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Design of Ensemble Neural Networks with Type-3 Fuzzy Aggregation using Particle Swarm Optimization and Genetic Algorithms for Ethereum Prediction

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Abstract. In this study, an ensemble neural network (ENN) for Ethereum time series prediction was optimized using particle swarm optimization and genetic algorithms. Additionally, Type-1, Type-2, and Type-3 fuzzy inference systems, of both Mamdani and Sugeno types, were designed for achieving the prediction. The integration performed with these fuzzy systems is achieved by utilizing the results from optimizing the ENN with each optimization algorithm. In this case, the Ethereum data is the series being used for testing the proposal. This approach aims to minimize prediction error by combining the responses of the ENN with Type-1, Type-2, and Type-3 fuzzy systems, each consisting of five inputs and consequently 32 fuzzy rules are utilized. The results show that the Type-1, Type-2, and Type-3 fuzzy system approach yields an accurate prediction of the Ethereum series, as further validated by statistical tests on the results of the fuzzy systems.

Keywords. Ethereum time series, type-3 fuzzy system, time series ensemble neural networks, Mamdani model; Sugeno model.

1 Introduction

In the modern world, we live surrounded by data constantly changing over time. These temporal variations hide valuable information, from energy consumption patterns and stock prices to weather fluctuations and business performance metrics. Time series analysis, a specific branch of statistical and mathematical analysis, offer powerful tools to understand, model and predict these changes [1-3].

A time series is nothing more than a sequence of data collected at regular intervals of time, with each point reflecting a unique moment in history. For example, the daily sales of a product, the temperature measured every hour, or the amount of web traffic to a site per minute [29, 36, 38]. These series not only capture current behavior, but also reflect long-term trends, recurring seasonality, and unpredictable patterns [4-7].

In machine learning, neural networks have proven to be powerful tools for solving complex problems in various areas such as computer vision, natural language, and time series prediction [8, 9].

However, despite their ability to model nonlinear patterns and relationships, individual networks can be limited by problems, such as overfitting or insufficient ability to capture all of the variability in the data [10-12].

To address these limitations, the ensemble neural networks approach arises. This method combines multiple neural networks with the aim of improving the precision and robustness of predictions, taking advantage of the diversity of models [13, 14]. By integrating several networks, the aim is to reduce the overall error by compensating for individual weaknesses and consolidating their strengths [15-19].

Recurrent Neural Networks are a type of neural network designed to compute sequences of data, such as time series, text, audio, or any information where the order of the data is relevant [19-21].

Unlike traditional neural networks (such as feedforward networks), RNNs can store information from previous inputs thanks to recurrent connections in their hidden layers. This allows them to model temporal and sequential dependencies [21-27].

Particle swarm optimization, known as PSO, is a technique inspired by the collective behavior of natural systems, such as swarms of birds or colonies of insects. James Kennedy and Russell Eberhart introduced it in 1995 as an optimization method based on collective intelligence [27-30].

The PSO is a population algorithm, which means that it operates on a set of potential solutions called a "swarm." Each element of the swarm, recognized as a “particle,” expresses a possible solution to the problem. These particles move in the multidimensional search space guided by their own experience and that of the group, seeking to find the optimal solution or close to it [31].

Genetic algorithms (GAs) stand out as a powerful and inspiring technique. Based on biological evolution and natural selection, these algorithms simulate processes, such as reproduction, mutation, and selection to solve complex problems. Since their conceptualization in the 1970s, genetic algorithms have found applications in a wide variety of fields, including engineering, computational biology, system design, and business intelligence [32-34].

The appeal of genetic algorithms lies in their ability to explore large search spaces and find approximate solutions to problems that would otherwise be intractable using traditional methods. Just as nature uses evolution to adapt and optimize, these algorithms allow researchers and practitioners to address challenges such as path optimization, molecular structure prediction, and industrial design improvement, just to name a few [34-36].

