NEURAL NETWORK TRAINING USING FLOWER POLLINATION ALGORITHM FOR BITCOIN PRICE PREDICTION

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ABSTRACT

One of the important uses of blockchain technology is cryptocurrencies. Interest in cryptocurrencies as a financial investment tool has increased recently. With the increasing interest, many cryptocurrencies have taken place in the market. The most popular among cryptocurrencies is bitcoin. Predictions and analyzes about the future are important in order to profit in bitcoin and other cryptocurrencies. For this, different traditional and artificial intelligence-based methods are used in the literature. One of the artificial intelligence techniques used is artificial neural networks (ANNs). One of the important processes of the ANN is the training process. In order to obtain effective results with the ANN, an effective training algorithm is needed. The flower pollination algorithm (FPA), which models the pollination process in nature, is one of the popular optimization algorithms. It has been used in the solution of many problems and has been accepted in the literature. In this study, an approach based on FPA and ANN is proposed for the prediction of bitcoin price. The weights of the ANN are determined using the FPA. With the proposed approach, time series analysis is performed using historical bitcoin prices. Daily bitcoin data between 1 April 2022 and 30 June 2022 is utilized. The applications are realized on different network structures for effective bitcoin price prediction. The results show that the proposed approach based on FPA and ANN is effective for the prediction of bitcoin price.

Keywords: Flower Pollination Algorithm, Bitcoin, Cryptocurrency, Neural Network

INTRODUCTION

Cryptocurrencies are one of the most popular research areas of recent times. The prediction of future prices on cryptocurrencies is among the important studies. Many approaches are used to predict the prices of cryptocurrencies. As in many areas, artificial intelligence techniques have been also utilized in the prediction and modeling of cryptocurrencies. One of the important artificial intelligence techniques used for this purpose is artificial neural networks (ANNs).

When the literature is examined, it is seen that there are many studies based on ANN on cryptocurrencies. Charandabi and Kamyar (2021b) used a feed forward neural networks (FFNNs) for price prediction of cryptocurrencies such as Bitcoin, Ethereum, Tether, Dogecoin, and Binance coin. Livieris, Stavroyiannis, Pintelas, Kotsilieris and Pintelas (2022) proposed an approach based on recurrent neural network (RNN) for forecasting the price of the four popular digital currencies with CCi30 index. Almasri and Arslan (2018) utilized an ANN model to predict cryptocurrencies close prices. Tan and Kashef (2019) realized a comparative study on predicting the closing price of cryptocurrencies. They evaluated the performance of approaches such as Bayesian Regression, Auto Regression, The Long Short-Term Memory and Support Vector Machines. Awotunde, Ogundokun, Jimoh, Misra and Aro (2021) used the LSTM model for cryptocurrencies price prediction. They compared the performance of the LSTM model with different approaches in terms of Bitcoin, Ether and Litecoin cryptocurrencies. Only a few studies on cryptocurrencies are included in this paragraph. Apart from these, there are many studies (Charandabi & Kamyar, 2021a; Fang et al., 2022; Khedr, Arif, El-Bannany, Alhashmi, & Sreedharan, 2021).

A good training process is required to create successful models with ANN. Therefore, the algorithms used in ANN training are important. Flower pollination algorithm (FPA) is one of the optimization algorithms that has been used successfully in solving many problems (Abdel-Basset & Shawky, 2019; Alyasseri, Khader, Al-Betar, Awadallah, & Yang, 2018; Chiroma et al., 2015). Therefore, ANN training is carried out using FPA for the prediction of bitcoin price. This study is one of the first studies in which FPA is used to predict bitcoin price. In this respect, it is innovative.

METHODS

Flower Pollination Algorithm

FPA is a meta-heuristic algorithm that models the pollination process in nature (Yang, 2012). FPA is built on the logic of global and local pollination. Biotic and cross-pollination is considered as global pollination process. In this process, pollinators realize the Levy flights. Abiotic and self-pollination are considered as local pollination. The pollinators and pollination types are shown in Figure 1 (Abdel-Basset & Shawky, 2019). In FPA, the transition between global pollination and local pollination realizes place according to switch probability (p). The pseudo code showing all the processes of the standard FPA is given in Figure 2.

