# Ant Colony Optimization for Cryptocurrency Price Prediction: A Novel Approach

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**Abstract — Cryptocurrency prices are volatile and cannot be predicted accurately, which is So we make many ineffective investment strategies and market decision's due to its volatile nature. To overcome these conditions, this paper introduces a price prediction model designed to address the inherent challenges in finding cryptocurrency prices. The approach integrates genetic algorithms (GA), Stacking algorithms, and ant colony Optimisation (ACO) to increase the price prediction accuracy. Genetic algorithms are used to optimize the parameters of the predictive models, ensuring more precise parameters for searching later. The stacking algorithm combines multiple predictive models for their collective strength's, this improves the total overall prediction rate of the price. Ant colony optimization is used to further refine the model by navigating the complex search space of combined multiple predictive models for all potential solutions. The combination of these techniques significantly improves prediction accuracy and robustness compared to conventional methods. This integrated approach provides valuable insights for investors and researchers, by giving more informed decision making in the dynamic cryptocurrency market.**

**Keywords Terms— Cryptocurrency, price prediction, Genetic Algorithms, Stacking Algorithm, Ant Colony Optimization, forecasting accuracy.**

## I. INTRODUCTION

**Cryptocurrencies** are digital or virtual currencies that represent cryptography for secure transactions and operate on decentralized networks. At their core, they rely on **blockchain technology,** which is a distributed ledger that records all transactions across a network of computers.[1] This ledger is composed of a chain of blocks, each containing a record of transactions. By decentralizing control of the currency and using a blockchain, cryptocurrencies ensure transparency and security, as no single entity has control over the entire network. The security of cryptocurrencies is maintained through **cryptographic techniques.** Each user has a pair of cryptographic keys: a **public key,** used for receiving funds, and a **private key,** used for authorizing transactions. This setup ensures that only the owner of the private key can access and transfer their funds. Transactions are validated through various **consensus mechanisms.** For instance, Bitcoin uses **Proof-of-Work (PoW),** where crypto miners solve complex problems to complete transactions and secure the network.[4] Other cryptocurrencies might use different consensus models, such as **Proof-of-Stake (POS).** Users manage their cryptocurrencies through **digital wallets,** which can be either software-based applications or hardware devices. These wallets store the cryptographic keys needed to access and manage the cryptocurrency holdings. Additionally, some cryptocurrencies, like Ethereum, support **smart contracts—**automated agreements encoded directly onto the blockchain. These smart contracts execute automatically when predefined conditions are met, adding another layer of functionality to the cryptocurrency ecosystem. Overall, cryptocurrencies combine blockchain technology, decentralization, and cryptographic security to facilitate secure and efficient digital transactions.[10]

**Market volatility** is the biggest challenge in the cryptocurrency sector, characterized by significant price fluctuations over short period of time. This volatility arises from various factors including **market speculation**, regulatory changes, technological advancements, and macroeconomic conditions.

Speculative trading often leads to rapid and unpredictable price shifts, while regulatory news can cause worse market reactions. Technological developments, such as upgrades or security breaches, further contribute to price instability. Additionally, global economic factors can drastically affect these fluctuations. Such high volatility complicates the use of cryptocurrencies as the stable stores of value or reliable units of account, posing risks for investors and effecting the formulation of stable investment strategies. [2]

**Transaction speed and fees** are critical issues affecting cryptocurrencies. Different digital currencies exhibit varying transaction speeds and fee structures. For example, Bitcoin transactions can suffer from delays and high fees during periods of busy network because the data nodes are overloaded and transaction processing capacity decreases. This can make Bitcoin less practical for everyday transactions compared to traditional payment systems. Although some cryptocurrencies, like Ethereum, offer faster transactions, but they too face scalability issues. High transaction fees can make small payments inefficient, prompting the need for innovative solutions like layer 2 technologies to increase transaction speed and reduce costs. However, finding the right balance between transaction speed, network security, and cost remains a significant challenge. [4]

The **irreversibility of transactions** is another important concern. Once a cryptocurrency transaction is confirmed on the blockchain, it cannot be reversed. This feature enhances security and prevents fraud, but introduces risks if mistakes occur or if users fall victim to scams. The inability to undo transactions requires careful attention and good security measures from users, Stressing the importance of double-checking transaction details before confirmation. It also means that resolving disputes or correcting mistakes can be particularly challenging, as there are no central authorities or intermediaries to mediate or reverse the transaction. Users must practise extreme caution and ensure that all transaction details are accurate and correct to avoid the risk of irreversible losses.

