reduces to a unitary nonlinear function related only to$r$with expression:

$$\Delta E = f(\Delta r)$$

Eq.is an abstract function whose exact expression is not known, but can be described by a polynomial fit, i.e., the energy difference is expressed as a polynomial in the radius difference, which is expressed as[25]:

$$\Delta E = a_0 + a_1 \Delta r + a_2 \Delta r^2 + \cdots + a_n \Delta r^n$$

where: $a_0, a_1, \cdots, a_n$ are the fitting coefficients. According to the results of previous studies by scholars[26], the ten orbitals corresponding to one energy unit of its leap are:

Table 1. Orbital radii for different levels

	1	2	3	4	5	6	7	8	9	10
r	-0.93	2.62	3.18	3.49	1.62	3.86	3.99	-1.49	2	-0.90
$\|r\|$	0.93	2.62	3.18	3.49	1.62	3.86	3.99	1.49	2	0.90
$\|r\|/2$	0.47	1.31	1.59	1.745	0.81	1.93	2.00	0.745	1	0.45

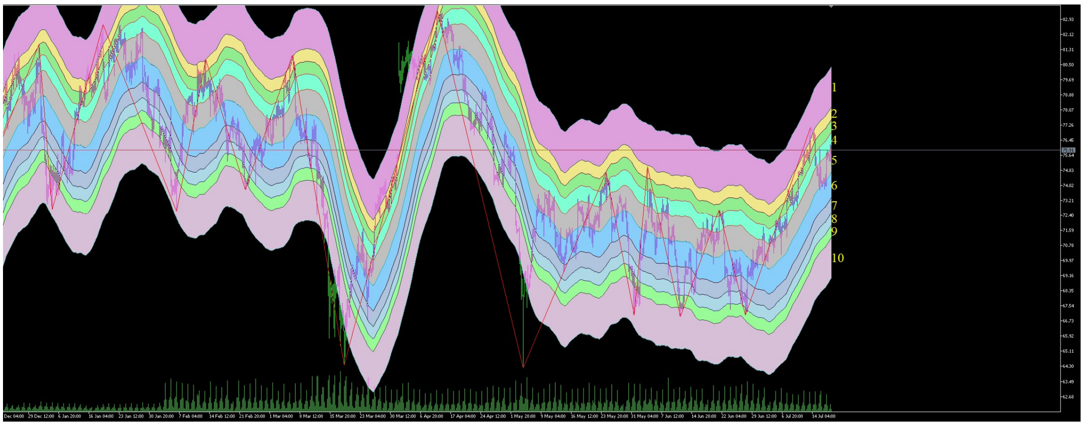

Figure 3. Simulated price jumping orbitals

As shown in Figure 3, the jumping behavior of price indicates that it moves and transitions between different energy levels. Along the horizontal axis, the price jumps repeatedly between ten different "orbitals" or "energy levels", indicating that its energy state is constantly changing and evolving.

This pattern of discontinuous and intermittent changes has some similarity to the jumping behavior of electrons in quantum mechanics. Electrons are constantly traveling between atomic orbitals absorbing or releasing different amounts of energy to create new states. Similarly, price jumps represent the market absorbing or releasing energy, resulting in changes in price levels. The intensity and radius of the jumps reflect the amount of energy, which affects the degree of price volatility.

Therefore, the jumps between price levels not only reveal their inner dynamics, but also reflect the energy and information changes in the market operation. The trajectories of price jumps provide clues for building more accurate forecasting models.

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4. Theoretical Basis of LSTM

