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Forecast of the optimal activation function for the stablecoins using neural network

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Abstract

Stablecoins are a special case of cryptocurrencies which emerged as a response to the high volatility generated in the cryptocurrency market, using a pegging mechanism the stablecoins obtain more stability that could be simulated using artificial neural network (ANN). The objective of this paper is to determine the best activation function between sigmoid, linear or tanh and to forecast a period of 4 days using a basic ANN that could help an investor to determine an entrance or exit point in a stablecoin. As a main result, in all cases the sigmoid activation function is the best option using ANN, although using a basic ANN doesn't present an accurate forecast in all cases; therefore, it could be used as a supplementary tool that would help the investor to forecast the stablecoin market and improve their portfolio. This was obtained by comparing statistically 50 registers obtained of root-mean-square-error (RMSE).

Keywords: stablecoins, activation function, artificial neural network, forecast.

1. Introduction

Since the appearance of the first cryptocurrency in the financial market there has been generated two different positions: rejection or acceptance. One of the main financial precepts, the increase of profit with the lower risk, seems relegated by the cryptocurrency effect which joints both concepts: a high profitability with extreme high volatility as shown by their main representative, Bitcoin. But part of this risky factor, as any stock may have, comes the important fact that the cryptocurrencies lack of all international acknowledgment as the financial legend Warren Buffet stated:

> "Cryptocurrencies basically have no value and they don't produce anything. They don't reproduce, they can't mail you a check, they can't do anything, and what you hope is that somebody else comes along and pays you more money for them later on, but then that person's got the problem. In terms of value: zero". (Buffet W., 2020).

But the tendencies of acceptance have showed different perspectives with the growing market capitalization, the possibilities of launching a central bank digital currency (CBDC) by the governments (CNBC, 2021) and the full acceptance in El Salvador (BBC News Mundo, 2021), among others tendencies.

The virtual coins have established a new type of investing whether it could generate extraordinary profits or show unmerciful drop downs, for example a $1,000 USD invested in August 2010 in Bitcoin would have been worth in August 2017 an estimated of $50

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million but an investment in Ethereum at the beginning of 2017 would have experienced a dramatic free fall from $317 USD/coin to $0.1 USD/coin in one single day (CNBC, 2017) and adding to this uncertainty of extreme profitability and volatility, nowadays the massive wave of cryptocurrency market reached over 8,600 cryptocurrencies in circulation. The whole crypto-market capitalization has an approximate value of $1.9 trillion USD (Coinmarketcap.com, 2021). The top twelve have a market capitalization above $8.5 billion and within this dozen, exist two stablecoins: Tether and USD Coin (Hecht A., 2021).

Probably to diminish the volatility stablecoins seem attractive because they address the stability issues by adapting pegging mechanism to a fiat currency (e.g. USD) or a commodity (e.g. gold and silver) (Wang G. J. *et al.*, 2020). The main difference of the stablecoins from their cryptocurrency brothers is that their value depends upon a traditional financial asset such as US dollar, oil, natural gas and gold (Tarasova T. *et al.*, 2019). Lund (2018) was one of the first to speak about a digital version of Central Bank's fiat currency and the multiple benefits of issuing a fiat currency through a blockchain technology. Blockchain (2019) made a classification of the stablecoins that is shown in the figure 1:

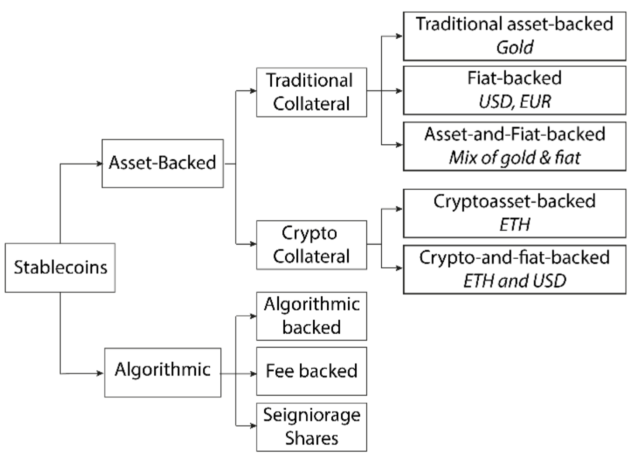

Figure 1. Classification of the stablecoins. (Blockchain, 2019)

Although their specific name and backup system, the stablecoins could exhibit a significant volatility that could deviate the cryptocurrency from its peg like the event on March 12, 2020 when the stablecoin DAI entered into a deflationary deleveraging caused by the pandemic SARS-COV 2. (Klages-Mundt A *et al.*, 2020). Such variability, as for all financial activities, could be studied under the different models created for cryptocurrency.