**Ant Colony Optimization (ACO)** is a **nature-inspired optimization algorithm**, modelled after the searching behaviour of real ants. Ants, in search of food, leave behind pheromone trails, which help others find the shortest path to the food source. Over time, these trails are strengthened by each ant, guiding the colony toward optimal solutions. This concept has been applied to solve complex optimization problems, making ACO a powerful tool in various fields, from routing in networks to machine learning.[5]

The context of **cryptocurrency price prediction**, ACO can be employed to optimize forecasting models and their parameter configurations, which are essential for generating accurate predictions. Cryptocurrency prices are influenced by numerous variables, and the search space for the best prediction model and its parameters is vast and complicated. By simulating the behaviour of ants, ACO efficiently explores this search space, identifying the most promising model configurations that give the highest prediction accuracy.

The key advantage of ACO in this setting is its **adaptive learning** process. Just like ants adjust their paths based on the pheromone concentration, the ACO algorithm iteratively refines its search for the best forecasting model based on the performance of previous iterations. This ensures that the model is continuously improving, even in a volatile and uncertain market environment. Traditional forecasting models often rely on static assumptions or historical data, which can lead to inaccuracies in highly [5] volatile markets. ACO, on the other hand, **dynamically adapts** to changing market conditions by exploring different model configurations in real-time. ACO's ability to converge toward **optimal solutions** quickly makes it highly efficient in finding the best-performing prediction models. This is particularly important in the cryptocurrency market, where timely and accurate predictions are crucial. Cryptocurrency markets are always busy, with prices often influenced by unpredictable events. ACO's **iterative nature** allows it to filter through this **noise** [11] and focus on building models that provide more stable and reliable predictions. By optimizing model parameters and refining the search space, ACO has the potential to offer **better prediction accuracy** compared to traditional methods. This leads to more reliable forecasts, helping investors make informed decisions.[11]

### A. Financial Signal Processing Techniques

In this section, an explanation is given about the trend indicators and oscillator types, which are among FSP methods used in the study. Trend indicators such as Simple and Exponential Moving Average (SMA, EMA), Average Directional Moving Index (ADX) and Parabolic Stop and Reverse (SAR) are explained in order. Besides, oscillator types such as Moving Average Convergence Divergence (MACD), Rate of change (ROC) and Commodity Channel Index (CCI) are also explained. Simple Moving Average (SMA) This trend indicator is created by taking the average of the price movements (such as close price time series data) within the specified period (N). The Simple Moving Average (SMA) equation is given in [19].

$$SMA[i] = \frac{1}{N}\sum_{n=1}^{N} C\,[i+n]$$

### Exponential Moving Average (EMA)

The Exponential Moving Average (EMA) equation is given as in [16].

$$EMA[i] = \left(\frac{2}{1+N}\right)(C[i] - EMA[i-1]) + EMA[i-1]$$

In this equation, 2/(1+N) is weighting factor for Exponential Moving Average (EMA) where N is selected time. For first calculation, initial value of EMA, EMA $[ii-1]$ is an average of all close prices over N number of periods. In the next steps, the values obtained here are used in (**3**) to calculate the EMA value for the whole time series.

### Average Directional Moving Index (ADX)

Average Directional Movement Index (ADX) indicator is developed by John Welles Wilder, JR. in 1978 [16]. ADX, called the Average Directional Index, is an indicator that takes values between **0-100**. The ADX line does not say whether the value will be high or low for next value, but it gives information about the strength of the data's movement in one direction [16]. It is calculated as in (**4**). N value represents the period value of the ADX indicator.

$$ADX[i] = \left(\frac{ADX[i-1](N-1) + DX[i]}{N}\right)$$

Directional Index $[ii]$ in (**4**) is calculated as in (**5**) by multiplying the ratio of the difference between Positive Directional Indicator (PDI) and Negative Directional Indicator (NDI) to the sum of PDI and NDI by **100**.