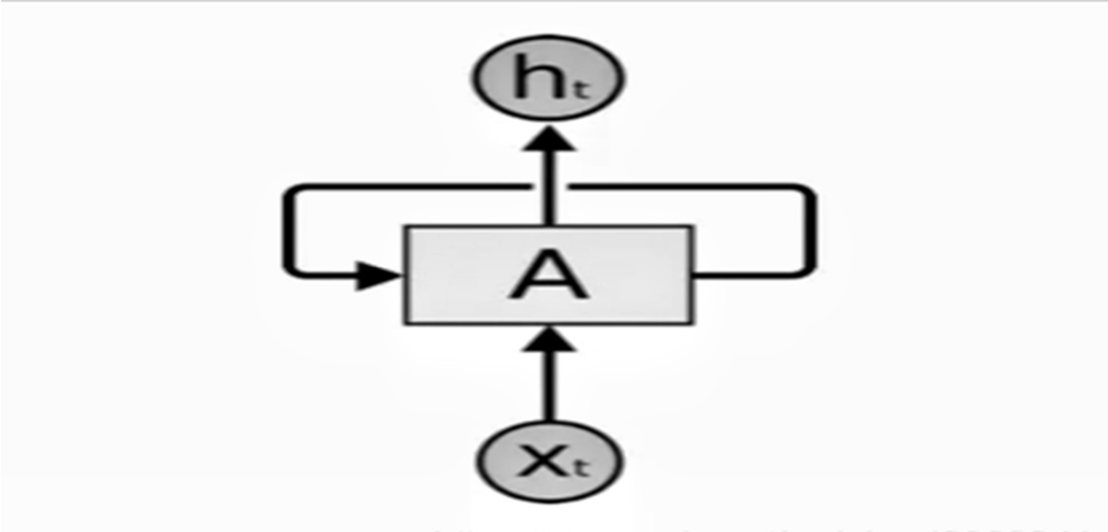

Figure 4. RNN neural network structure

In order to deeply analyze the structure of Long Short-Term Memory (LSTM) model, this paper will first explore the construction of Recurrent Neural Network (RNN). RNN is a neural network with a recurrent mechanism, whose main characteristic is the ability to persist information, which gives it a significant advantage in solving nonlinear time series problems. Figure 4 illustrates the basic structure of an RNN network. In Fig. 4, module A of the RNN network receives inputsX_l, and generates outputsh_l. This looping mechanism allows information to be passed from the current step to the next. In fact, an RNN can be viewed as multiple copies of the same neural network, where each neural network module passes information to the next.

This view reveals the temporal dynamics of RNNs, i.e., their ability to process sequential data. On this basis, it will help to better understand the structure and operation of LSTM models. So, if this loop is unfolded, the structure shown in Fig. 5 is obtained:

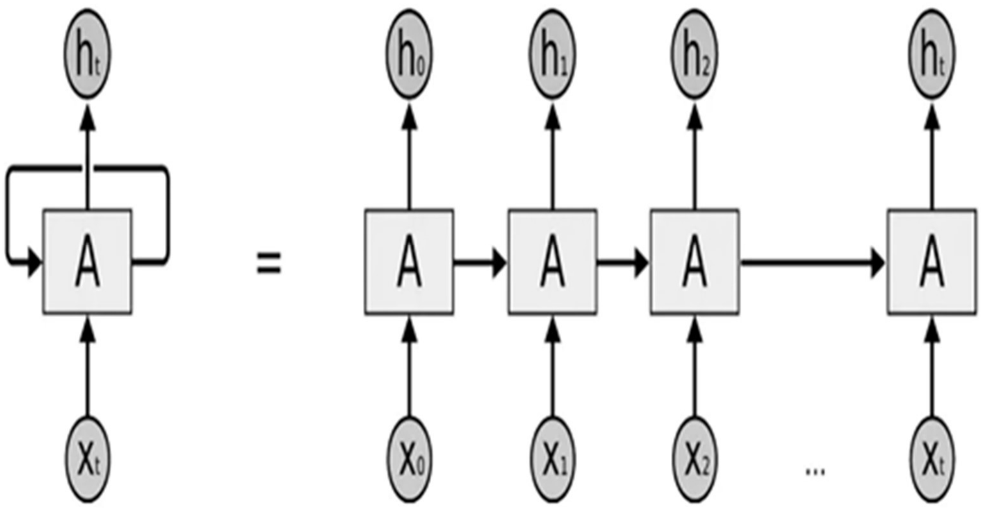

Figure 5. RNN Neural Network Expansion Structure

The chain structure of recurrent neural network (RNN) clearly reflects its intrinsic relevance to the processing of time series data. With its natural network structure, RNN shows significant

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advantages in processing such data, and has been well applied in fields such as speech recognition and image processing. However, RNNs often suffer from the gradient vanishing problem in practice, which means that the influence of subsequent time nodes on earlier time nodes is gradually weakened.

To overcome these difficulties encountered by RNNs, Hochreiter and Schmidhuber (1997) proposed a new neural network model, Long Short-Term Memory (LSTM). The LSTM is formally similar to a traditional RNN with hidden layers, but replaces the ordinary nodes in the hidden layers with specially designed memory units. LSTM introduces "input gates", "output gates" and "forget gates" based on the structure of RNN. This improved design effectively solves the gradient vanishing problem (Graves, 2012), which makes LSTM more advantageous in dealing with long-term dependency problems, and the specific structure of the model is shown in Figure 6.

