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Introduction of an Optimal Portfolio Recommendation System Using Quantum Potential

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ABSTRACT

In today's world, with the evolution of science and technology and the increasing complexity of human life, the vast and growing volume of information in various fields has made the decision-making process to achieve the desired goal very challenging. To address this challenge, recommender systems have emerged, striving to suggest the desired and useful option from among the possible choices based on the applicant's interests, needs, and past analyses. A recommender system is a system that, based on the analysis of existing data from variables and applicants, recommends and introduces the most appropriate findings to the applicants. In this paper, using data related to the multi-year performance of several stock companies, we aim to introduce a recommender system that can recommend a suitable portfolio to investors. By a suitable portfolio, we mean one that offers the highest profit with the least risk to the investor. The basis of this work is using a method developed as an interdisciplinary activity by economists and physicists applying the laws governing complex systems, known as quantum potential. Here, we present a model using the quantum potential method, where the input is data related to company performance and stock market data, and the output is an optimal portfolio comprising suitable weights of each company's stocks.

1. INTRODUCTION

One of the applications of recommender systems is their use in economics and financial management [1-5]. Human knowledge in the financial field dates back to the 1960s. Since then, fundamental financial theories such as the Efficient Market Hypothesis, the Capital Asset Pricing Model, pricing methods, and Modern Portfolio Theory have been proposed. One of the main goals of this article is to predict the evolution of stock markets. These markets have highly complex interactions and are modeled as complex systems. Predicting their evolution always involves uncertainty. The stock exchange, as one of the most complex interactional systems, cannot determine the profit related to each stock using deterministic methods. Therefore, probabilistic and statistical models must be used to describe such systems. For example, powerful statistical physics methods are used to model markets. In this regard, Bachelier [6] researched stock market index pricing and used the Brownian random walk method to obtain an

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appropriate differential equation for the probability distribution of price changes. This innovative statistical approach was the starting point for some alternative models. For example, Mandelbrot [7] proposed a model showing that the Lévy distribution or other stable distributions are better than Gaussian distributions for examining the distribution of real data. Additionally, Black and Scholes [8], based on the probability distribution of random steps, derived a formula for pricing promotional indexes and European stocks. Over time, the field of econophysics has grown as an interdisciplinary approach using physical methods in economics and complex financial markets. Both classical and quantum mechanics models have been used, and many studies have been conducted over the past 20 years to complete and develop econophysics, which we will discuss later.

Due to the strong correlations and interactions of markets, quantum mechanics can be used as a suitable tool to study the evolution of these intertwined systems. Khrennikov, a pioneer in this field, applied quantum mechanics to model some financial systems [9]. In a series of articles, Choustova introduced mathematical modeling based on classical and quantum mechanics to study the dynamics of financial systems [10-12]. They argued that real financial conditions involve both hard and soft components. The hard components (e.g., industrial production, mines and natural resources, goods and services) may be governed by classical mechanics, while the soft components (e.g., the psychological and physiological behavior of traders, financial information) are described by Bohmian quantum mechanics. An important feature of Bohmian quantum mechanics is the concept of quantum potential, which plays a crucial role in applying this method to financial issues. This approach helps describe the collective behavior of complex financial systems without considering the detailed interactions between their individual components.

Recommender systems are designed to help users prioritize appropriately. One of their applications is predicting user interests in the financial field. Recommender systems are rapidly growing and showing their impact on financial activities, considering that a good recommendation often turns into an actual purchase. One of the important quantities in economics is investment risk. One of the objectives of this paper is to define a quantitative and measurable definition of risk. We will use the quantum potential method to achieve this. After quantitatively defining risk, we will attempt to introduce a recommender system based on which we can provide an optimal investment portfolio using quantum potential within the framework of econophysics.

2. QUANTUM POTENTIAL

Studying financial phenomena using the concept of quantum mechanics is one of the new and successful methods in examining financial markets as complex systems where investors interact like particles in multi-particle physical systems. Due to the uncertainty in the financial market, advanced tools and theories of statistical physics and quantum mechanics are used to model the dynamics governing financial systems. In contrast, results obtained within the framework of Newtonian classical mechanics are assumed to be deterministic. In this framework, the position and momentum of a particle are precisely determined at any given time. Using such a framework only describes the dynamics of financial asset prices without fluctuation. In quantum mechanics, however, the position of a particle is never precisely determined, and a probability space for all possible positions of the particle at any moment in time can be estimated. In the next section, we will introduce quantum potential as an effective method for studying complex financial systems where results are not deterministically predictable.

