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Simulating the Dynamics of Stock Price via PSO-Assisted Quantum Anharmonic Oscillator Model: Case of Jakarta Composite Index

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Abstract

The Jakarta Composite Index (JCI) stock price dynamics have been modeled by a quantum anharmonic oscillator and the PSO (Particle Swarm Optimization) Algorithm. Some of the constants that affect the probability density of return are the ability of the market makers to control the market (γ), the behavior of contrarians and the trend followers to the price return (c), and the investor behavior towards perceived volatility (k). The simulation results have produced the slightest error of the JCI at 8.36% for the opportunity density and 3.6% for the stock price returns. Forward prediction for the next three months using the exponential smoothing method resulted in a 17.77% error in the opportunity density of the stock price return and a 10.6% error in the stock price return. Based on those results, it can be concluded that the stock price dynamics can be modeled using an anharmonic quantum oscillator where the value of liquidity and volatility in the previous period affects the investor and the stock's price return in the next period.

INTRODUCTION

The stock price prediction is one of the essential pieces of information needed by the investor in deciding whether or not they will place their fund in a particular asset during a certain period of a year with the hope of earning income and or receiving the increasing investment value [1], [2]. This prediction aims to maximize profits, minimize risks, and avoid bursting the economic bubble. An economic bubble occurs when prices do not match their fundamental values within a specific time due to random shocks [3]. Some phenomena of the economic bubble bursting include the South Sea Bubble, the dot-com bubble, and the housing bubble [4]. The bursting of an economic bubble can cause prices to drop dramatically, so predictions are needed to avoid this. It is essential to accurately predict stock price dynamics based on natural or physical models such as harmonic (or anharmonic) oscillator models. In that part, this study is aimed to contribute.

The stock market is complex, so a model is needed to predict its movements. The movement of stock prices follows a random number known as the random walk theory. The random walk theory states that future price movements cannot be predicted using past data because the price in the market reflects the information available. The market will react quickly to the information and then quickly readjust to find a new equilibrium price [5], [6]. Several models for predicting economic phenomena include Fisher Black and Myron Scholes in 1973, who produced the Black Scholes model [7] and Merton model of option pricing [8].

The quantum harmonic and anharmonic oscillator model is perhaps the most used model to describe the dynamics of the system in many cases, such as atomic [9], [10], nuclear [11], [12], or even econophysics [13], [14] problems. Our study is a modification of Gao's work in Ref [14], with the addition of the PSO algorithm for parameter optimization and the local market (Jakarta Composite Index) as the data source. The simplicity of the model and its intuitive picture make this model easy to modify and absorb more factors and terms depending on the nature of the problems.

This study aims to model the dynamics and predict the stock's return price of the Jakarta Composite Index using a quantum anharmonic oscillator model and PSO optimization.

METHODS

The quantum anharmonic oscillator system is simply a harmonic oscillator system with some distortion to its motion, as shown by the addition of the Morse potential. The Hamiltonian of the quantum anharmonic model can be written as

$$H_0(x) = -\frac{\hbar}{2\mu}\frac{d^2}{d^2x} + D_e(1 - e^{-a(r-r_e)})^2 \tag{1}$$

In our case, the dynamics of the stock's return price particle are described by the dynamics of the particle's wavefunction. Since we are dealing with a dynamics case that depends on time, so we should start with the time-dependent Schroedinger equation, as shown below

$$i\hbar\frac{\partial}{\partial t}\psi(r,t) = \boldsymbol{H}\,\psi(r,t) \tag{2}$$