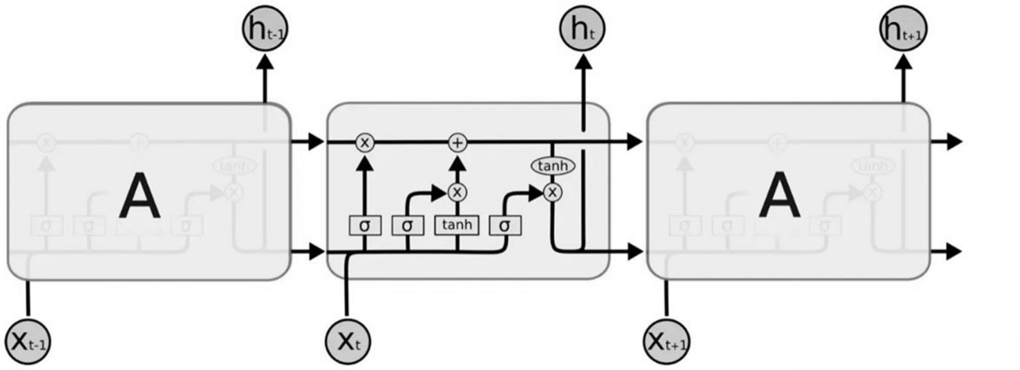

Figure 6. lstm neural network structure

Long Short-Term Memory (LSTM) is a kind of Recurrent Neural Networks (RNNs), which is especially suitable for processing and predicting important events with very long intervals and delays in time series. LSTM solves the problem of gradient vanishing and gradient explosion of traditional RNNs when dealing with long sequences by introducing the concept of "gate".

One LSTM model uses "forget gates" to determine what information to lose and what to keep in the cell state. The"forget gate" readsh_{l-1}andx_t, and computes the "forget gate" via a sigmoid functionf_t:

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right)$$

The second is to determine what information is being stored in the cell state. contains two parts here: one part is the sigmoid layer, also known as the "loser gate layer", which determines what values will be updated; the second part is thetanh$\bar{C_t}$, $\bar{C}$layer, and which is then added to the state. to the state. Next, the state is updated using these two pieces of information.

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$$
$$\bar{C_t} = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C)$$

Third, determine how to update the information. Next, update the old cell stateC_{l-1}toC_tMultiply the old stateC_{t-1}byf_l, and discard the information that was determined to need to be discarded. Then add$i_t \cdot \tilde{C}_t$. These are the new candidate values, varying according to the extent to which the decision is made to update each state.

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$$C_t = f_i \cdot C_{t-1} + i_t \cdot \tilde{C}_t$$

Fourth, an "output gate" is used to determine what information to output. This output will be based on the cell state. First, the cell state to be output is determined by the sigmoid layer; second, the cell state is processed through thetanhlayers (to get a value between -1 and 1) and multiplied by the output of the sigmoid gate, which ultimately outputs just the portion of the output that is determined.

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o)$$
$$h_t = o_t \cdot \tanh(C_t)$$

In equations (1) - (6), W_i, W_f, W_c, W_0 are the weight vectors, and b_i, b_f, b_c, b_0 are the corresponding deviation vectors. The above are the more common LSTM models. There are many other forms of LSTM models, such as GRU models. It is found that the prediction results of these different LSTM models are not very different [27].

5. Empirical Analysis

The prices used in this paper are the data of U.S. West Texas Intermediate futures crude oil, which is abbreviated as WTI crude oil, and it is one of the three major traded crude oil varieties in the world today. In this paper, the sample time period of crude oil is selected from January 2020 to January 2023, and the price of U.S. West Texas Intermediate crude oil, which represents the level of international oil prices, is selected for analysis in each cycle. The data is obtained from the U.S. General Energy Administration; the monthly average of U.S. crude oil inventories is selected from the inventory side.