In 1952, David Bohm proposed a theory later known as Bohmian quantum mechanics. In this picture of quantum mechanics, the dynamic equations governing the evolution of a system are obtained by introducing the concept of particle and wave simultaneously. In quantum mechanics, each particle is assigned a wave function. The root of this concept lies in the wave property or, based on Heisenberg's uncertainty principle, the particle's spread introduced by Niels Bohr by presenting the relationship between the particle's momentum and its wavelength. Whenever we can find the wave function of a particle, we obtain all the information about that particle. This wave function satisfies the Schrödinger equation, and consequently, if we can solve the Schrödinger equation for any system, the dynamics of that system will be determined. In fact, the Schrödinger equation in quantum mechanics plays the role of Newton's second law in classical mechanics; in other words, Newton's law describes the dynamics of a particle in classical mechanics, and the Schrödinger equation describes the wave dynamics in quantum mechanics.

By introducing the wave function of a particle, $\psi(q,t)$, which is defined as follows:

$$\psi(q.t) = R(q.t)\,exp(i\frac{S(q.t)}{h}). \tag{1}$$

In the Schrödinger Equation

$$ih\frac{\partial\psi}{\partial t} = -\frac{h^2}{2m}\frac{\partial^2\psi}{\partial q^2} + V\psi. \tag{2}$$

Two coupled differential equations for the wave amplitude, R(q,t) , and its phase, S(q,t) , are derived as follows (Holland, 2000):

$$\frac{\partial R^2}{\partial t} + \frac{1}{m}\frac{\partial}{\partial q}(R^2\frac{\partial S}{\partial q}) = 0, \tag{3-a}$$

$$\frac{\partial S}{\partial t} + \frac{1}{2m}(\frac{\partial S}{\partial q})^2 + (V - \frac{h^2}{2mR}\frac{\partial^2 R}{\partial q^2}) = 0. \tag{3-b}$$

where m represents the particle's mass and q denotes the particle's position at time t. h is Planck's constant. In Equation 3-b, in addition to the classical potential V), another potential is defined as follows:

$$U(q,t) = \frac{h^2}{2mR}\frac{\partial^2 R}{\partial q^2} \tag{4}$$

which is called the quantum potential [13]. This nomenclature arises due to the presence of the quantum parameter h, which equals zero in the classical limit. In other words, in the Newtonian classical mechanics limit, this term does not play a role in the system's dynamic evolution.

In applying this method to the evolution of financial systems within the framework of econophysics, the physical quantities of material particles must be correspondingly defined with the quantities and variables describing financial systems. In this context, q(t) represents the profit of goods, m and h respectively represent the market value of stocks and the uncertainty in price changes, and S(q,t) denotes the phase of market quantities. In this paper, since we deal with each market separately without coupling with other markets, m, S(q,t), and h are assumed to be constant. However, when at least two different markets are coupled, the values of m and S for each market must be separately specified.

3. PLOTTING QUANTUM POTENTIAL FOR DIFFERENT INDICES

The data used in this paper are extracted from the Thomson Reuters database for the Dow Jones Industrial Average (DOW), the S&P 500, the German stock index (DAX), the Canadian stock index (FTS), the Tokyo stock index (TOP), and the Korean stock index (KOR) as developed markets, and the Shanghai stock index (SHA) and the Tokyo stock index (NIK) as emerging market indices, from January 2010 to December 2017. In the following sections, we will examine the behavior of the quantum potential for these indices.