While the stock's return price is defined as

$$r(t, \Delta t) = \frac{p(t)-p(t-\Delta t)}{p(t-\Delta t)} \tag{3}$$

Where p is the stock's price, which depends on time, and ħ can be assumed as the uncertainty in irrational transactions. The assumption applied to this model is that the market is stationary, and there are three market participants: market makers, contrarians, and trend followers. Market makers are intermediaries between buyers and sellers or also called brokers. Contrarians are investors who always make decisions contrary to the existing trend. Meanwhile, trend followers are risk aversion or conservative investors who will make decisions according to the trend. With this assumption, the three participants' behavior in making stock movement decisions will influence the potential interpretation. In this study, the Morse potential was not used, but rather a non-linear Schroedinger potential obtained from Reference [14] as shown below

$$V(r) = \frac{\gamma+c}{2}r^2 - \frac{kc}{4}r^4 \tag{4}$$

The parameter γ was defined as the market makers' ability to control the market, while c is defined as the behavior of trend followers and contrarians in responding to the price return and k as the uncertainty of the decision-making process when volatile (r^2) is high. The Schroedinger equation for this statement is

$$\left[-\frac{1}{2}\frac{d^2}{dr^2} + \left(\frac{\gamma+c}{2}r^2 - \frac{kc}{4}r^4\right)\right]\varphi(r) = E\varphi(r) \tag{5}$$

The probability density (or the opportunity density) of the stock's return price is defined as

$$\rho(r,t) = |\psi(r,t)|^2 = |\varphi(r)|^2 \tag{6}$$

Based on Ref (Gao et al. 2016), the analogy of the physics parameter to the economic parameter is shown in Table 1. Using those analogies, we can model the dynamics of economic parameters through a physics model. The stock price data of JCI in this research was taken from the yahoo website (http://finance.yahoo.com) from January to December 2017. The equation (6) was then solved using the Runge_Kutta Fehlberg method (RKF45) [15] using the MATLAB program. The tolerance value for Runge-Kutta Fehlberg is $10^{-6,}$ and the values of c_1 and c_2 on PSO are 0.5 for each.

Table 1. The analogy of physics parameters and economic parameters

Symbol	Physics parameter	Economic parameter
r	Particle's position	Stock's price return
γ	Spring constant	The ability of market makers to control the market
c	Spring constant	The behavior of contrarians and trend followers upon stock's price return
k	Anharmonic constant	The contrarian and trend followers doubt deciding on volatility
r^2	Squared of particle position	Volatility
$\varphi(r)$	Time independent wavefunction	The wavefunction of stock's price return

The PSO algorithm is a nature-inspired algorithm that is very fast and powerful in reaching the global minimum or the intended solution of a particular problem [16], [17]. The two most important steps are given below

$$x_i(j) = x_i(j-1) + v_i(j) \quad (7)$$

$$v_i(j) = v_i(j-1) + c_1 \times rand \times (Pbest - x_i) + c_2 \times rand \times (Gbest - x_i) \quad (8)$$

To validate the results of our simulation, we calculate the Mean Square Error (MSE) following this relation

$$MSE = \frac{1}{n}\sum_{t=1}^{n}(x_t - f_t)^2 \quad (9)$$

The value of the economic parameters obtained from the PSO-optimized quantum anharmonic oscillator model then deployed to the exponential smoothing method to predict the probability of the stock's price return via

$$S_{t+1} = \alpha X + (1-\alpha)S_t \quad (10)$$

Where S_{t+1} is the predicted parameter's value, a is the smoothing parameter (valued between 0 to 1), X is the real value of the parameter, and S_t It is the guessed value of a parameter from the previous prediction. After getting the parameters and the estimated probability of stock price returns, validation of the model can be done by calculating the mean absolute percentage error (MAPE) through the equation below:

$$MAPE = \frac{\Sigma_{t=1}^{n}\left|\frac{x_t - f_t}{x_t}\right|}{n} x100 \quad (11)$$

RESULTS AND DISCUSSIONS

The PSO-optimized value of each economic parameter is shown in Table 2. The comparison between the actual data and the simulation results for three quarters in 2017 is shown in Fig 1(a) through 1(c), while Figure 1(d) shows the comparison between actual data and the simulation in an entire year. The Mean Square Error (MSE) for each period is also shown in that Table. The value of k in January-March and April-June 2017 shows that investors are more risk-averse than k in other months. Refers to unstable prices in both periods resulting in high price volatility, as seen in Figures

1(a) and 1(b), indicating that the price in those months changed drastically and caused a slight state of panic in investors due to high volatility. The value of *c* in July-September, which is smaller compared to the previous months, indicates a market's domination by the trend followers. The smaller value of γ in the January-March and April-June 2017 periods indicate a smaller trading volume compared to other periods, which might come from the panic investor who feels the price volatility is quite large and triggering a panic selling by investors (where selling is not proportional to market's demand), resulting in reduced liquidity. The value of E in the July-September period shows a value close to the value of the ground state energy (Egs=488.28) which indicates a more stable price than before. The psychological-based decision-making in the stock price dynamics, such as fuzzy opinion [18], memory effect [19], and brain activity [20], have been discussed elsewhere.