$$DX[i] = \frac{100(PDI[i] - NDI[i])}{(PDI[i] + NDI[i])} \tag{5}$$

PDI and NDI are expressed as the ratio of Positive Directional Movement (+DM) to True Range (TR) and Negative Directional Movement (-DM) to TR respectively in (**6**,**7**).

$$PDI[i] = \frac{\sum_{n=1}^{N} +DM\,[i]}{\sum_{n=1}^{N} TR[i]} \tag{6}$$

$$NDI[i] = \frac{\sum_{n=1}^{N} -DM\,[i]}{\sum_{n=1}^{N} TR[i]} \tag{7}$$

where TR, +DM and -DM are calculated as in (**8**,**9**,**10**). C, H and L represent close, high, and low prices time series data respectively.

$$TR[i] = max\begin{cases} H[i] - L[i] \\ |H[i] - C[i-1]| \\ |L[i] - C[i-1]| \end{cases} \tag{8}$$

$$+DM[i] = \begin{matrix} H[i] - H[i-1] & (H[i] - H[i-1]) > (L[i-1] - L[i]) \\ 0 & otherwise \end{matrix} \tag{9}$$

$$-DM[i] = \begin{matrix} L[i-1] - L[i] & (L[i-1] - L[i]) > (H[i] - H[i-1]) \\ 0 & otherwise \end{matrix} \tag{10}$$

### Parabolic Stop and Reverse (SAR)

This indicator is developed by John Welles Wilder, JR. to find potential reversals price direction in volatile markets [14]. The SAR value is calculated as in (**11**).

$$SAR[i] = SAR[i-1] + \alpha(EP - SAR[i-1]) \tag{11}$$

In (**11**), EP is constantly updated as the highest of highs in the uptrend and the lowest of the lows in the downtrend. The $\alpha\alpha$ value represents the acceleration factor. $\alpha\alpha$ is **0.02** by default and can be increased by **0.02** step size to a maximum value of **0.2**. This is where the expression 'parabolic' comes from as prices tend to stay in a parabolic curve in a strong trend.

Moving Average Convergence Divergence (MACD)

The MACD (Moving Average Convergence Divergence) indicator is developed by Gerard Appel in the 1970s [16]. MACD indicator is calculated as in (**12**), depending on the difference between the short-time and long-time exponential moving average (EMA) values.

$$MACD[i] = EMA_{short}[i] - EMA_{long}[i] \tag{12}$$

This is defined as the MACD line. A third time series called signal is obtained by averaging this value over a certain period. In addition, the histogram time series is obtained by visualizing the difference between MACD line and signal. MACD values **12**, **26** and **9** are typically used [17].

### Rate of change (ROC)

The Rate of Change (ROC), also known as Momentum, is another financial signal processing technique that measures the momentum of price movements. It compares the current price of any security with the previous price of the N period. The ROC value is calculated using the equation in (**13**).

$$ROC[i] = 100\frac{C[i] - C[i-1]}{C[i-1]} \tag{13}$$

### Commodity Channel Index (CCI)

The Commodity Channel Index is an oscillator introduced by Donald Lambert in 1980 [18]. It measures the current price level relative to the average price level in each time. The CCI value is calculated as the ratio of the difference between the Typical Price (TP) and the SMA value of close to the Mean Deviation (MD) value as in (**14**) [19].

$$CCI[i] = \frac{1}{0.015}\frac{TP[i] - SMA[i]}{MD[i]} \tag{14}$$

C, H and L represent close, high, and low prices time series data respectively.

the H, L and C time series data, as in (**15**).

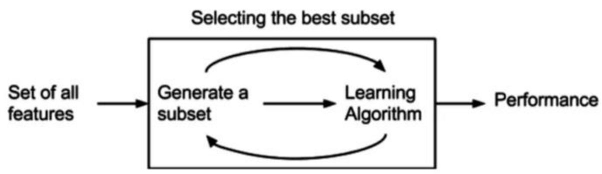
$$TP[i] = \frac{H[i] + L[i] + C[i]}{3} \quad (15)$$

The MD value is calculated as in (16) as the mean value of the difference between TP and SMA value for a given N period.

$$MD[i] = \frac{1}{N}\sum_{n=1}^{N} |TP[i+N] - SMA[i+N]| \quad (16)$$

## II. PROPOSED METHODOLOGY

Our proposed Ant Colony Optimization for crypto currency prediction predominantly consists of two steps. Our two steps are data analysis to extract all the data required to predict the price of crypto currency and second step is feature selection which describes the proposed methodology to predict the price of crypto currency.