3.1. Daily Quantum Potential and PDF for the Dow Jones Index

For example, to understand the concept of quantum potential in its application to economic issues, we examine this quantity for the Dow Jones Index. In applying the above method to a particular stock exchange,q(t) denotes the market profit, and m and h respectively denote the market value and the uncertainty in price and price changes. S(q,t) represents the phase of market quantities. As mentioned earlier, since we are dealing with an isolated market here, h, m, and S are assumed to be constant. For an isolated market without interactions with other markets, the phase of the wave function behaves like a constant value. In fact, in physics, relative phase differences always have meaning, and if the market is isolated, the relative phase difference will have no meaning. Another example in this context is potential, which is meaningless for a single point and is always defined as the potential difference between two points. Consequently, the phase S will behave like a constant. m and h are also included in the normalization constant, which can be determined by normalizing the wave function. Suppose p(t) and dt respectively represent the price and the time interval of price changes. Usually, when dealing with large numbers, we work with their logarithms instead of the actual numbers. The quantity R(q,t) is defined as the probability distribution function (PDF) for market profit at time t , and it is denoted as the PDF or probability distribution function. This function, which will play a significant role in defining the quantum potential, can be extracted for all indices using the data described in section 4. The results obtained for price, market profit, and daily PDF for the Dow Jones Index are plotted in Figures 1-a, 1-b, and 1-c, respectively. In Figure 1-a, showing the price changes of this index over time, the overall trend is an increase in price over time. However, this increase is observed over several years, while short-term intervals (days, weeks, months) show both increases and decreases. This result is reflected in Figure 1-b, which shows profit changes over time. In fact, the changes in profit over time in the normalized range (-0.1 to 0.1) indicate profits and losses. However, over a relatively long period, the market has been profitable since the price in Figure 1-a is generally increasing. Figure 1-c shows the behavior of profit or the PDF around zero, indicating the percentage of profits and losses in the range (-0.1 to 0.1).

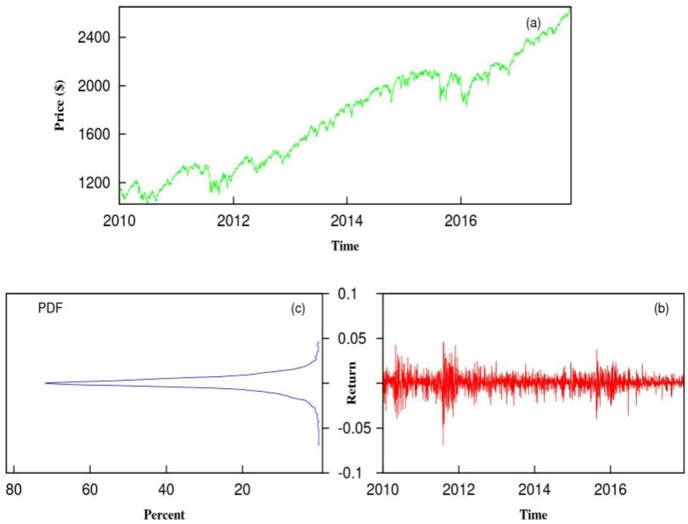

Fig.1. (a) Dow Jones Index Price over Time; (b) Profit Behavior over Time for the Same Index; (c) Profit PDF for the Same Index

By having the daily PDF for the Dow Jones Index, which corresponds to R(q,t) in Equation 4 defining the quantum potential, we can obtain the daily quantum potential by twice differentiating (either numerically or by fitting an analytical function) according to equation 4. This daily quantum potential from January 2010 to December 2017 is plotted in Figure 2.

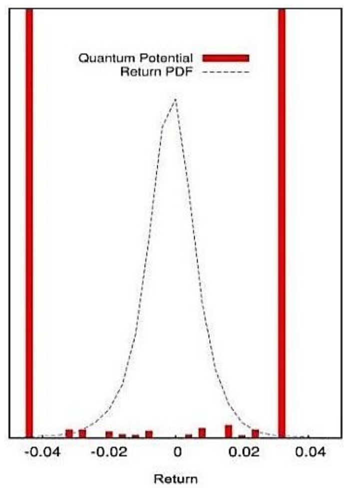

Fig.2. Daily Quantum Potential and PDF for Price Returns from January 2010 to December 2017 for the Dow Jones Index