The contribution of this study lies in the development of the neural ensemble and its optimization using PSO and GAs, along with the design of Type-1, Type-2, and Type-3 fuzzy systems to handle uncertainty in the prediction process of the ensemble neural network (ENN). This approach is tested with the forecast the Ethereum time series. A fuzzy system is proposed as a model for combining the outputs of the ENN for improving prediction. In previous research, Type-1 and Type-2 fuzzy systems were initially utilized, but this study introduces the Mamdani and Sugeno Type-3 fuzzy systems, consisting of 5 inputs and one output, labeled "predicted," with 32 fuzzy rules for time series prediction. Additionally, a comparison was made, demonstrating that Type-3 systems deliver favorable results for time series forecasting.

The article is structured as: Section 2 explains the fundamental concepts of Type-3 theory, Section 3 outlines the model, Section 4 presents the simulation results of the proposed method, and Section 5 provides the conclusions.

2 Type-3 Fuzzy Systems

Fuzzy sets are an extension of classical sets, allowing us to handle uncertainty and vagueness. They are based on fuzzy logic, which is a generalization of Boolean logic, and is utilized to model situations where concepts are imprecise or uncertain.

A type-1 fuzzy system is the most common and refers to those systems in which real numbers between 0 and 1 represent the memberships of the fuzzy sets. In these systems, the membership function (MF) is a single function that assigns a membership value for each element in the domain, and that value is a real number between 0 and 1 [32-35].

Type-2 fuzzy systems are a generalization of their type-1 counterparts. In a type-1 fuzzy system, each input and output value are represented by a single fuzzy number (given by a MF) [36-39]. However, in a type-2 fuzzy system, uncertainty is associated with the input and output values and the shape of the membership functions [40-42].

In type-3, the membership functions are even more complex, allowing degrees of uncertainty to be represented not only in the input values but also in the degrees of membership themselves. In this case the fuzzy system has a higher level of abstraction and is mainly used in advanced research and cases with a lot of imprecision or variability [43-47].

Interval Type-3 Fuzzy Logic Systems (IT3FLSs) are postulated below. In non-singleton interval type-3 Mamdani fuzzy logic system (NSIT3 MAMIT3FLS) [33, 34], the structure of Zadeh's kth generic rule is:

$$\begin{gathered} R_2^K{:}IFx_1{=}i\mathbb{F}_1^K and \dots and\ x_1\ is\ \mathbb{F}_i^k and \dots x_n\,, \\ is\ \mathbb{F}_n^k\,THENy_1 is\ \mathbb{G}_J^K, \dots ym\ is\ \mathbb{G}_m^K, \end{gathered} \tag{1}$$

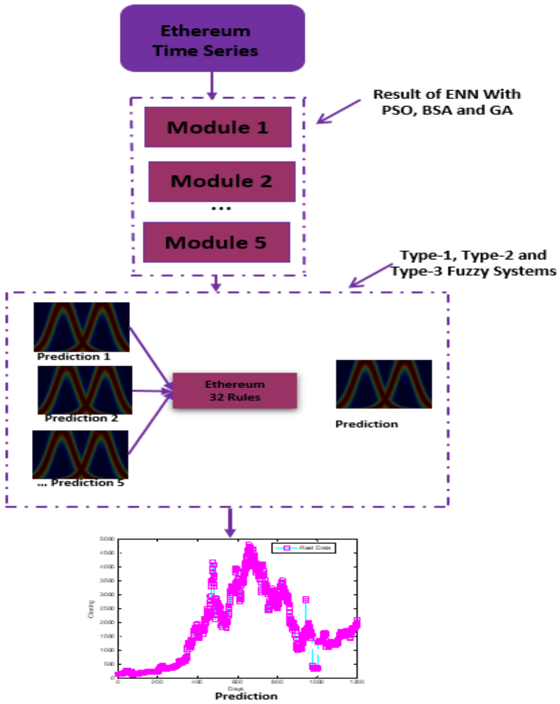

Fig. 1. Designed model

where i=1…, n (number of inputs), j=1…, m (number of outputs) y k = 1…, r (number of rules). In the approach based on Zadeh rules and a MAMIT3FLS, we must represent the rule antecedents as a fuzzy relation $\mathbb{A}^k$, using the Cartesian product with interval type-3 fuzzy sets (IT3 FSs), $\mathbb{F}_1^K$, and the implication with the consequent of the j output, $\mathbb{G}_j^k$; then, the fuzzy relationship ij of rule $\mathbb{R}$ is postulated as:

$$\mathbb{A}^k = \mathbb{F}_1^K \text{ X} \ldots \text{ X } \mathbb{F}_n^k, \tag{2}$$

$$\mathbb{R}_j^k = \mathbb{A}^k \rightarrow \mathbb{G}_j^k, \tag{3}$$

when is $\mathbb{R}_j^k$ described as membership of the rules, $\mu_{\mathbb{R}_j^k}(x, y_j)$ is formulated as:

$$\mu_{\mathbb{R}_j^k}(x, y_j) = \mu_{\mathbb{A}^k} \rightarrow \mathbb{G}_j^k(x, y_j). \tag{4}$$

Consequently, when Mamdani implication is used, $\mathbb{A}^k \rightarrow \mathbb{G}_j^k$, with the multiple antecedents $\mathbb{A}k$, and consequents $\mathbb{A}^k$, these are connected by the meet operator (⊓), then:

$$\mu_{\mathbb{A}^k \rightarrow \mathbb{G}_j^k}(x, y_j) = \mu_{\mathbb{F}_1^k} \times \ldots \times \mathbb{F}_n^k \rightarrow \mathbb{G}_j^k(x, y_j)\ \mu_{\mathbb{F}_1^k} \times \ldots \times \mathbb{F}_n^k\ (x)\ \sqcap \mathbb{G}_j^k(y_j), \tag{5}$$

$$\mu_{\mathbb{A}^k \rightarrow \mathbb{G}_j^k}(x, y_j) = \mu_{\mathbb{F}_1^k}(x_1) \sqcap \ldots \sqcap \mu\mathbb{F}_n^k(x_n) \sqcap \mathbb{G}_j^k(y_1) = [\sqcap_{i=1}^n \mu_{\mathbb{F}_1^k}(x_1)] \sqcap \mu_{\mathbb{G}_j^k}(y_j). \tag{6}$$

Input n-dimensional, is given by the fuzzy relationship $\mathbb{A}_X$Whose MF is:

$$\mathbb{A}_{x'}(\text{x}) = \mu_{\mathbb{X}_1}(x_1|x_1') \sqcap \ldots \sqcap \mu_{\mathbb{X}_n}(x_n|x_n') = \sqcap_{i=1}^{n} = \mu_{\mathbb{X}_i}(x_1|x_1'), \tag{7}$$

each relation of the fuzzy rule $\mathbb{R}_j^k$ determines a fuzzy set of $\mathbb{A}_X$ the consequent rule $\mathbb{B}_j^k = \mathbb{A}_{x'}$ o $\mathbb{R}_j^k$ in Y t such that:

$$\mu_{\mathbb{B}_j^k}(y_j|\boldsymbol{x}') = \mu_{\mathbb{A}_j^k} \text{ o } \mathbb{R}_j^k(y_j|\boldsymbol{x}') = \sup[\mathbb{A}_{x'}(\text{x}) \sqcap \mu_{\mathbb{A}_j^k} \rightarrow \mathbb{G}_j^k(x, y_j)],\ \text{y} \in Y. \tag{8}$$

3 Proposed Model

The method consists of creating the recurrent ENN and optimization with PSO and GAs. The optimization was carried out regarding the number of modules, layers, and neurons of the ENN. The outputs of these ENNs are combined with the fuzzy systems.

The method consists of the optimization of ENNs with PSO and GA, and the outputs of these ENNs are combined with type-2 and type-3 fuzzy systems. Figure 1 shows the architecture of the model, where the results of the ENNs for Ethereum are integrated with a fuzzy system, and in this way, we obtain the final prediction and the error.