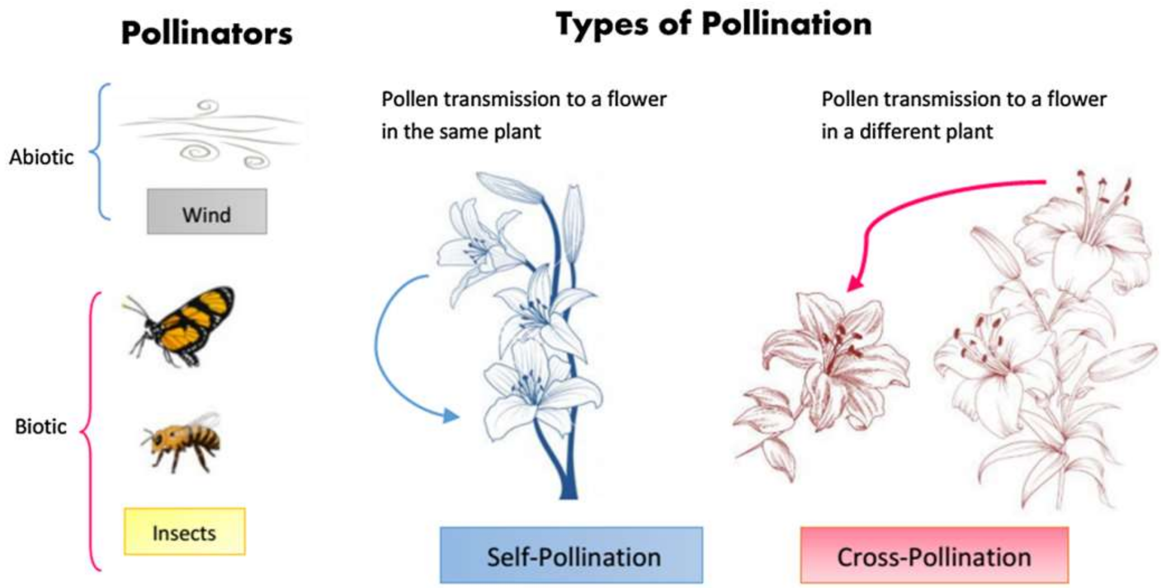

Figure 1. The pollinators and pollination types (Abdel-Basset & Shawky, 2019)

Flower Pollination Algorithm (or simply Flower Algorithm)

Objective min *or* max $f(\mathbf{x})$, $\mathbf{x} = (x_1, x_2, ..., x_d)$
Initialize a population of n flowers/pollen gametes with random solutions
Find the best solution $\mathbf{g}_*$ *in the initial population*
Define a switch probability $p \in [0, 1]$
while *(t <MaxGeneration)*
  for $i = 1 : n$ *(all n flowers in the population)*
    if $rand < p$,
      Draw a (d-dimensional) step vector L which obeys a Lévy distribution
      Global pollination via $\mathbf{x}_i^{t+1} = \mathbf{x}_i^t + L(\mathbf{g}_* - \mathbf{x}_i^t)$
    else
      Draw ϵ *from a uniform distribution in [0,1]*
      Randomly choose j and k among all the solutions
      Do local pollination via $\mathbf{x}_i^{t+1} = \mathbf{x}_i^t + \epsilon(\mathbf{x}_j^t - \mathbf{x}_k^t)$
    end if
    Evaluate new solutions
    If new solutions are better, update them in the population
  end for
    Find the current best solution $\mathbf{g}_*$
end while

Figure 2. Pseudo code of the proposed Flower Pollination Algorithm (FPA) (Yang, 2012)

Artificial Neural Networks (ANNs)