In this figure, the quantum potential is shown with continuous red walls, and the PDF function is depicted with a dashed black line. The horizontal axis represents profit, and the vertical axis indicates the potential height. The concept of these walls is fascinating. Essentially, the walls prevent unlimited changes in profit [14]. In other words, if we ask ourselves why the profit or price change of goods does not change irrationally from today to tomorrow, the reason is this potential barrier that prevents rapid price changes or windfall profits. The importance of quantum potential lies in this behavior. To illustrate this point, consider the air particles in a room. These particles are allowed to move within the room at high speeds (340 meters per second) because no force hinders this movement. However, upon hitting the room's walls, they stop and bounce back. The walls act like a potential that exerts an infinite force on the particles, preventing them from exiting the room. Quantum potential provides an analytical reason for the stability of prices based on physical laws, making it intuitive for the human mind to understand why the price of goods does not change drastically overnight. Another example is the trajectory of a projectile in the presence of Earth's gravitational field. We all have the experience that the trajectory of a projectile in Earth's gravitational field is parabolic. If we ask ourselves why this path is parabolic, we must write the equations of motion for a projectile in the gravitational field, and we will see that the trajectory equation is analytically a parabola.

Quantum potential, as an analytical method, allows us to conduct a deeper study of financial issues and gain information about market evolution due to influencing factors as a complex system. Additionally, by comparative study of the market's constituent elements, using quantities defined in physics, we can better understand them. For example, in the next chapter, we will define a quantitative and measurable criterion for the concept of risk in the financial market economy, which will enable us to measure the risk for each index and compare the risks of different indices.

3.2. Plotting Quantum Potential for Other Indices

The daily quantum potential for other indices, similar to what was done for the Dow Jones index, was extracted based on profit from January 2010 to December 2017, and plotted sequentially in Figures 3-a to 3-h for the S&P, FTS, DAX, TOP, SHA, KOR, and NIK indices.

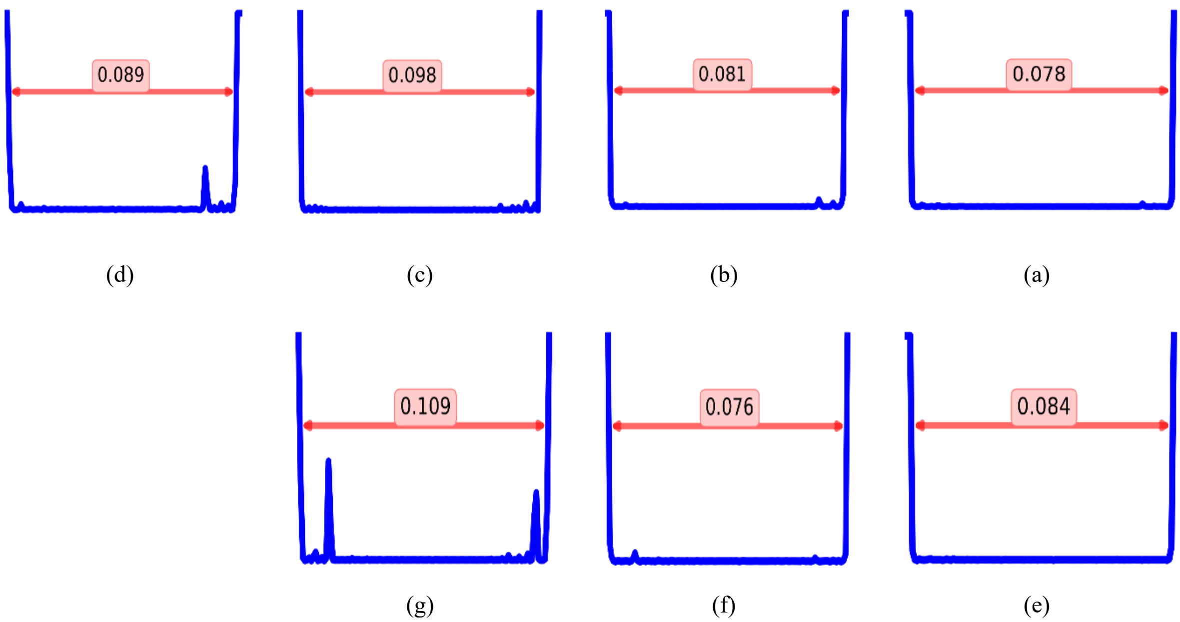

Fig.3. (a) Quantum Potential for the Daily S&P Index; (b) Quantum Potential for the Daily FTS Index; (c) Quantum Potential for the Daily DAX Index; (d) Quantum Potential for the Daily TOP Index; (e) Quantum Potential for the Daily SHA Index; (f) Quantum Potential for the Daily KOR Index; (g) Quantum Potential for the Daily NIK Index

The horizontal axis, similar to Figure 2, shows the profit and loss, which is not written to avoid clutter. In these figures, the distance between the two walls is crucial and is noted on each figure. In Figure 3-a, which shows the quantum potential for the S&P index, the number representing the distance between the walls indicates the index's risk, which will be explained later. The noises observed in this quantum potential are due to the random nature of profit changes over time. These changes manifest in the PDF function and ultimately in the quantum potential. These noises also behave as potential, creating bumps in price changes.