### A. Exploratory Data Analysis

A typical investor is more concerned with the high and low values of crypto currency. High and low values of a currency for that day sets the main nodes between which other nodes are chosen for the ants to traverse using ant colony optimization. Investor is also concerned about limited data because this market often neglects basic data like earnings, another major concern for the investors is price fluctuations because coins value at times fluctuates with huge difference. The study's usage of datasets demonstrates how many factors affects the price of crypto currency. To predict the price using ant colony optimization various number of nodes are used. The main nodes being Open value node, Close value node, High node, and Low node. The more traversed route by ants is the price fluctuations for that day.

### B. Neural Network (NN)

Neural network is a machine learning algorithm, which could be said as a subset of deep learning. This algorithm is designed such that it imitates the human brain, a structure consisting of interconnected layers of nodes and neurons. in this the hidden layers to process information through the weighted connections and activation functions as selected. finally, we get an output; layer which produced the predictions. the training proves involves the forward and back propagation, where data continuously generate outputs and adjusts weights, biases, and therefore minimizes the error if margin using optimization Tion algorithms such as ant colony optimization, loss functions to quantify prediction accuracy, and optimization methods to refine the network.

### C. Optimization for Price Projection

**Transition Probability**

$$p_{ij}^{k}(t) = \begin{cases} \dfrac{\tau_{ij}^{\alpha}(t)\eta_{ij}^{\beta}(t)}{\sum\limits_{u\in\mathcal{N}_i^k(t)} \tau_{iu}^{\alpha}(t)\eta_{iu}^{\beta}(t)} & \text{if } j \in \mathcal{N}_i^k(t) \\ 0 \text{ otherwise} & \end{cases} \quad ,k = 1,\cdots,n_k$$

**1. ACO Algorithm:** The Classic ACO algorithm, where N will be the number of price nodes, and k will be the number of ants, made the following changes to replicate the ant's behaviour. T is a pheromone matrix which made up of all the pathways. The matrix's rows represent the collection of pheromone values for potential price values from open value node.

$\eta_{ij}(t) = [d_{ij}(t)]^{-1,}$ Improves attractiveness of edge (i,j).

($d_{ij}$ is difference between i and j values)

**Pheromone evaporation:**

$$\tau_{ij}(t) \leftarrow (1-\rho)\tau_{ij}(t)$$

Pheromone Intensity evaporates slowly to prevent the premature convergence of ants and to force ants to explore more paths or routs. Where $\rho \in$ **(0,1)** is evaporation rate. (**0** and **1** are not inclusive)

**Update of pheromone intensity/concentration:**

$$\tau_{ij}(t+1) = \tau_{ij}(t) + \sum_{k=1}^{n_k} \Delta\tau_{ij}^{k}(t), k = 1,\cdots,n_k$$