The results of our simulations are not much different compared to the actual data for each period (Figure 1(a), (b), and (c)). The discrepancy between the probability density of the actual stock's price and the simulated stock's price is relatively low to medium, as can be seen from the MAPE values. The error percentage (MAPE value) in January-March, April-June, and July-August are 8.36%, 10.95%, and 8.93%, respectively. The stock's price return error for each period is found to be 3.6%, 11.09%, and 8.92%, respectively. Unfortunately, for a full-year period (January-December 2017), the error of the stock's price probability density and the error of the stock's price return is a bit larger at 15.72% and 21.48%, respectively, as shown in Figure 1(d).

The market will be at equilibrium when supply and demand are at equilibrium. The amount of demand and supply is influenced by three participating agents: market makers or brokers, contrarians, and trend followers. Market makers control the market so that the market remains in a state of equilibrium. So the value of γ represents the liquidity of the market. Contrarians and trend followers are two profiles that represent the characteristics of investors in the market, which is symbolized by the value of *c*. When the price in the market is in a state of significant volatility, was panic felt by all shareholders denoted by the value of *k*. The value of E represents the market price in a particular state (or energy level). Similar to a particle in an excited energy level, the particle will return to the ground state because the particle is in an unstable state in the excited state. The stock price is assumed to be a particle that will return to the ground state if it is in an excited energy level.

Tabel 2. The value of each economic parameter calculated by the PSO-optimized anharmonic quantum oscillator model

Period	Parameter values				MSE
	γ	k	c	E	
January-March 2017	7.3694×10^{7}	2.9397×10^{6}	6.5774×10^{8}	1593.3	0.001168
April-June 2017	6.3844×10^{7}	3.9962×10^{6}	6.5445×10^{8}	1911.3	0.002266
July-September 2017	7.3956×10^{7}	2.9941×10^{6}	6.6415×10^{7}	845.55	0.000996