ANNs are formed by connecting many artificial neurons. In Figure 3, the general structure of an artificial neuron is given. As can be seen, an artificial neuron consists of inputs, weights, bias, transfer (summing) function, activation function and output. As a result of the operations to be realized in the transfer and activation function, the output of the artificial neuron is obtained. In an ANN, the output of one artificial neuron can be the input of another artificial neuron. These calculations continue throughout the network. There are many types of ANNs. In this study, a feed forward neural network (FFNN) is used. A FFNN model basically consists of three layers. These are input, hidden, and output. The calculations shown in Figure 3 are performed for neurons in the hidden and output layers. Increasing the number of neurons in a network also increases the number of parameters to be adjusted in the training process. During the training process, the weight and bias values of the neurons are constantly updated to reach the optimum model. When the stopping criterion is met, the training process is stopped. An error value or number of iterations can be used as the stopping criterion (Kaya, 2022) (Kaya & Baştemur Kaya, 2021).

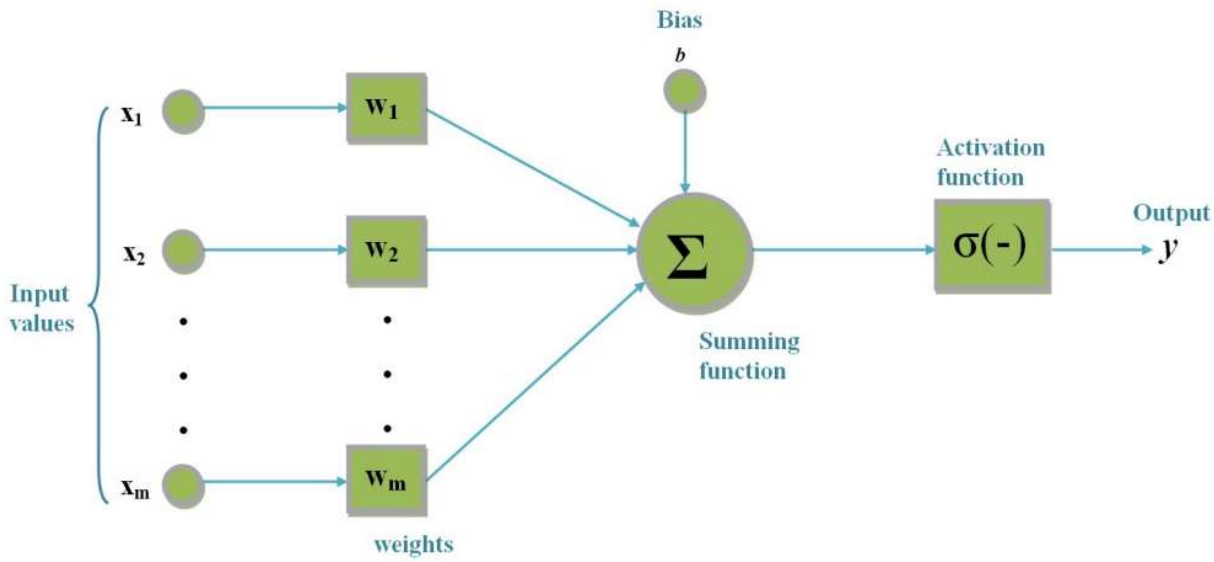

Figure 3. General structure of an artificial neuron

RESULTS

In this study, FFNN training is carried out by using FPA for the prediction of bitcoin price. Daily bitcoin data between 1 April 2022 and 30 June 2022 is used in applications. 80% of the data is utilized in the training process and the remaining 20% is used in the testing process. The bitcoin close price of the next day is estimated using the bitcoin close prices of the previous two days. The block diagram of the proposed system is given in Figure 4. Here, it is seen that the bitcoin price of the next day is estimated by using the bitcoin prices of the previous two days. Training of FFNN using FPA continues until the stopping criterion is met to construct the effective FFNN model. There is an error based on the difference between the real bitcoin price and the predicted bitcoin price. This error is used to measure the performance of the network. These data are scaled in the [0,1] range because the real bitcoin data are large. The mean squared error (MSE) is utilized as the error value. Population size, number of generations and switch probability, which are control parameter values of FPA, are chosen as 20, 2500 and 0.8, respectively. Each application is run 30 times to obtain statistical results.