There have been several studies about the use of neural network (NN) for cryptocurrency value forecast, Kristjanpoller W. and Minutolo M. C. (2017) proposed a hybrid artificial neural network-generalized autoregressive conditional Heteroskedasticity (ANN-GARCH) model to analyze Bitcoin from 2011 to 2017.

Lahmiri S. and Bekiros S. (2018) proved that a long-short term memory (LSTM) deep learning system could efficiently predict the movements of three active cryptocurrencies showing that they followed a long-memory feature. Tarasova *et al.* (2020) generated a mathematical model that establishes a relation between the exchange rates of the cryptocurrency Bitcoin and the internet activities related to the specific cryptocurrency. Nakano M. and Takahashi A. (2020) used an AutoEncoder, which is a type of ANN using three hidden layers with rectified linear unit (ReLU) activation function, the model was created with 500 epochs in order to manage a portfolio that includes cryptocurrency. A comparison between different statistical machine learning approaches was done by Lahmiri S. and Bekiros S. (2019) which included the NN: Feed forward (FFNN), bayesian regularization (BRNN) and the radial basis function (RBFNN) concurring that the best predictive model for the Bitcoin high frequency was the FFNN and the BRNN.

Atsalakis G. S. (2018) compared a Neuro-Fuzzy controller named PATSOS against an ANN with one hidden layer and a sigmoid function as the activation function for Bitcoin. Lahmiri S. and Bekiros S. (2021) used a deep feed-forward neural network (DFFNN), that consists in a multiple-hidden layer structure to forecast a high-frequency trading fluctuation of Bitcoin, they used 3 hidden layers with 20 neurons each and a learning rate α of 0.001. McNally *et al.* (2018) compared for Bitcoin two types of NN: Bayesian optimized recurrent neural network (RNN) and LSTM, using 20 nodes, 10 to 10000 and 50 to 100 epochs respectively with a length in time of 24 days for the RNN and 100 days for the LSTM, they were cautious selecting the right parameters in order to avoid overfitting. The activation functions used were Tanh, ReLu and Sigmoid, where Tanh was the best activation function although it outperformed by a not significant margin. Nakano *et al.* (2018) made a study with multiple layered cases comparing also different activation functions, different inputs, different outputs and different additional technical indicators, they succeeded in the development of an improved Bitcoin's trading strategy for the 15 minutes time interval, as they explained; increasing the number of layers produced a more accurate result but there is a turning point in which the excessive number of layers cause trouble to the learning capabilities of the NN, also pointing out that the activation function ReLu is the most suited function for the high frequency trading.

At last, Lahmiri S., Saade R. G., Morin D. and Nebede F. (2020) used ANN in an ensemble predictive system with RBFNN and generalized regression neural network (GRNN) in conjunction with FFNN, using one hidden layer and a sigmoid activation function to estimate the daily trading volume of Bitcoin.

Considering the circumstances and the previous studies the objective of this paper is to determine the best activation function between sigmoid, linear or tanh that could help an investor to determine an entrance or exit point in a stablecoin. The paper is structured as follows: the main problem is established in the second section, the third and the fourth sections consist respectfully of the methodology used and the obtained results. In the fifth section an example is shown using the best activation function. The conclusions are provided in section 6.

2. Problem

Considering the mentioned perspectives and positions, in an investment portfolio to reduce risk is important to consider a diversification and for that, stablecoins have the support that could benefit the portfolio with a lower profit but also with a significantly reduced volatility. Having said that, the optimal portfolio could be achieved through the simulation and forecast using ANN.

It is important to point out that there are many studies related to the forecast of the cryptocurrency but the number reduce significantly when we are dealing with the stablecoins, therefore; and due to the stablecoins' newness, the studies that could be done are related more to an exploratory research. So, the main problem relies on the possibility to use ANN to forecast the stablecoins and if doing so, there are several parameters to consider, such as: the learning algorithm, number of hidden layers, number of nodes, number of epochs and the activation function. With the first three parameters as constant, it is sought the best fitting activation function that could eventually yield the best portfolio.