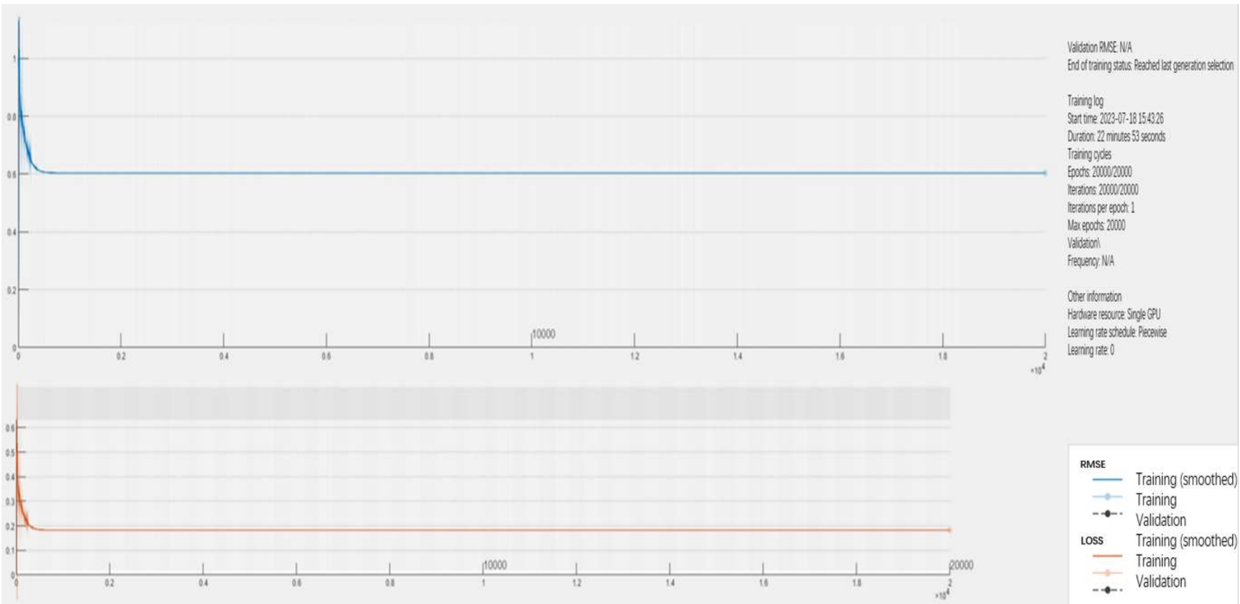

Figure 7. Training process diagram

According to the training log, it can be seen that the model is gradually trained and optimized after 20,000 iterations, and the log is printed once every 50 iterations. During the training process, the RMSE (Root Mean Square Error) of the model for each batchsize of data is decreasing, from 1.00 at the beginning to 0.60 at the end; the loss function value is also decreasing from 0.5 to 0.2, which indicates that the fitting effect of the model is steadily

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improving as the training proceeds. At the same time, the base learning rate gradually decays from 0.005 to 1e-13, which helps to allow the model to be fine-tuned and eventually converge in the later stages of training. The training time gradually increases from 4 seconds to 22 minutes because the training time per batchsize increases as the model complexity increases. Finally, the correlation coefficient of the model is close to 0.5, which indicates that the model fits well. In summary, after the model is trained by 20,000 iterations, the effect is good, the RMSE and loss converge to a smaller value, and the correlation coefficient R is higher, which basically meets the expectation of the training effect, and the effect can be further improved by adjusting the parameter or improving the structure of the model.