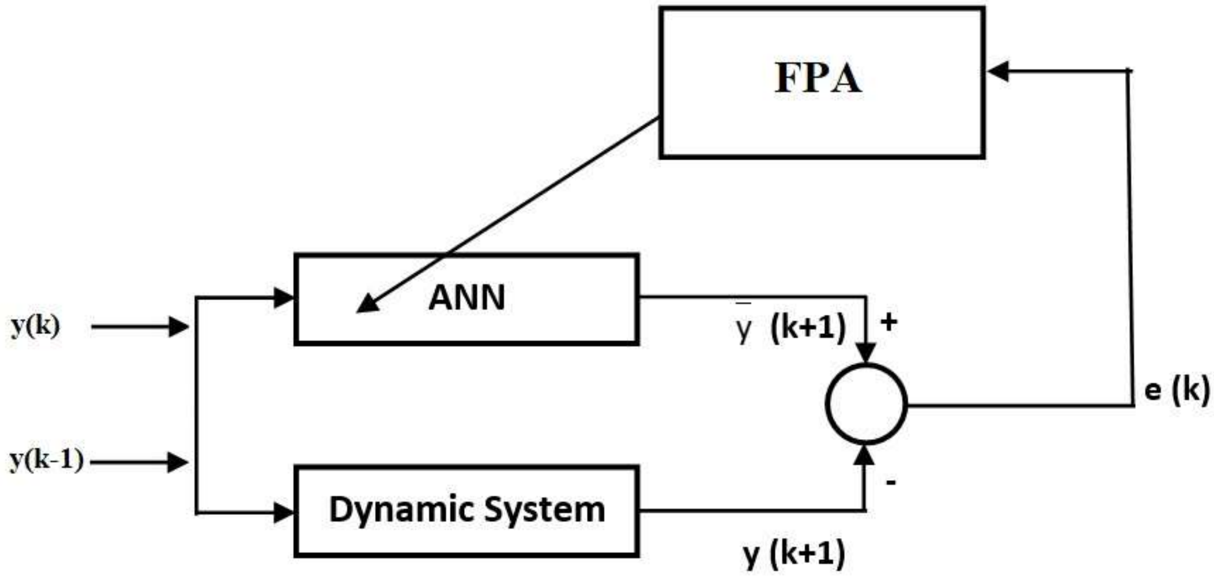

Figure 4. The block diagram of the proposed system

The training results obtained using FPA are given in Table 1. As can be seen, five different network structures are used. In Table 1, the best, worst and mean error values are obtained for each network structure. In addition, standard deviation values are also included. In general, as the number of neurons increases, the mean error values also improve. The best mean value is found as 0.00192667 with 2-15-1 network structure. Also, the best value is 0.00173942. Considering the obtained error values, it is seen that all standard deviation values are effective.

Table 1. Comparison of training results obtained with different network structures

Network Structure	Best	Mean	Worst	SD
2-3-1	0.00185954	0.00203741	0.00229653	0.000110411
2-6-1	0.00179283	0.00195329	0.00210788	6.99944e-05
2-9-1	0.00183487	0.00195252	0.00209181	6.40990e-05
2-12-1	0.00178016	0.00193906	0.00208940	7.18352e-05
2-15-1	0.00173942	0.00192667	0.00220745	0.000101565

Table 2 contains the test results. Table 2 has the same structure as Table 1. As in the training results, the best test error and best mean test error are found with 2-15-1 network structure. These values are 0.00079091 and 0.00143022 respectively. The effective standard deviation values are also reached in the test results.

Table 2. Comparison of test results obtained with different network structures

Network Structure	Best	Mean	Worst	SD
2-3-1	0.00085637	0.00156043	0.00284089	0.000452072
2-6-1	0.000887183	0.00146251	0.00274709	0.000402138
2-9-1	0.000828337	0.00146856	0.00220895	0.000397451
2-12-1	0.00083094	0.00151311	0.0025967	0.00043296
2-15-1	0.00079091	0.00143022	0.0026791	0.000493294

Figure 5 shows the comparison graphic of scaled real and predicted bitcoin prices. This figure is created by considering the best error value. As can be seen, there is a parallelism between the real output and the predicted output. When the relevant figure is evaluated within the limitations of the study, it is seen that the predicted bitcoin prices are very close to the real prices. Comparison of real and predicted outputs for test data are given in Table 3. As is known, test data is not used in the training process. In other words, an analysis is carried out on data that the network does not know at all during the testing phase. The low error rate is one of the important indicators that the model is successful. The mean absolute percentage error (MAPE) is used here. The MAPE value calculated by considering all test data is 2.13. This value shows that the model created for bitcoin price prediction is successful.