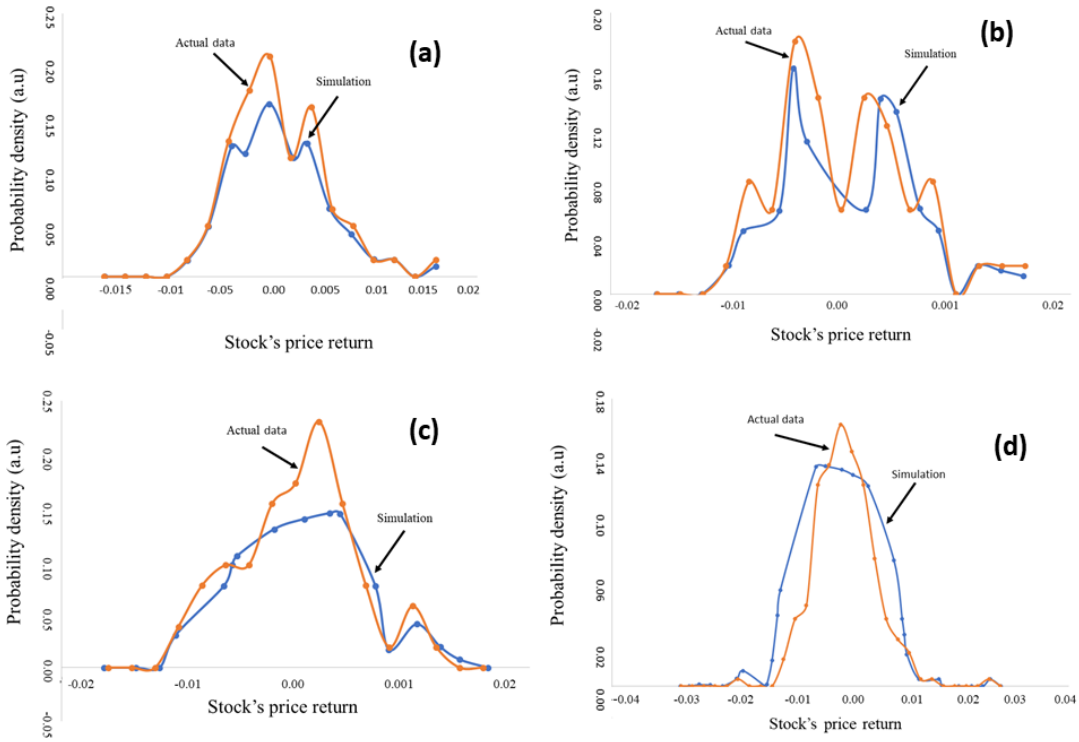

Figure 1. The probability density (opportunity density) of the stock's price return of JCI obtained from the PSO-optimized quantum harmonic oscillator model in the period of (a) January to March 2017, (b) April to June 2017, (c) July to September 2017, and (d) January to December 2017.

The characteristics of participating agents from the Jakarta Composite Index market for one year are guessed using the Runge-Kutta Fehlberg tolerance value, c_1 and c_2 on PSO are the same as the Jakarta Composite Index market with a period of three months. The values obtained for γ, *k*, *c*, and *E* are 4.8441 x 10^7, 2.9833 x 10^6, 5.527 x 10^7, and 742.1, respectively. If the parameter values are compared with the parameter value from one month, the values of *γ* and *c* are smaller than their average values for three months, and this might happen because some investors invest only in the short term, need some cash (or fresh funds), or purely due to investment strategy. Meanwhile, a smaller value of *c* indicates that contrarian investors dominate investors with short-term investment strategies. The value of *k* in the Jakarta Composite Index market in any period is almost the same, indicating that investors in the market, both in the long and short term, have the exact nature if stock prices experience volatility. The amount of Eigen energy in the Jakarta Composite Index market in one year is smaller than the three months, indicating that prices are mainly at the ground state energy level. This finding might come from the fact that in the three months, the time interval is not long enough to make the stock's price return to the ground state (initial stable state). The comparison between the actual data and the simulation results of the Jakarta Composite Index from January to September 2017 in three months can be seen in Figure 1 (a), (b), and (c). Those results resemble the state of excited energy in quantum physics, while in one year, the graph resembles the ground state in quantum physics (Figure 1(d)).

Future predictions are made by assuming that the density of future probabilities is influenced by the response of market makers and investors to the return on the stock price in the market denoted by the parameter an (a = γ + c), and the response of investors to volatility b (where b = k.c). The value of parameters *a* and *b* in the future is calculated using the Exponential Smoothing method (see Equation 10), with values of α =0.2 and 0.5. Value *a* and *b* are selected by looking at the slightest error from the previous period. The parameter values of *γ* , k, and c are taken from the simulation from the previous periods (January to September 2017). Based on those parameters data, we simulated the stock's price return Index dynamics for the next three months, from January to March 2018. From the simulation, it was found that the value of parameter *a* was 4.33×10^8, and *b* of 1.24×10^{15} *E* was 1298.925 (compared to the ground state energy E_{gs}=488.28). Based on the value of *E*, it can be concluded that the stock's price return in that period (January to March 2018) is exciting. The market's liquidity is also predicted to decline, and investor behavior toward volatility tends to be more risk-averse than before. The stock's price return influenced that condition in the previous period which was dominated by the ground state condition where the prices tend to be more stable.

Validation of the model to estimate the magnitude of the opportunity density of stock price returns in the future is done by calculating the error using MAPE. The result shows that the error in the probability density for the January-March 2018 period is 17.77%, with the resulting error in the return value of 10.6% (see Figure 2). Those predicted values indicate that our predictions' results can represent the market's actual state in the future quite nicely. This finding also indicates that the stock's liquidity and the volatility felt by investors in the previous period will affect the size of the stock price in the future (next period).