Figure 1 illustrates the model, which begins with the historical data. The optimization algorithm, based on particle swarms, then determines the number of modules in the ENN, ranging from 1 to 5. It also identifies the number of layers within each module, which can be between 1 and 3, and the number of neurons per layer, ranging from 1 to 3. The responses from the neural network ensemble are combined using an integration method, where

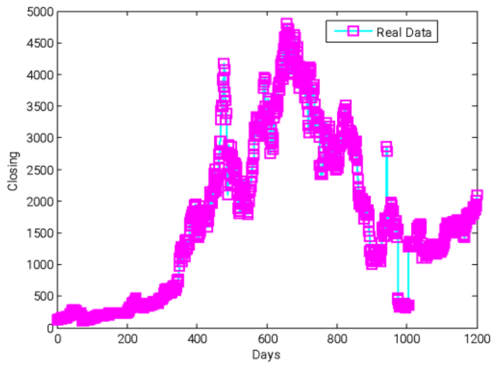

Fig. 2. Ethereum time series

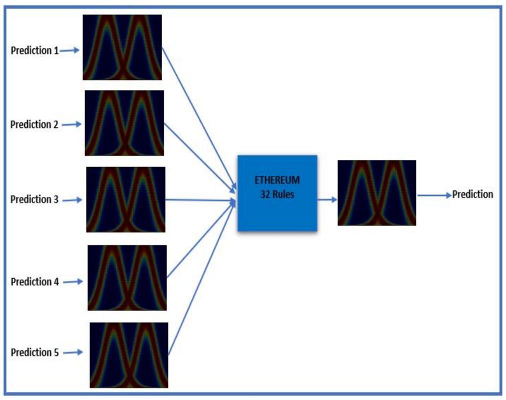

Fig. 3. Type-3 Fuzzy System for the Ethereum series

Mamdani and Sugeno Type-3 fuzzy systems are applied. Both the input and output variables of the fuzzy system utilize Gaussian membership functions.

Performance of the Type-3 fuzzy integration is evaluated with various MFs for the fuzzy rules. For the Type-3 fuzzy integrators, two MFs, labeled "low prediction" and "high prediction," are used for both inputs and outputs of the fuzzy system. These MFs are of Gaussian, Generalized Gbell, Trapezoidal, and Triangular types, with different lag and scale parameters, as detailed in the tables, to achieve better time series prediction.

If we have 5 modules in the ENN, the fuzzy system includes 5 input variables. The rules applied are based on the potential combinations determined by the number of inputs and MFs in the fuzzy system. Given 5 inputs and two MFs for each, there are 32 possible rule combinations.

3.1 Time Series Prediction

Ethereum (ETH) is one of the largest cryptocurrencies following Bitcoin. It is a decentralized platform that enables the development of smart contracts and decentralized applications (dApps). ETH serves as the fuel for transactions and operations within the Ethereum network. Initial coin sale (ICO) was held in 2014, where approximately $18 million was raised. 2015: It started with a price of approximately 0.30 USD per ETH. 2017: ETH reached $1,400 in January 2018 during the cryptocurrency boom. 2021: Thanks to the surge in interest in smart contracts and DeFi (decentralized finance) applications, it reached an all-time high price of $4,891 in November 2021. 2022-2023: The price fluctuated due to market volatility, ranging between $1,000-2,000.

Ethereum time series: This work determines two periods to evaluate the proposed method. From 01/01/20 to 04/14/23, we plot the historical data in the x-axis, in this case, the day, and in the y-axis the closing of Ethereum (as shown in Figure 2). In the experiments, 70% of the data were used for the ensemble neural network training and 30% to test the network [48]. The type-3 system for integrating the outputs of the ENN is in Figure 3.

4 Simulation Results

This section presents the experimental results and comparisons for the Ethereum Time Series, using a (Type-1, Type-2, and Type-3) fuzzy integration method and Comparisons between particle optimization and the genetic algorithms are also shown.

Statistical tests were performed with the results of two fuzzy systems type-1, type- 2 and type-3 of Mamdani and Sugeno type, also using the different Gaussian, generalized bell and triangular systems.

Table 1 displays the rules of the fuzzy system, which are based on 5 inputs, each having two membership functions. This results in 32 possible fuzzy rules. These rules are applied to Type-1, Type-2, and Type-3 fuzzy systems, where "Lw" represents low and "Ht" represents high.