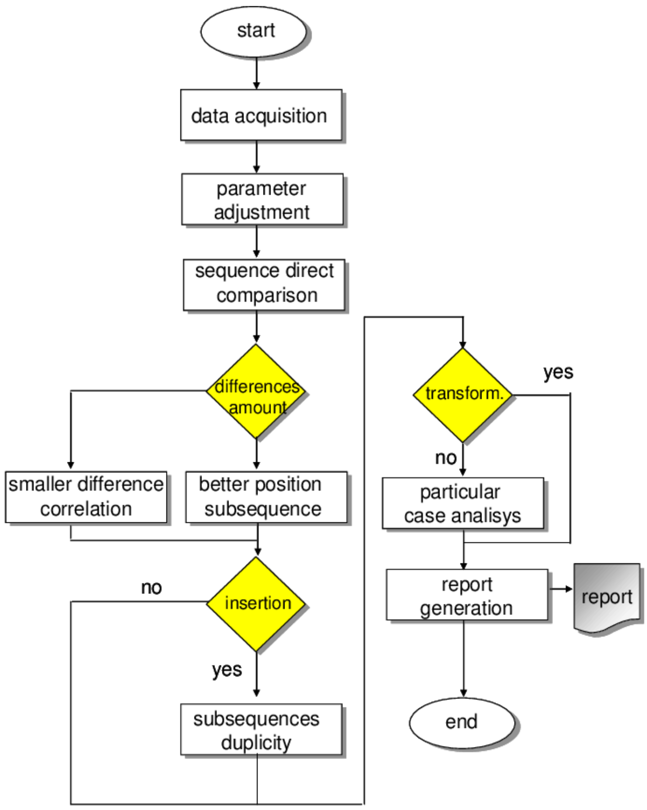
- **Ant-cycle AS:** $\Delta\tau_{ij}^{k}(t) = \begin{cases} \frac{Q}{f(x^k(t))} & \text{if edge } (i,j) \text{ occurs in path } x^k(t) \\ 0 \text{ otherwise} & \end{cases}$

After all the ants have constructed their paths from start value node to close value node, and all loops are removed, then the pheromone intensity is adjusted for each (i,j) edge or path. (i and j are two adjacent nodes)

$x^k(t)$ is a set of all the values of node's traversed by 'k' ant, that is all values of ant k. $f(x^k(t))$ is a sum all the values of $d_{ij}$ , that is quality of price predicted.

**2. Swarm Optimization:** Swarm optimization is a optimization technique where particles move in the given space in search of optimized solution. This method is done by gaining knowledge in two ways where particles either obtains knowledge about the solution from its own experience in that respective path or information about the best possible solution given by entire swarms.

Ant colony is considered as a swarm optimization technique because of the functionality of ant colony technique. Ants work together to solve the problem. Ants communicate with other ants by releasing pheromones which tells other ants the path to be chosen this is a Swarm optimization principle. Each ant independently works and gains knowledge about the best solution to the problem and over all best solution is taken from a collection of ant solutions more ants travel in one path pheromone in path will be more which tells other ants to choose that path this is also a swarm optimization concept.




## D. DATASET

This dataset is a consolidation of historical financial data of the cryptocurrency in the market. It has been published by Phil Mohun. The data spans through approximately **28,000** rows of data, which contains key attributes such as currency name, date, open, high, low, close, trading volume, and market capitalization. Compiled through a custom script that scrapes historical price information, the data aims to address knowledge gaps in the understanding of the price dynamics. This research exploits this dataset for, identifying optimal trading days, and evaluating market volatility. Analysis it has been instrumental in providing the insights of cryptocurrency market behaviour, with the broader goal of quantitative analysis in a rapidly evolving investment space.

## **III.** EXPERIMENTAL STUDY AND RESULTS

The ACO algorithm helped to "learn" which patterns in the data produced the highest profits by prioritizing sequences that led to better outcomes. Our study concludes in discovering the most significant parameter presented to us in a dataset for the volatility of the remarket. This has been achieved by keeping several nodes as the function of parameters and therefore traversing therefore them using the concept of Ant colony Optimization (ACO). Therefore, using such basis, it is our conclusion to proves an approach or a foundation for creating a prediction model to maximize the profit over a span of the week. Further, this is an insight to on how we could use optimization technique to create a prediction model where one could have lesser margin of error.

The study normalizes the data, and then calculates various features in the search of finding the most critical parameters. feature selection was performed using Ant Colony Optimization (ACO), with CCI (Commodity Channel Index with a window size of 10) identified as the most critical feature, followed by MACD, ADX (Average Directional Index with a window size of **3**), and SMA(Simple Moving Average with a window size of **2**). The model's performance was evaluated using RMSE and MAE, with visualization tools providing insights into feature importance and model accuracy. The machine learning algorithm we have chosen is Neural Network.