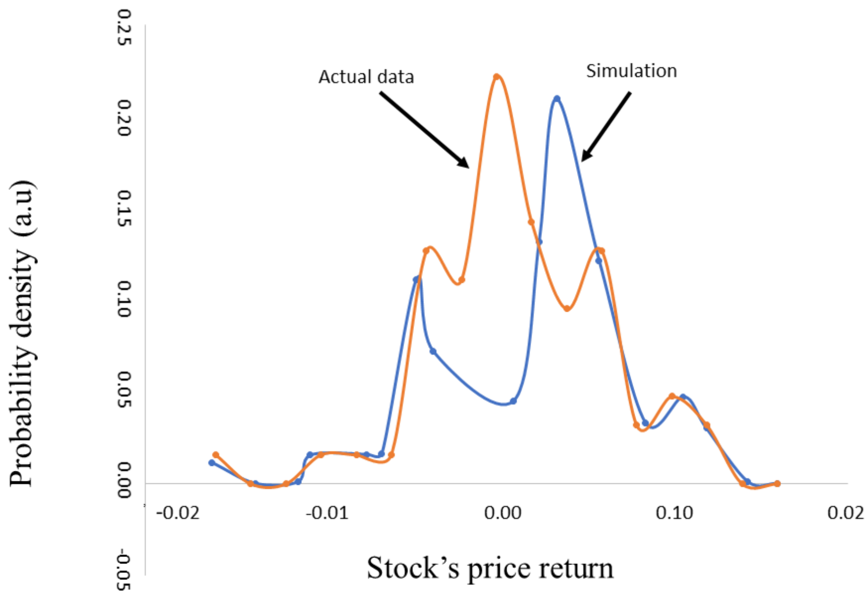

Figure 2. The comparison between the prediction (simulation) probability density of the stock's price return was obtained from the PSO-optimized quantum harmonic oscillator model from January to March 2018.

CONCLUSION

The characteristics of investors and market makers on the Jakarta Composite Index investors have been modeled using an anharmonic quantum oscillator model and solved numerically by Runge Kutta Fehlberg method and Particle Swarm Optimization. The value of the opportunity density of stock's price returns on the market is assumed to be influenced by the market's balance of demand and supply. Market demand and supply are assumed to be influenced by investors' characteristics, the volatility felt by investors, and how market makers control market liquidity. The results of the simulation on the Jakarta Composite Index (both in the fragmented three months periods and in the one-year) produce minor errors, with minor errors of probability density (opportunity density) of the stock's price return is 8.36%, and the tiniest error in stock's price return 3.6% in January to March 2017 period. The value of the parameters γ, k, and c on the Jakarta Composite Index market for three sets of three-month periods from January to September 2017 is used to predict the size of parameters *a* and *b* to predict the stock's price return in the future (next period of January to March 2018) by using the Exponential Smoothing method. This model prediction resulted in an error in the opportunity density of 17.77% and a mistake for a share price return of 10.6% Those results indicate that the value of liquidity and volatility in the previous period affected the investors' behaviour and the stock's price return in the following period.

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REFERENCES

[1] C. R. da Cunha, *Introduction to Econophysics*. 2021. doi: 10.1201/9781003127956.

[2] J. Mimkes, "Introduction to Econophysics," *Int. J. Product. Manag. Assess. Technol.*, vol. 7, no. 1, 2019, doi: 10.4018/ijpmat.2019010101.

[3] A. Evgenidis, A and Fasianos, "Unconventional Monetary Policy and Wealth Inequalities in Great Britain," *Oxf. Bull. Econ. Stat.*, vol. 83, no. 1, pp. 115–175, 2020, [Online]. Available: https://doi.org/10.1111/obes.12397

[4] W. T. Ziemba, S. Lleo, and M. Zhitlukhin, *STOCK MARKET CRASHES: Predictable and Unpredictable and What To Do About Them*. 2017. doi: 10.1080/14697688.2018.1464792.