Table 1. Fuzzy rules for predicting Ethereum

Pred 1	Pred 2	Pred 3	Pred 4	Pred 5	Prediction
Lw	Lw	Lw	Lw	Lw	Lw
Ht	Ht	Ht	Ht	Ht	Ht
Lw	Lw	Lw	Lw	Ht	Lw
Ht	Ht	Ht	Ht	Lw	Ht
Lw	Lw	Lw	Ht	Ht	Lw
Ht	Ht	Ht	Lw	Lw	Ht
Lw	Lw	Ht	Ht	Ht	Ht
Ht	Ht	Lw	Lw	Lw	Lw
Lw	Ht	Ht	Ht	Ht	Ht
Ht	Lw	Lw	Lw	Ht	Lw
Lw	Ht	Lw	Ht	Lw	Lw
Ht	Lw	Ht	Lw	Ht	Ht
Lw	Ht	Lw	Lw	Lw	Lw
Ht	Lw	Ht	Ht	Ht	Ht
Lw	Lw	Ht	Lw	Lw	Lw
Ht	Ht	Lw	Ht	Ht	Ht
Lw	Lw	Lw	Ht	Lw	Lw
Ht	Ht	Ht	Lw	Ht	Ht
Lw	Lw	Ht	Ht	Lw	Lw
Ht	Ht	Lw	Lw	Ht	Ht
Lw	Ht	Ht	Lw	Lw	Lw
Ht	Lw	Lw	Ht	Ht	Ht
Lw	Lw	Ht	Ht	Lw	Lw
Ht	Ht	Lw	Lw	Ht	Ht
Lw	Ht	Ht	Lw	Ht	Ht
Ht	Lw	Lw	Ht	Ht	Lw
Lw	Ht	Lw	Ht	Lw	Lw
Ht	Lw	Ht	Lw	Ht	Ht
Lw	Ht	Ht	Ht	Ht	Lw
Ht	Lw	Lw	Ht	Ht	Lw
Lw	Ht	Lw	Ht	Ht	Ht
Ht	Lw	Ht	Lw	Lw	Lw

Table 2 displays the results of PSO from 29 experiments, but only 10 best results are shown. The prediction error is 0.010604 and is shown in row 1.

In this table, NM refers to the number layers, NN means the number neurons, and PE indicates the prediction error and the average Duration of the experiments is: 0.2:12:35.

Table 3 shows the results of the Mamdani type-1 fuzzy integration using the Gaussian, generalized bell, triangular, and trapezoidal membership functions and AV represents the average prediction error of 29 experiments using the PSO.

Table 4 demonstrates the result of Integration with the Sugeno type-1 fuzzy system with the

Table 2. PSO results for the ERNN for Ethereum time series.

NM	NL	NN	PE
2	1	11,17, 23,4	0.010604
2	2	14, 24	0.010645
3	2	24,18,12 24,22,18, 25,8,20	0.010626
2	3	3,4,20 9,12,17	0.010634
2	2	6,9,3,16	0.10631
2	2	15,20,22,9	0.010613
2	2	18,12	0.0010628
3	1	11,4,26	0.010642
2	2	13,13,8,20	0.0106329
2	2	11,17,19,4	0.010646

Table 3. Results of Mamdani type-1 (PSO).

Gaussian	Bell Generalized	Triangular	Trapezoidal
0.2716	0.2470	0.2563	0.2598
0.2717	0.2470	0.2556	0.2598
0.2716	0.2470	0.2562	0.2598
0.2716	0.2470	0.2563	0.2598
0.2716	0.2470	0.2563	0.2599
0.2716	0.2470	0.2563	0.2599
0.2716	0.2471	0.2563	0.2597
0.2717	0.2470	0.2562	0.2598
0.2717	0.2470	0.2562	0.2598
0.2716	0.2470	0.2563	0.2598
0.2716	**0.2470**	**0.2561**	**0.2598**

Table 4. Results of Sugeno type-1 (PSO)

Gaussian	Bell Generalized	Triangular	Trapezoidal
0.5336	0.5971	0.6248	0.5764
0.5536	0.5978	0.6258	0.5765
0.5536	0.5971	0.6248	0.5763
0.5536	0.5971	0.6248	0.5764
0.5536	0.5972	0.6248	0.5764
0.5536	0.5972	0.6248	0.5764
0.5536	0.5972	0.6248	0.5764
0.5536	0.5972	0.6248	0.5765
0.5536	0.5971	0.6248	0.5764
0.5536	0.5971	0.6247	0.5764
0.5587	**0.6024**	**0.6301**	**0.5816**

Gaussian, generalized bell, triangular, and trapezoidal MFs and AV represents the average prediction error of 29 experiments using the PSO.