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |y_i - \widehat{y_i}|$$

where,

$n$: $number\ of\ observation$

$y_i$: $the\ actual\ value\ of\ the\ i^{th}\ observation$

$\widehat{y_i}$: $the\ predicted\ value\ of\ the\ i^{th}\ observation$

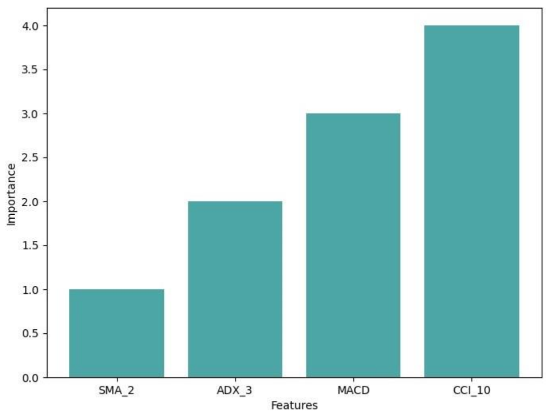
$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(\hat{y}_i - y_i)^2}{n}}$$

$\hat{y}_1, \hat{y}_2, \ldots, \hat{y}_n$ are predicted values

$y_1, y_2, \ldots, y_n$ are observed values

$n$ is the number of observations

Our approach is to first extract the data out of the dataset mentioned above according the name of the cryptocurrency we have selected .data extracted are open price, m high price, low price, close price, and volume, per day. The mathematical indicators are calculated as mentioned above (SMA, ADX, MACD, ROC,CCI).Then we normalize this mathematical indicator between **0** and **1**. All features are scaled to values between **0** and **1** to ensure equal weight during training. Now all the features are taken as input and therefore, and are used Splits data into training **(80%)** and testing **(20%)**.And then the forward propagation and back propagation calculates the margin of error . This research highlights the potential of combining technical analysis with machine learning for prediction. Future work can incorporate advanced architectures like Neural Network or Reinforcement Learning for improved accuracy.




This study presents a cryptocurrency price prediction model designed to forecast Tezos, Binance-Coin, Bitcoin prices using technical indicators and a neural network for regression. The model uses a pipeline that processes historical data, and obtain features like moving averages, trends strength, and momentum indicators, and normalizes inputs for better performances. The neural network, built with2 hidden layers using ReLU activation and a linear output layer, was tested on the Tezos, Binance Coin, Bitcoin dataset.

The model's performance of Binance-Coin is evaluated: Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE). It got an RMSE of **1371.43** USD, representing an average error of **4.57%** approximately when compared to an assumed average Binance-Coin price of **30,000** USD. The MAE was **528.76** USD, to an average error of **1.76%**.

The model's performance of Tezos is evaluated: Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE). This obtains RMSE of **1.5047** USD, representing an average error of **5.02%** approximately when compared to an assumed average Tezos price of **30** USD. The MAE was **0.5511** USD, to an average error of **1.84%**.

The model's performance of Bitcoin: Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE). It achieved an RMSE of **1371.23** USD, an average error of **1.49 %** approximately when compared to an assumed average Bitcoin price of **92,000** USD. The MAE was **507.82** USD, to an average error of **0.55%**.

## **III.** CONCLUSION

These findings suggest that success in trading can often trickle down to aligning the intensity and frequency of trades. This means that focusing on a strategy that captures high-volume trades during active periods is likely to provide the strongest returns, especially when applied in regular cycles.

## REFERENCES

[1] Ramya, N., 2022, April. Crypto-currency price prediction using machine learning. In 2022 6th International Conference on Trends in Electronics and Informatics (ICOEI) (pp. 1455-1458). IEEE.

[2] Rathan, K., Sai, S.V. and Manikanta, T.S., 2019, April. Crypto-currency price prediction using decision tree and regression techniques. In 2019 3rd International Conference on Trends in Electronics and Informatics (ICOEI) (pp. 190-194). IEEE.

[3] Wimalagunaratne, M. and Poravi, G., 2018, May. A predictive model for the global cryptocurrency market: A holistic approach to predicting cryptocurrency prices. In 2018 8th International Conference on Intelligent Systems, Modelling and Simulation (ISMS) (pp. 78-83). IEEE.

[4] Sharma, K.P., Singh, S.K., Choudhary, A. and Goel, H., 2023, January. Price Prediction of Bitcoin using Social Media Activities and Past Trends. In 2023 13th International

Conference on Cloud Computing, Data Science & Engineering (Confluence) (pp. 516-521). IEEE.