[5] D. Durusu-Ciftci, M. S. Ispir, and D. Kok, "Do stock markets follow a random walk? New evidence for an old question," *Int. Rev. Econ. Financ.*, vol. 64, 2019, doi: 10.1016/j.iref.2019.06.002.

[6] V. E. Tarasov, "Fractional econophysics: Market price dynamics with memory effects," *Phys. A Stat. Mech. its Appl.*, vol. 557, 2020, doi: 10.1016/j.physa.2020.124865.

[7] F. Black and M. Scholes, "The pricing of options and corporate liabilities," *J. Polit. Econ.*, vol. 81, no. 3, 1973, doi: 10.1086/260062.

[8] R. C. Merton, "THEORY OF RATIONAL OPTION PRICING.," *Bell J Econ Manag. Sci*, vol. 4, no. 1, 1973, doi: 10.2307/3003143.

[9] T. Sumaryada, B. Maha Putra, and S. Pramudito, "Quantum anharmonic oscillator plus delta-function potential: A molecular view of pairing formation and breaking in the coordinate space," *Eur. J. Phys.*, vol. 38, no. 3, 2017, doi: 10.1088/1361-6404/aa5e0e.

[10] T. Honda and T. Sako, "Distribution of oscillator strengths and correlated electron dynamics in artificial atoms," *J. Phys. B At. Mol. Opt. Phys.*, vol. 53, no. 17, 2020, doi: 10.1088/1361-6455/ab9c35.

[11] N. Soheibi, M. Eshghi, and M. Bigdeli, "Study of odd-A nuclei with an energy-dependent γ -unstable harmonic-oscillator-like potential and deformation-dependent mass term," *Eur. Phys. J. Plus*, vol. 135, no. 1, 2020, doi: 10.1140/epjp/s13360-019-00081-4.

[12] M. S. Yousef, M. S. Yousef, and H. M. Elsharkawy, "Expansion of deformed harmonic oscillator wavefunctions in terms of spherical wavefunction bases: Deformation effects," *Phys. Scr.*, vol. 95, no. 7, 2020, doi: 10.1088/1402-4896/ab96dd.

[13] C. Ye and J. P. Huang, "Non-classical oscillator model for persistent fluctuations in stock markets," *Phys. A Stat. Mech. its Appl.*, vol. 387, no. 5–6, 2008, doi: 10.1016/j.physa.2007.10.050.

[14] T. Gao and Y. Chen, "A quantum anharmonic oscillator model for the stock market," *Phys. A Stat. Mech. its Appl.*, vol. 468, pp. 307–314, 2016, doi: 10.1016/j.physa.2016.10.094.

[15] S. Paul, S. P. Mondal, and P. Bhattacharya, "Numerical solution of Lotka Volterra prey predator model by using Runge-Kutta-Fehlberg method and Laplace Adomian decomposition method," *Alexandria Eng. J.*, vol. 55, no. 1, 2016, doi: 10.1016/j.aej.2015.12.026.

[16] J. Kennedy and R. Eberhart, "Particle swarm optimization," in *IEEE International Conference on Neural Networks - Conference Proceedings*, 1995, vol. 4. doi: 10.4018/ijmfmp.2015010104.

[17] M. A. M. De Oca, "Particle Swarm Optimization Introduction," *Optimization*, 2007.

[18] L. X. Wang, "Modeling Stock Price Dynamics with Fuzzy Opinion Networks," *IEEE Trans. Fuzzy Syst.*, vol. 25, no. 2, 2017, doi: 10.1109/TFUZZ.2016.2574911.

[19] F. Garzarelli, M. Cristelli, G. Pompa, A. Zaccaria, and L. Pietronero, "Memory effects in stock price dynamics: Evidences of technical trading," *Sci. Rep.*, vol. 4, 2014, doi: 10.1038/srep04487.

[20] M. Stallen, N. Borg, and B. Knutson, "Brain activity foreshadows stock price dynamics," *J. Neurosci.*, vol. 41, no. 14, 2021, doi: 10.1523/JNEUROSCI.1727-20.2021.