As previously mentioned, quantum potential in physics governs the behavior of fundamental particles and atoms in the microscopic world but also finds applicability in other fields. The social psychology behavior of humans engaged in market trading seems to resemble the quantum behavior of fundamental particles. Just as fundamental particles are entangled from a quantum mechanical perspective despite having no interaction from a classical mechanical view, humans, although not physically interacting when far apart, are socially entangled. It appears that the physical and present interactions of humans in a market (hard behavior) can be described by classical potential, while their psychological behavior (soft behavior) can be described by quantum potential.

As observed in Figure 3-b, the width of the quantum potential for the FTS index is greater than that of the S&P index. The difference in the width of the potential from one index to another is significant and rooted in the nature of the respective indices. As we will discuss later, we have successfully defined a measurable characteristic for each market, which is the commercial risk of the markets. In Figure 3-c, the quantum potential for the DAX index is plotted, and its width has increased compared to that of the FTS index. It seems that the high walls on either side of the profit range in the quantum potential function exhibit a universal behavior. In other words, all indices and markets worldwide follow this pattern, which indicates the absence of sudden price changes. This behavior can be attributed to similar social behavior among humans globally. No human society anywhere in the world accepts sudden price changes or exorbitant profits. This behavior, rooted in the collective psychological behavior of humans, is an intertwined and soft characteristic that can be explained by quantum potential, as opposed to hard economic attributes such as natural resources and goods, which are explained by classical potential.

In Figure 3-d, the quantum potential for the TOP index is plotted, and its width is less than that of the DAX index. In Figure 3-e, the quantum potential for the SHA index is plotted, and its width is less than that of the TOP index. As previously mentioned, the formulation of a portfolio is a linear combination of different indices. In this formulation, the higher the risk of a market, the smaller its weight in the linear combination of the portfolio. This quantitative and measurable definition of risk allows us to reduce the presence of high-risk markets in the portfolio. Ultimately, it will be possible to recommend a suitable portfolio to an investor based on this formulation before investment. In Figure 3-f, the quantum potential for the KOR index is plotted, and its width is less than that of the SHA index.

An interesting behavior observed in all the above figures is the increase in noise at the far left and right ends of the horizontal axis. The concept of this behavior, which is again a universal characteristic for all indices, can be considered a distinguishing feature of all indices: the resistance of markets to high profits or losses. In other words, near the middle of the horizontal axis, the noise is minimal, but as we move towards higher profits and losses, the noise increases. Social psychology suggests that people are unwilling to buy expensive goods, and this collective behavior prevents the growth of profits or losses in markets. This characteristic, which stems from human psychological behavior, is a soft behavior that we expect to be reflected in quantum potential. The importance of quantum potential lies in explaining such behaviors. In Figure 3-h, the quantum potential for the NIK index is plotted, and its width is greater than that of the KOR index. In this figure, as in the others, noise is observed at the sides of the potential.

One of the advantages and merits of Bohmian quantum mechanics over other interpretations, such as the Schrödinger picture of quantum mechanics, is that many complex and enigmatic characteristics of particles are embedded in the quantum potential. Behaviors that are not easily expressed in the Schrödinger picture are explained by the quantum potential.

When applying quantum potential to fields other than physics, such as economics, psychology, sociology, and others, the unique attributes of quantum potential become even more prominent and significant. To clarify this point, we revisit the examples mentioned earlier: human psychological behaviors such as avoiding overspending, being frugal, avoiding price gouging, fraudulent behaviors, profiteering, etc., are not easily formulable. However, here we see that these soft behaviors, deeply rooted in human psychology, are mysteriously embedded within the concept of quantum potential and reflected in it without being explicitly included by us. Thus, the importance of quantum potential in studying and examining very complex systems is considerably enhanced. The behaviors discussed in explaining the above figures demonstrate the capabilities of quantum potential in elucidating the behavior of complex systems. As previously mentioned, complex systems exhibit overall self-consistent behaviors that cannot be understood solely by examining their constituent parts and are entirely different from them. This overall behavior, which is the macroscopic characteristic of complex systems, is not similar to their microscopic behavior and must be studied using the methods governing the evolution of complex systems. These behaviors relate to the overall structure of complex systems, which controls the behavior of their constituent parts.