[5] Jangra, R. and Kait, R., 2017, February. Analysis and comparison among ant system; ant colony system and max-min ant system with different parameters setting. In 2017 3rd international conference on computational intelligence & communication technology (CICT) (pp. 1-4). IEEE.

[6] Rahmat, N.A. and Musirin, I., 2012, June. Differential evolution ant colony optimization (DEACO) technique in solving economic load dispatch problem. In 2012 IEEE International Power Engineering and Optimization Conference Melaka, Malaysia (pp. 263-268). IEEE.

[7] Liu, Y. and Wang, L., 2017, March. Resource scheduling for HF reception based on improved ant colony optimization algorithm. In 2017 IEEE 2nd Advanced Information Technology, Electronic and Automation Control Conference (IAEAC) (pp. 2266-2270). IEEE.

[8] Rahmat, N.A., Musirin, I. and Abidin, A.F., 2014, March. Differential Evolution Immunized Ant Colony Optimization Technique (DEIANT) in solving economic dispatch by considering prohibited operating zones. In 2014 IEEE 8th International Power Engineering and Optimization Conference (PEOCO2014) (pp. 455-460). IEEE.

[9] Ratanavilisagul, C. and Pasaya, B., 2018, July. Modified ant colony optimization with updating pheromone by leader and re-initialization pheromone for travelling salesman problem. In 2018 International Conference on Engineering, Applied Sciences, and Technology (ICEAST) (pp. 1-4). IEEE.

[10] Ariyasingha, I.D.I.D. and Fernando, T.G.I., 2016, December. A modified Pareto strength ant colony optimization algorithm for the multi-objective optimization problems. In 2016 IEEE International Conference on Information and Automation for Sustainability (ICIAfS) (pp. 1-6). IEEE.

[11] Zheng, W., Jin, X., Deng, F., Mo, S., Qu, Y., Yang, Y., Li, X., Long, S., Zheng, C., Liu, J. and Xie, Z., 2018, June. Database query optimization based on parallel ant colony algorithm. In 2018 IEEE 3rd International Conference on Image, Vision and Computing (ICIVC) (pp. 653-656). IEEE.

[12] Dudek, G., Fiszeder, P., Kobus, P. and Orzeszko, W., 2024. Forecasting cryptocurrencies volatility using statistical and machine learning methods: A comparative study. Applied Soft Computing, 151, p.111132.

[13] Rizzuti, L., Parente, M. and Trerotola, M., 2023. A Profitable Trading Algorithm for Cryptocurrencies Using a Neural Network Model. Available at SSRN 4471119.

[14] Harb, E., Bassil, C., Kassamany, T. and Baz, R., 2024. Volatility interdependence between cryptocurrencies, equity, and bond markets. Computational Economics, 63(3), pp.951-981.

[15] Rathee, N., Singh, A., Sharda, T., Goel, N., Aggarwal, M. and Dudeja, S., 2023. Analysis and price prediction of cryptocurrencies for historical and live data using ensemble-based neural networks. Knowledge and Information Systems, 65(10), pp.4055-4084.

[16] KARASU, S., and NA YALÇIN. "Digital Currency Time Series Prediction Based on Financial Signal Processing, Ant Colony Optimization and Machine Learning Techniques."

[17] Sahu, Sonal, et al. "Analyzing Portfolio Optimization in Cryptocurrency Markets: A Comparative Study of Short-Term Investment Strategies Using Hourly Data Approach." *Journal of Risk and Financial Management* 17.3 (2024): 125.

[18] Yurtsal, Ahmet, Yunus Karaömer, and Ali̇ İhsan Benzer. "A Swarm Intelligence Optimization Algorithm for Cryptocurrency Portfolio Optimization." *Anemon Muş Alparslan Üniversitesi Sosyal Bilimler Dergisi* 10.1 (2022): 347-363.

[19] Karasu, S., & Altan, A. (2022). Crude oil time series prediction model based on LSTM network with chaotic Henry gas solubility optimization. Energy, 242, 122964.

[20] Widodo, A., & Yang, B. S. (2007). Support vector machine in machine condition monitoring and fault diagnosis. Mechanical systems and signal processing, 21(6), 2560-2574