3. Methodology

The figure 2 shows the steps that were followed.

The methodology consists of a three main phases: preparation; modelling, verification and validation; analysis and forecast.

Preparation: Defines the concepts to use and connects them to the data. Consist of conceptualization, data gathering and data preparation.

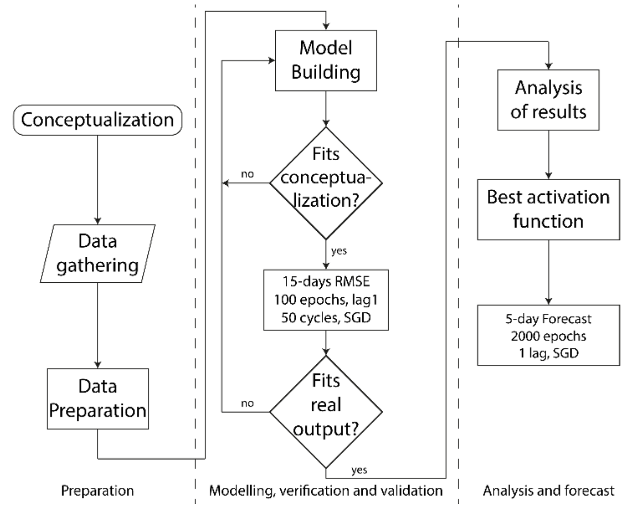

Figure 2. Based on Sachiko S. O. and Flores de la Mota I., (2019)

Conceptualization. - In this stage it was defined the objective of the project, it was analyzed the tools and the data required.

Data gathering. - It was downloaded the data from two main sources: www.coingecko.com and www.coindesk.com. Only the first 10 stablecoins with more market capitalization, according to www.coingecko.com, were considered for the present paper.

Data preparation. – To compare the activation function, it was considered the same date for each cryptocurrency starting the study on March 23, 2020 to February 16, 2021 that are equivalent to 331 days and it was only used the registered closing price. The crytocurrency TerraUSD was launched after March 23, 2020 therefore the data used in this case consists of 138 days.

Modelling, verification and validation: In this phase the ANN algorithm is determined to fit the conceptualization and to define the best activation function. Consist of Model building and the determination of the RMSE.

Model's programming. - It was used Python with the library nnet-ts to create the neural networks that consists of 10 stablecoins with 3 hidden layers with 7, 5 and 3 nodes respectively (see Appendix A: Python's ANN code). It was programmed 100 epochs and a lag of 1, the predicted results consisted of 15 days after February 16, 2020. The activation functions used for comparison were lineal, sigmoid and tanh. The nnet-ts library uses the sequential model from keras, an Application Programming Interface (API) for Python, in which the training process uses the optimizer stochastic gradient descent (SGD), that learns according to the equation 1 (Ketkar N. 2017; Bottou L. 2010):

Where θ is the collection of all the weights and bias terms of all the layers of the network; f_{NN} is the overall function representing the NN; $l\left(f_{NN}((x,\theta),y)\right)$ is the loss function and $\propto$ is the learning rate.

$$\theta_s = \theta_{s-1} - \alpha \cdot \nabla l\left(f_{NN}((x,\theta),y)\right) \tag{1}$$

A verification process comes after the model building in which the logic of the predicted 15 days was proved as expected to the conceptualization.

RMSE determination. - With the algorithm created, it was calculated the RMSE for each activation function. It is important to mention that the ANN consists of a black box that starts its approach randomly resulting in different outcomes every time the program runs, therefore a loop of 50 cycles were programmed to obtain different RMSE that could be statistically compared.

A validation process comes after the RMSE determination where it was concluded if the used model fits properly with the real output sustained by the RMSE calculated.

Analysis and forecast: Determines the best activation function and establishes an example. Consist of analysis of results; best activation function and runs an example using the best activation function for a 4-day forecast.

Analysis of results. – With the 50 RMSE obtained for each activation function in each stablecoin a basic statistical study was performed considering the mean, standard deviation, coefficient of variation and the skewness.

Best activation function. - The coefficient of variation was used to compare between the results to define the best activation function.