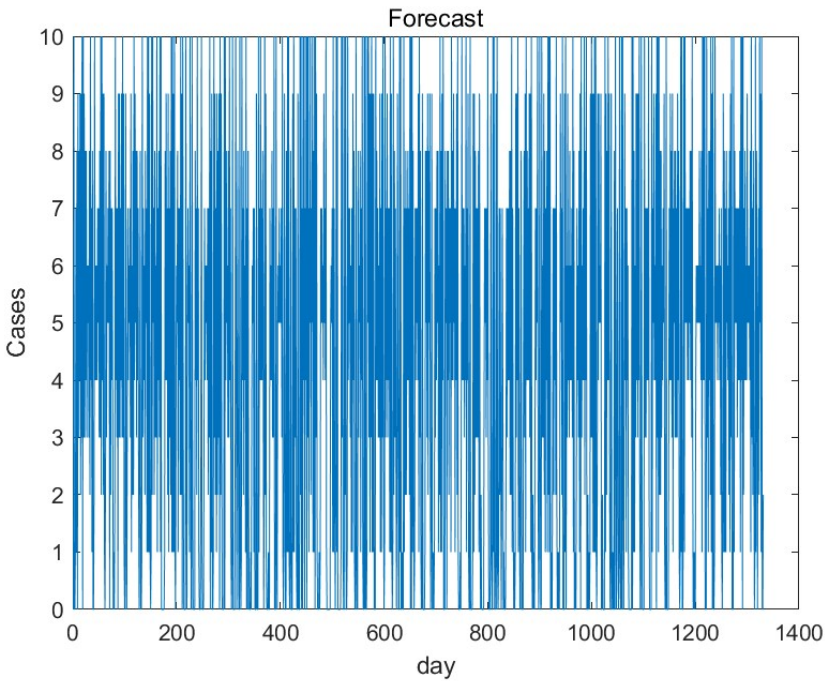

Figure 8. Prediction result

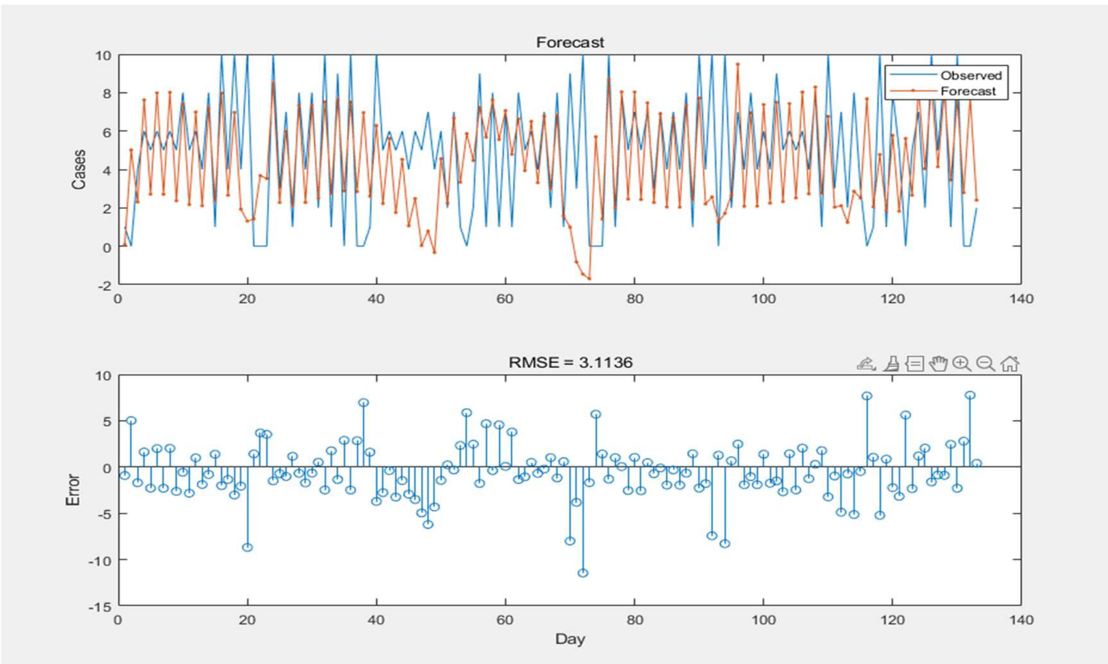

Figure 9. Predicted results

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Figure 8 shows the ten values of the price leaps, and the horizontal coordinate is the number of observations. According to the prediction results shown in the table, it can be seen that the machine learning model based on the quantum leap theory established in this study makes up to 2000 rounds of iterative prediction of the target variables. In the iterative process, the model gradually acquires the intrinsic connection between variables by simulating the evolution of the leap paths in the quantum system, and is used for prediction.

From the quantitative evaluation indexes, the RMSE of the iterative prediction method reaches 3.1136 with a correlation coefficient of 0.48084, while the RMSE of the observation update prediction method reaches 3.1659 with a correlation coefficient of 0.48904. This indicates that both prediction methods are able to model and predict the variables effectively. Especially, the correlation coefficient is close to 0.5, which indicates that the quantum leap paths can reflect the close intrinsic connection between the variables.

From the prediction sequences, most of the prediction points are close to the target variables, which proves that the quantum leap path simulates the evolutionary trend of the variables. Individual prediction points have some errors, which is acceptable considering the random perturbation of the target variable itself. Overall, the prediction results fit the distribution of the variables better.