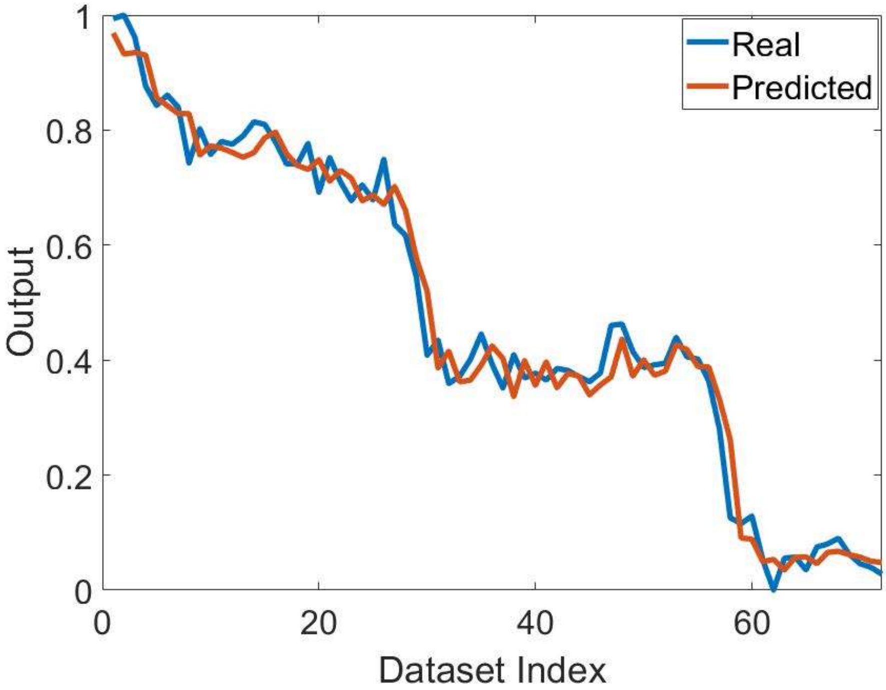

Figure 5. Comparison of scaled real and predicted bitcoin prices

Table 3. Comparison of real and predicted outputs for test data

No	Real	Predicted
1	43503.85	43484.52
2	40127.18	41134
3	39716.95	40249.57
4	39740.32	40662.34
5	39241.12	39979.58
6	38529.33	37837.42
7	35501.95	35075.55
8	29047.75	28142.83
9	30425.86	29367.48
10	30323.72	29568.17
11	28627.57	29427.74
12	29799.08	29894.26
13	31370.67	29973.28
14	28360.81	29488.44
15	20381.65	21063.24
16	20710.6	20742.61
17	21027.3	20819.54
MAPE		2.13

This study has limitations in terms of population size, number of generations, network structure, system inputs and selected data. It should be noted that these results are valid within these limitations. These limitations can be examined in different studies to achieve more effective results. Different population sizes can be tried. The effect of different number of generations on performance can be evaluated. Results can be obtained for more network structures. The input structure of the system can be changed. In the case of three or more inputs, the results obtained can be examined.

CONCLUSION

Predicting the prices of cryptocurrencies is one of the popular topics that has been studied recently. In this study, an approach based on FPA and FFNN is proposed for the price prediction of cryptocurrencies. The applications are performed for the largest cryptocurrency, bitcoin. Daily bitcoin data between 1 April 2022 and 30 June 2022 is used in applications. When the training and test results are evaluated together, it is seen that the proposed approach is effective in predicting the bitcoin price. More general comments can be made for the success of the proposed approach by performing analyzes on more cryptocurrencies in future studies.

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