Forecast. - A 4-day simulation of the four lowest coefficients of variation was performed, considering all the historical data up to April 5, 2021 using the optimal activation function with 2000 epochs and a lag of 1, an average of 10 cycles were used as an output for the forecast in order to contemplate all the different results that present the ANN.

4. Results

As it is shown in figure 3 in all the stablecoins, the best activation function determined by the coefficient of variation, is the sigmoid.

Stablecoin	Symbol	Peg	Days	Best activation function	Mean RMSE	Standard Deviation	Coefficient of variation	Asymmetry coefficient
Tether	USDT	TC	331	sigmoid	9.40E-03	0.000807269	8.59E-02	-5.18E-02
USD Coin	USDC	TC	331	sigmoid	1.06E-02	0.001163203	1.09E-01	-8.29E-02
Binance USD	BUSD	TC	331	sigmoid	1.24E-02	0.00210092	1.70E-01	-6.97E-01
Dai	DAI	CC	331	sigmoid	1.13E-02	0.0015349	1.36E-01	-6.04E-01
TerraUSD	UST	A	138	sigmoid	1.22E-02	0.001781595	1.46E-01	2.79E-01
Paxos Standard	PAX	TC	331	sigmoid	1.03E-02	0.001149311	1.11E-01	-4.54E-01
HUSD	HUSD	TC	331	sigmoid	1.38E-02	0.002058824	1.49E-01	1.80E-01
TrueUSD	TUSD	TC	331	sigmoid	1.17E-02	0.001870885	1.61E-01	2.51E-01
Susd	SUSD	A	331	sigmoid	2.28E-02	0.001164376	5.11E-02	-3.86E-01
Neutrino USD	USDN	A	331	sigmoid	1.84E-02	0.002730081	1.48E-01	8.07E-02

TC	Traditional Collateral
CC	Crypto Collateral
A	Algorithmic

Figure 3. Results.

The mean and standard deviation as it is shown are extremely low and the one that presented the lowest coefficient of variation is the stablecoin SUSD with a value of 0.0511. Almost all the studied stablecoins present a relative asymmetry except for the cases of the stablecoins Binance USD and DAI that presented a moderate negative asymmetry.

		Mean RMSE		
Stablecoin	Symbol	Linear	Sigmoid	Tanh
Tether	USDT	0.0185171	0.009397	0.019178
USD Coin	USDC	0.0209743	0.0106343	0.0189123
Binance USD	BUSD	0.0201467	0.0123607	0.0209159
Dai	DAI	0.0241968	0.011288	0.0180561
TerraUSD	UST	0.038204	0.0121644	0.0242791
Paxos Standard	PAX	0.0189158	0.0103146	0.0187086
HUSD	HUSD	0.0311474	0.0137887	0.0172109
TrueUSD	TUSD	0.0222802	0.0116548	0.018753
Susd	SUSD	0.0275021	0.0227853	0.0281821
Neutrino USD	USDN	0.0421586	0.018401	0.0189871

Worst performer
Best performer

Figure 4. Comparative results.

In figure 4, a comparative table is shown in which it could be seen the performance of the three activation functions: linear, sigmoid and tanh. In almost all the cases, a 70%, the worst activation function was the linear. In the case of the stablecoin SUSD the figure 5 shows its main statistically values:

	SUSD RMSE's results		
Activation Function	**Linear**	**Sigmoid**	**Tanh**
Max	0.0388587	0.0251396	0.0386005
Min	0.019	0.0195959	0.0196469
Median	0.0272575	0.0229564	0.028017
Mode	#N/D	0.023622	0.0236854
		0.0231948	0.0340588
		0.0235797	
Range	0.0198587	0.0055437	0.0189536

Figure 5. SUSD statistical RMSE results.

In figure 5 the range in each activation function for the SUSD stablecoin represents a significant difference, also considering the coefficient of variation in figure 3 it is shown that using the sigmoid activation function the ANN is more accurate.

5. Forecast

According to the lowest coefficient of variation, the figure 6 shows a 4-day simulation that was performed to the stablecoins SUSD, Tether USDT, USD Coin USDC and Paxos Standard PAX using the sigmoid activation function, a lag of 1 with 2000 epochs. Due the nature of the ANN in the variation in results an average of 10 cycles was considered to the forecast.