4. QUANTITATIVE DEFINITION OF RISK IN THE INVESTMENT MARKET

Investment and commercial transactions, as financial decisions, always involve two components: "risk" and "return." On one hand, investors seek to maximize their profit from an investment, and on the other hand, they face the uncertainty of financial markets, which in turn causes uncertainty in achieving investment returns, or risk. In other words, all investment decisions are based on the relationship between the inevitable elements of risk and return. Given the clear consensus on the positive relationship between risk and return, quantum potential is used as a useful indicator to compare the risk of different indices against each other [15,16]. That is, the higher the return (profit and loss), the greater the risk of that market, as indicated by the greater distance between the walls. However, the higher the average return, the higher the profit of that market, and if the average return is lower, the loss of that market is higher. As a result, a suitable market is one with low risk and a higher average return, and conversely, an unsuitable market is one with higher risk and a lower average return.

As shown in Table 1, for all indices, the risk increases with the increase in the average return from daily to annual periods. This is due to the collective behavior of stock markets, showing lower average returns for the short term and higher average returns for the long term. The Shanghai index, as an emerging market, has the lowest average return and the highest risk in almost all daily, monthly, quarterly, and annual periods. Conversely, relatively narrower quantum potential walls indicate lower risk for the Dow Jones and S&P 500, which we expect to be the behavior of developed market indices. Therefore, the distance between the quantum potential walls indicates risk. These results are consistent with Drabi and Lissour's findings [17], which showed that emerging markets are riskier than developed markets. In Table 1, the lowest risk and highest average return are highlighted in blue, while the highest risk and lowest average return are highlighted in red. According to this table, we observe that the risk and average return of all indices from 2010 to 2017 increase from daily to annual periods. An interesting result in Table 1 is the relationship between risk and average return, meaning that, for example, for S&P and DOW, lower risk is associated with higher average return, and for SHA, higher risk is associated with lower average return. Consequently, finding a suitable market by minimizing risk will inherently maximize the average return.

Table 1. Risk and Average Return of Selected Indices Based on Quantum Potential. The lowest risk and highest average return are shown in blue, and the highest risk and lowest average return are shown in red.

Indicators	Average daily return	Daily risk	Average monthly return	Monthly risk	Average quarterly return	Seasonal risk	Average annual return	Annual risk
S&P	0.000412	0.078	0.010201	0.207	0.030409	0.311	0.122219	0.320
FTS	0.000155	0.081	0.003943	0.223	0.011295	0.295	0.046462	0.403
DAX	0.000369	0.098	0.009583	0.292	0.029337	0.373	0.110266	0.544
TOP	0.000322	0.089	0.007772	0.309	0.023195	0.378	0.097561	0.675
SHA	0.000014	0.084	0.000751	0.350	0.003189	0.426	0.023361	0.487
KOR	0.000184	0.076	0.004702	0.220	0.014707	0.320	0.038373	0.432
NIK	0.000364	0.109	0.008993	0.317	0.026646	0.366	0.113871	0.658
DOW	0.000409	0.071	0.010020	0.226	0.029489	0.280	0.113295	0.369

Thus far, within the framework of the quantum potential model, we have defined a measurable quantity for risk based on the distance between the walls of the quantum potential for each index and determined the investment risk for each index. At this stage, everything is ready to define a suitable stock portfolio. In other words, we now have the necessary tools to recommend a suitable stock portfolio to investors by combining different indices. If we denote the distribution function of a desired stock portfolio by $\mathrm{PDF_{tot}}$ and the weight coefficient of the n-th index by $\mathrm{P_n}$, and the distribution function of the n-th index by $\mathrm{PDF_n}$, the distribution function of this stock portfolio $\mathrm{PDF_{tot}}$is defined as a linear combination of the $\mathrm{PDF_n}$ functions as follows:

$$PDF_{tot} = \sum_{n=1}^{m} P_n \; PDF_n \tag{5-a}$$

$$\sum_{n=1}^{m} P_n \; = 1 \tag{5-b}$$

where m is the total number of indices in the portfolio, which is 8 in this paper, and the sum of the probabilities must equal one. If we aim to find a suitable stock portfolio, we need to find appropriate weight coefficients that minimize the portfolio's risk. If the weight coefficients are correctly chosen, this risk, which is the minimum value and is obtained by the distance between the walls of the total quantum potential corresponding to the total probability distribution function in Equation 5-a, will be minimized. In other words, finding a suitable stock portfolio depends on finding the appropriate weight coefficients that minimize the risk. Therefore, after calculating the total quantum potential corresponding to the total probability distribution function in Equation 5-a, we seek the set of P_n values that minimize the distance between the walls of this quantum potential, which represents the risk of the suitable stock portfolio.

This task is performed in software using a genetic algorithm, and the results are presented in Table 2.

Table 2. P_n values for daily risk of different indices

Indicators	S & P	FTS	DAX	TOP	SHA	KOR	NIK	DOW
P_n	0.22	0.09	0.03	0.11	0.12	0.09	0.07	0.27

These results are plotted in Figure 4, where the horizontal axis represents the indices and the vertical axis shows P_n for the 8 indices.

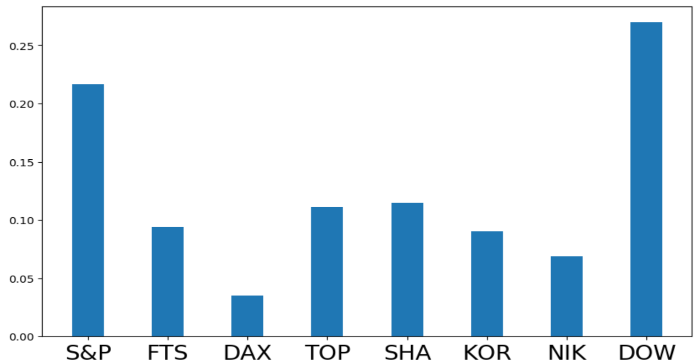

Fig.4. Graph of Pn Values for Daily Risk of Various Indices

By having the P_n values, we have found the desired solution, i.e., by combining the appropriate daily weights from the probability distribution functions of the indices, we determine the suitable stock portfolio with the least risk, which can be recommended to investors. This quantity for the daily risk of the suitable stock portfolio is found to be 0.081. Similarly, by having the P_n values, the monthly, quarterly, and annual risks of various indices for the suitable stock portfolio can be calculated, and the results are shown in Table 3.

Table 3. Risk of Suitable Stock Portfolio Over Daily, Monthly, Quarterly, and Annual Periods

Time Period	Daily	Monthly	Seasonal	Annual
Appropriate portfolio risk	0.081	0.254	0.330	0.439

As observed in Table 3, the risk values represent a weighted average of the risk values in Table 2, which seems to be a logical expectation.

This model can be applied to any number of indices. In this paper, 8 indices were assumed, but fewer or more indices can be chosen to find the suitable stock portfolio.

5. DISCUSSION AND CONCLUSION

In this paper, we aimed to present a recommender system within the framework of econophysics for selecting a suitable stock portfolio using the quantum potential method. For this purpose, we extracted 8 stock indices from the Thomson Reuters database, namely the Dow Jones Industrial Average (DOW), S&P 500, DAX, FTS, TOP, and KOR as developed markets, and SHA and NIK as emerging markets, from January 2010 to December 2017, and calculated their return probability distribution functions and then their quantum potentials. By using a measurable definition for risk, which is the length of the quantum potential walls, and the average return of these markets as two determining factors in investment decisions, we were able to present a suitable stock portfolio for the 8 markets mentioned above. In fact, the recommender system introduced here operates based on a quantitative definition of risk, which is one of the advantages of the quantum potential method, and aims to encourage investors to select a stock portfolio with minimized risk and maximized average return. The minimum risk value is obtained by a linear combination of the probability distribution functions of different indices with appropriate weights, which are obtained using the genetic algorithm method.

Transparency Statement

The data supporting this study are available upon reasonable request to the corresponding author, subject to ethical and confidentiality considerations.

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Declaration of Interest

The authors declare that they have no competing interests.

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