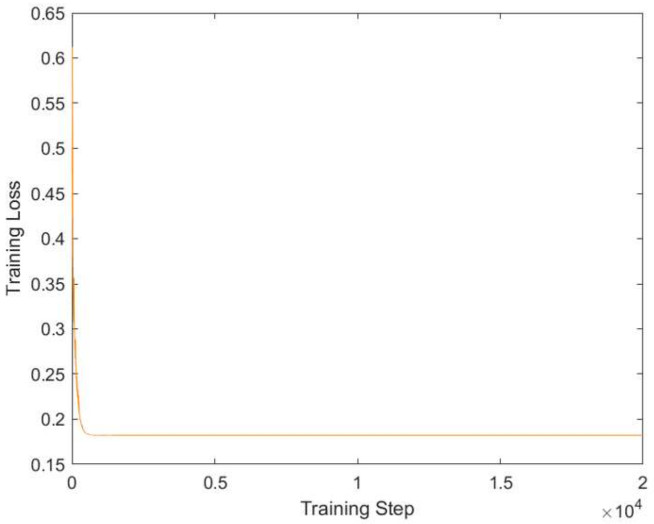

Figure 10. Training loss function image

According to the loss function image, it can be seen that the loss function value of the model shows a more obvious decreasing trend during the training process, indicating that the model is gradually approaching the optimal solution during the iteration process and the performance is improved. Specifically, in the early stage, the loss function value is high, close to 0.5, indicating that the initial prediction effect of the model is poor. Subsequently, in the first 200 rounds of training, the value of the loss function decreases rapidly to around 0.2, and the model improves rapidly. After 200 rounds, the loss function value continues to decrease, but the speed slows down, and the model enters the refining stage. As the number of iteration rounds increases, the loss function value gradually approaches 0.2, but it is difficult to achieve a significant further decline. The loss function image shows the typical machine learning model training process loss function with the law of iterative decline. The loss decreases rapidly in the initial stage, and it is difficult to further decrease the loss in the refinement stage. This indicates that the model has achieved good training results overall, and basically reached the goal of loss function minimization. However, there is some underfitting phenomenon, and the model structure and hyperparameters can be further optimized to obtain a lower loss function value.

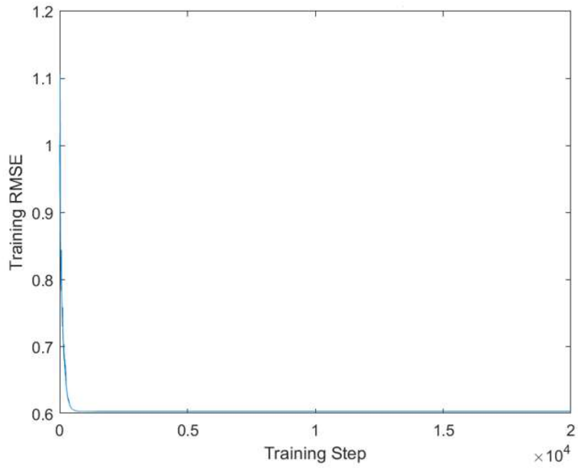

Figure 11. Root Mean Square Error (RMSE) of the training process

From the change curve of the root mean square error (RMSE) during the training process, it can be seen that the model prediction error decreases rapidly in the early stage of training, and then tends to stabilize. Specifically, in the first 200 rounds of training, the RMSE value drops rapidly from 1.0 to about 0.67, and then slightly fluctuates but basically stays near 0.6. This indicates that the prediction effect of the model is significantly improved in the early training stage, and then it enters a stable optimization state. The shape of the RMSE curve is relatively smooth, and there is no sharp fluctuation or dispersion, which indicates that the training process is smooth, the parameters are reasonably adjusted, and there is no serious overfitting or underfitting.

Generally speaking, the RMSE curve decreases to a relatively stable level with a fast speed, and then maintains a smooth trend, which reflects that the model is well trained and finally reaches an optimal generalization state. The parameters can be further fine-tuned to further reduce the RMSE and improve the prediction accuracy of the model. However, the current training state is ideal.

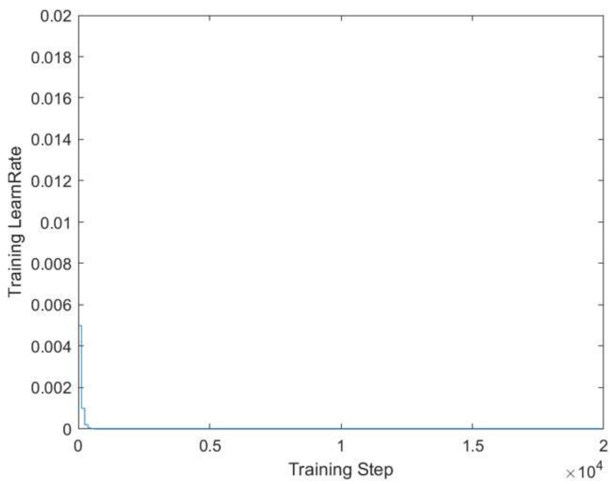

Figure 12. Training learning rate change image

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From the learning rate change curve, the training adopts the learning rate scheduling strategy of exponential decay. In the early training, the learning rate is fixed at a high value of 0.005, so that the model quickly approaches the optimization direction. After the first 200 rounds, the learning rate starts to decay by a factor of 10. This is because as the number of training rounds increases, the model parameters approach the optimized values and need to be tuned more carefully to avoid large parameter jumps.