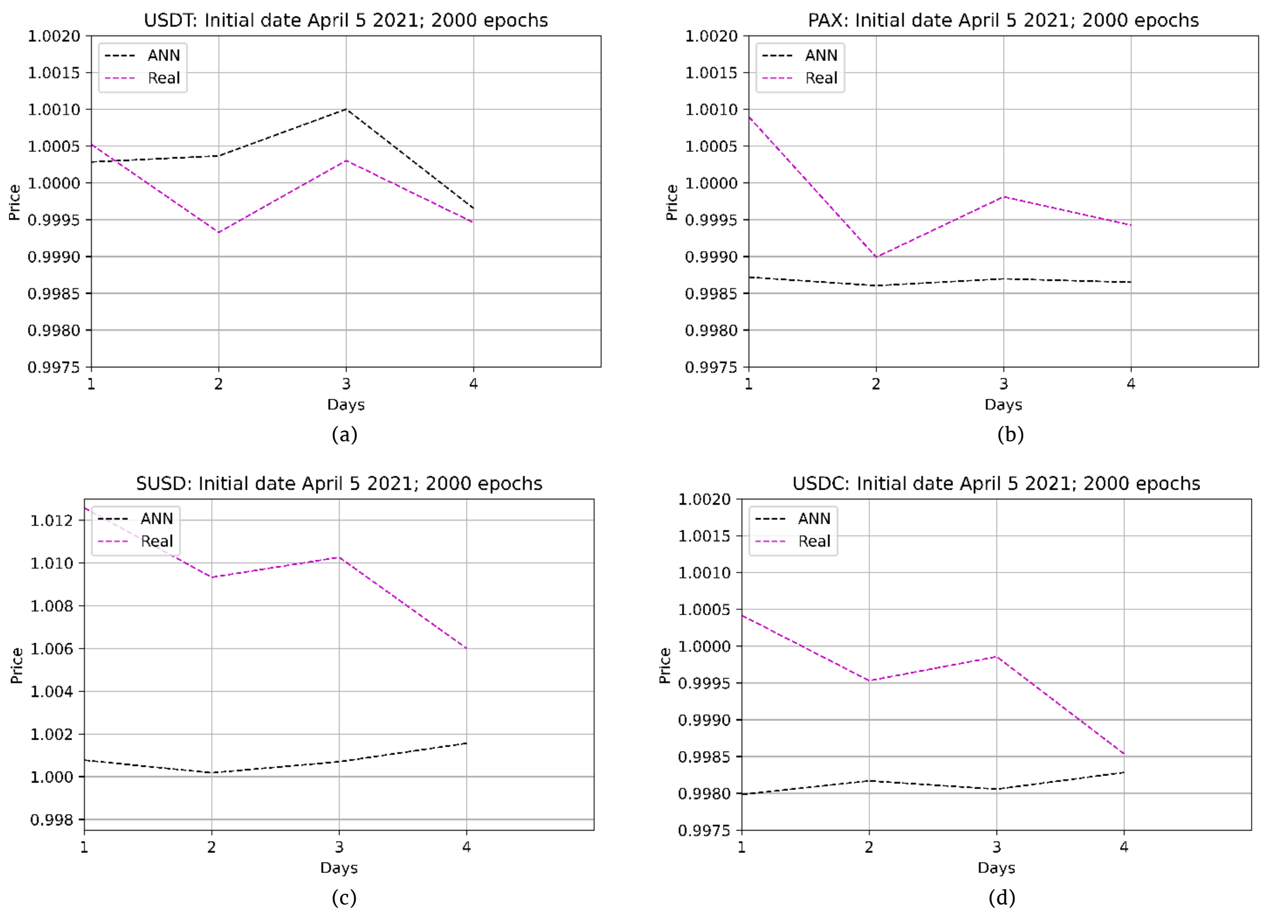

Figure 6. 4-day forecast using the sigmoid activation function of the stablecoins: (a) USDT, (b) PAX, (c) SUSD and (d) USDC

Stablecoin	Symbol	Days	Epochs	RMSE	Correlation
Tether	USDT	2208	2000	6.44E-04	0.52530434
Paxos Standard	PAX	922	2000	1.30E-03	0.91649374
Susd	SUSD	991	2000	9.14E-03	-0.5847367
USD Coin	USDC	913	2000	1.66E-03	-0.9808442

Figure 7. Forecast using all the historical data, the sigmoid activation.