The learning rate decays to the order of 1e-10 and then remains stable, which means that the model training has entered the late stage of stabilization and refinement. At this time, the effect of further learning rate decay is not obvious, and other regularization techniques are needed to improve the generalization ability of the model. The learning rate scheduling strategy is set reasonably, which not only ensures fast training at the initial stage, but also ensures stable convergence at the later stage. As the training enters the stabilization period, the exponential decay of the learning rate is relatively smooth. This reflects that the learning rate scheduling plays a good role in controlling the overall process of model training.

Table 2. Iterative Learning Tabular Chart

Number of rounds	Time Consumption	RMSE	Loss	Learning Rate
1	00: 00: 03	1.00	0.5	0.0050
50	00: 00: 06	0.81	0.3	0.0050
100	00: 00: 09	0.75	0.3	0.0050
150	00: 00: 12	0.70	0.2	0.0010
200	00: 00: 14	0.67	0.2	0.0010
300	00: 00: 19	0.63	0.2	0.0002
400	00: 00: 26	0.61	0.2	4.0000e − 05
500	00: 00: 33	0.61	0.2	4.0000e − 05
550	00: 00: 36	0.61	0.2	8.0000e − 06
0.61 0.2	00: 00: 40	0.61	0.2	8.0000e − 06
650	00: 00: 43	0.60	0.2	1.6000e − 06
0.60 0.2	00: 00: 54	0.60	0.2	3.2000e − 07
0.60 0.2	00: 01: 01	0.60	0.2	6.4000e − 08
0.60 0.2	00: 01: 08	0.60	0.2	6.4000e − 08
1400	00: 01: 35	0.60	0.2	1.0240e − 10
1650	00: 01: 52	0.60	0.2	4.0960e − 12

This table shows how the performance of a machine learning model changes as the number of training rounds increases. Specifically, the table records a total of 1650 rounds of model training, and reports the training of the model every 50 rounds. The table records the training time, model MSE RMSE, loss value and learning rate for each 50 rounds in the order of the number of training rounds from top to bottom.

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As can be seen from the table, with the increase of the number of training rounds, the RMSE root mean square error of the model decreases from 1.0 to 0.6, and the loss value decreases from 0.5 to 0.2. This indicates that the prediction error of the model is decreasing with the training. This indicates that the prediction error of the model is gradually decreasing with the training, and the effect of fitting the training data is gradually improving. In the first 200 rounds of training, the learning rate is kept at 0.005; after that, the learning rate gradually decreases, down to the order of 1e-12 in the final stage. The decay of the learning rate helps the model to carry out detailed optimization in the late stage of training, and gradually approach the local optimal solution of the loss function.

Overall, this table well reflects the quantitative relationship between the performance of the machine learning model and the number of iteration rounds in the training process, as well as the general method of controlling the training process by adjusting the learning rate. It can be used as a quantitative basis for analyzing and demonstrating the training effect of machine learning models.

6. Policy Recommendations

Indeed, the establishment of a comprehensive quantitative financial regulatory system is a crucial step. To this end, it is necessary to formulate a comprehensive set of quantum financial regulatory laws and regulations, clarify the responsibilities and rights of the regulatory authorities, and stipulate the specific regulatory contents and procedures. At the same time, the accumulation of financial risks can be effectively prevented through the establishment of an access management system for quantum financial products and the strict examination and approval of products and services entering the market. Strengthening the daily monitoring and risk assessment of quantum financial institutions to detect and intervene in hidden risks in a timely manner. In addition, through the establishment of a quantum financial consumer protection mechanism, the legitimate rights and interests of investors are safeguarded.

Meanwhile, the development and utilization of quantum financial tools is an important way to promote financial innovation. A special fund for the research and development of quantum financial instruments has been set up to stimulate the enthusiasm of enterprises and research institutes for the research and development of quantum financial instruments with the help of financial support and preferential policies. Encourage financial institutions to develop new types of financial commodities such as quantum futures, quantum options, quantum funds, etc., in order to enrich the types of market products and meet the diversified needs of investors. In addition, a professional quantum financial instrument assessment organization should be formed to conduct in-depth research and assessment of the risk-return characteristics of new products, so as to provide reference for investors and regulatory authorities.

For the stabilization of market prices, the establishment of a target price mechanism plays an important role. The Quantum Economics Research Institute was established to provide a reasonable expected range for the prices of important financial assets through in-depth data analysis and model forecasting. Issuing quantum target price guidelines to guide market prices to converge towards a reasonable range. Meanwhile, asset allocation using quantum target prices can better balance risk and return and maintain the stability of the financial market.

Of course, strengthening the cultivation of quantum financial talents is the foundation for advancing the development of quantum finance. Set up quantum economics and quantum finance majors in higher education, pay attention to cultivating students' theoretical education and practical ability, and cultivate a group of composite talents who understand economics and finance as well as quantum technology. Upgrade the skills of financial practitioners by organizing training in cutting-edge quantum financial technologies. At the same time, set up a

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special program for quantum financial talents to attract and introduce top talents at home and abroad, so as to provide strong talent support for the development of quantum finance.

Finally, strengthen international cooperation and share the development opportunities and challenges of global quantum finance. Actively join and participate in international quantum economic organizations to discuss the development and governance of quantum finance with global partners. Establish strategic cooperative relationships with foreign quantum financial institutions to learn from each other and their successful experiences and cases. At the same time, establish the International Quantum Finance Research Center as a platform to gather global quantum finance research power and jointly promote the research and application of quantum finance. This will not only enhance the influence in the global quantum finance field, indeed, the establishment of a comprehensive quantum finance regulatory system is a crucial step. To this end, it is necessary to formulate a comprehensive set of quantum financial regulatory laws and regulations, clarify the duties and rights of the regulatory authorities, and stipulate specific regulatory contents and procedures. At the same time, the accumulation of financial risks can be effectively prevented through the establishment of an access management system for quantum financial products and the strict examination and approval of products and services entering the market. Strengthening the daily monitoring and risk assessment of quantum financial institutions to detect and intervene in hidden risks in a timely manner. In addition, through the establishment of a quantum financial consumer protection mechanism, the legitimate rights and interests of investors are safeguarded.

At the same time, the development and utilization of quantum financial tools is an important way to promote financial innovation. Setting up a special fund for the research and development of quantum financial instruments, with the help of financial support and preferential policies, to stimulate the enthusiasm of enterprises and research institutions for the research and development of quantum financial instruments. Encourage financial institutions to develop new types of financial commodities such as quantum futures, quantum options, quantum funds, etc., so as to enrich the types of products in the market and meet the diversified needs of investors. In addition, a professional quantum financial instruments assessment organization should be formed to conduct in-depth research and assessment of the risk-return characteristics of new products, so as to provide reference for investors and regulators.

For the stabilization of market prices, the establishment of a target price mechanism plays an important role. Set up the Quantum Economics Research Institute to provide a reasonable expected range for the prices of important financial assets through in-depth data analysis and model forecasting. Issuing quantum target price guidelines to guide market prices to converge towards a reasonable range. Meanwhile, asset allocation using quantum target prices can better balance risk and return and maintain the stability of the financial market.

Of course, strengthening the cultivation of quantum financial talents is the foundation for advancing the development of quantum finance. Set up quantum economics and quantum finance majors in higher education, pay attention to cultivating students' theoretical education and practical ability, and cultivate a group of composite talents who understand economics and finance as well as quantum technology. Upgrade the skills of financial practitioners by organizing training in cutting-edge quantum financial technologies. At the same time, set up a special program for quantum financial talents to attract and introduce top talents at home and abroad, so as to provide strong talent support for the development of quantum finance.

Finally, strengthen international cooperation and share the development opportunities and challenges of global quantum finance. Actively join and participate in international quantum economic organizations to discuss the development and governance of quantum finance with global partners. Establish strategic cooperative relationships with foreign quantum financial institutions to learn from each other and their successful experiences and cases. At the same

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time, establish the International Quantum Finance Research Center as a platform to gather global quantum finance research power and jointly promote the research and application of quantum finance. This will not only enhance the influence in the global quantum finance field, the.

Establishing the International Quantum Finance Research Center as a platform to gather global quantum finance research power and jointly promote the research and application of quantum finance. This will not only enhance the influence in the global quantum finance field, but also lead the development trend of global quantum finance, while sharing the development opportunities and challenges of global quantum finance. Through in-depth cooperation with international counterparts, we can better promote the globalization of quantum finance and contribute to the healthy and stable development of the global economy.

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