The results of each stablecoin which includes all the historical data is expressed in figure 7. In all the stablecoins, using a bigger number of epochs cause a decrease in the correlation and an increase in the RMSE which indicates that the model could had suffered an over-learning process that deteriorates the forecast. Using less epochs resulted in a less accurate model with a bigger RSME. As it could be seen in the figure 6 the RMSE is lower than the RMSE showed in figure 4, after the fifth day in all the stablecoins, the model tends to loss its accuracy underperforming against the real values.

The forecast of Tether proved to be the most accurate with the lower RMSE, this could be attributed to the fact that the data consisted of more than double from the other stablecoins. The correlation was the smallest but the graphic in figure 4 (a) show with clarity the high and low points near the real value.

In the other three graphics the RMSE is very small but the graphics in figure 4 (b), (c) and (d) lack the accuracy to follow the real value; even though they have a high correlation the model had its complications to follow the minimal variations that exist in the stablecoins.

6. Conclusion

The present study defined that the best activation function using ANN for the stablecoins is the sigmoid, the forecast obtained in the case of the USDT stablecoin with 2000 epochs could be useful for an investor, but not all the results showed this particular utility. Using the most basic ANN it was proved that the stablecoins could be modeled better using the sigmoid activation function. Although the low RMSE presented on each programmed cycle, it would be hard for an investor to know the exact day to enter or exit the crypto-currency market as showed in the SUSD, USDC and Pax cases and this difficulty may be derived for the fact that the closing price of the stablecoins have very small difference (change of thousandths), also the fact that it could be necessary more data.

This paper was done using the basic ANN as an exploratory research in stablecoins to compare activation function obtaining a lowest 4-day RMSE of 0.000644 in the stablecoin USDT, in comparison with other relevant study done by Lamiri and Bekiros, 2021 about Bitcoin's high frequency data, the study had 65,535 observations with 80% for training and 20% for testing using DFFNN, the lowest RMSI obtained was of 1.4406 with a Levenberg-Marquardt algorithm which was truly accurate for the Bitcoin's volatility.

This means that the stablecoin market represents a difficulty to the basic ANN to successfully forecast the fore coming days. Nevertheless for an investor, that in advance knows that nowadays there is not any precise forecast method, the ANN could be used as a tool to complement different techniques, such as the Fibonacci's graphics or the tendencies showed with the Moving Average Convergence Divergence (MACD), Average Directional Index (ADX), Bollinger bands or Relative Strength Index (RSI) among others. And there is also a possible way to improve the ANN forecast model as a future research: First, the model could be used in an intra-day operation that brings more data to the model. Second, the present method used the nnet-ts in Python but it could be used a LSTM model, Elman NN or Jordan NN that could optimize the simulation using the pegging mechanism as an input and the volatility such as the Cboe Volatility Index (VIX). Third, the number of epochs that optimize the simulation could be calculated for each stablecoin considering the caution that with more epochs the result could perform worst.

For these possible ways to improve the use of ANN, in the present paper was proved that the best activation function to use in any case for the stablecoins is the sigmoid activation function between linear and tanh, although more studies and development in the NN proposed and tested are required to further improve the forecast that will benefit the investor's portfolio.

Appendix A. Python's ANN code

The libraries and the ANN's configuration code used:

```
from nnet_ts import *
import matplotlib.pyplot as plt
```

```
import numpy as np
from scipy import stats

from sklearn.metrics import mean_absolute_error
from sklearn import preprocessing

var_disparo = "sigmoid"
#var_disparo = "tanh"
#var_disparo = "linear"

scaler = preprocessing.MinMaxScaler(feature_range=(0,1))

 time_series = np.log(time_series)
 time_series = time_series.reshape(-1,1)
 time_series = scaler.fit_transform(time_series)
 time_series = time_series.reshape(-1)
 ahead = 4
 pred =[]

for i in range (0, ahead):
    neural_net = TimeSeriesNnet(hidden_layers = [7, 5, 3], activation_functions = [var_disparo, var_disparo, var_disparo])
    neural_net.fit(time_series, lag = 1, epochs = 100)
    pred.append(neural_net.predict_ahead ( n_ahead = 1))

pred1 = scaler.inverse_transform(pred)
pred1 = np.exp(pred1)
```

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