Table 5 demonstrates the results of the Mamdani type-2 fuzzy integration using the Gaussian, generalized bell, triangular, and trapezoidal membership functions and AV represents the average prediction error of 29 experiments using PSO.

Table 6 shows the results of the Sugeno type-2 fuzzy integration using the Gaussian, generalized bell, triangular, and trapezoidal membership functions and AV represents the average prediction error of 29 experiments using PSO.

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Table 5. Results of type-2 fuzzy Integration (PSO)

Gaussian	Bell Generalized	Triangular	Trapezoidal
0.4138	0.4335	0.3390	0.4596
0.4130	0.4333	0.3984	0.4600
0.4138	0.4335	0.3990	0.4596
0.4137	0.4335	0.3990	0.4596
0.4137	0.4335	0.3990	0.4596
0.4138	0.4335	0.3990	0.4596
0.4137	0.4335	0.3990	0.4596
0.4137	0.4335	0.3990	0.4596
0.4138	0.4335	0.3990	0.4596
0.4138	0.4335	0.3990	0.4596
0.4204	**0.4385**	**0.4019**	**0.4647**

Table 6. Results of Sugeno type-2 fuzzy Integration (PSO)

Gaussian	Bell Generalized	Triangular	Trapezoidal
0.1386	0.0606	0.1483	0.1484
0.1386	0.0606	0.1483	0.1483
0.1386	0.0606	0.1483	0.1484
0.1385	0.0606	0.1483	0.1483
0.1386	0.0606	0.1483	0.1483
0.1386	0.0606	0.1483	0.1483
0.1386	0.0606	0.1483	0.1486
0.1386	0.0606	0.1483	0.1484
0.1386	0.0606	0.1483	0.1483
0.1384	0.0606	0.1483	0.1484
0.13852	**0.0606**	**0.1483**	**0.14834**

Table 7. Results integration Mamdani type-3 Gaussian membership functions (PSO)

Experiments	Duration	Prediction Error
1	01:18:34	0.3962
2	01:18:39	0.3962
3	01:19:33	0.3962
4	01:18:16	0.3962
5	01:18:16	0.3747
6	01:19:51	0.3962
7	01:19:16	0.3962
8	01:17:49	0.3962
9	01:18:21	0.3752
10	01:17:46	0.3753
AV	**01:19:23**	**0.3824**

Table 7 demonstrates the results of integration with the Mamdani type-3 fuzzy system with Gaussian MFs, and AV represents the average time and prediction error of 29 experiments using PSO.

Table 8 shows the results of the Mamdani type-3 fuzzy integration using the Generalized Gbell membership function and AV represents the average time and prediction error of 29 experiments using PSO.

Table 8. Results integration Mamdani type-3 Gbell Membership functions

Experiment	Duration	Prediction Error
1	01:18:34	0.3358
2	01:18:34	0.356
3	01:18:35	0.3559
4	01:18:54	0.3358
5	01:18:16	0.3559
6	01:19:11	0.3358
7	01:19:16	0.3358
8	01:17:49	0.3558
9	01:18:21	0.3559
10	01:18:34	0.3358
AV	**01:18:29**	**0.3461**

Table 9. Results integration Mamdani type-3 Triangular Membership functions

Experiments	Duration	Prediction Error
1	00:47:04	0.5379
2	00:47:13	0.5380
3	00:47:07	0.5379
4	00:47:10	0.5379
6	00:49:19	0.5382
7	00:46:35	0.5379
8	00:46:31	0.5379
10	00:46:55	0.5379
16	00:47:27	0.5379
30	00:47:28	0.5379
AV	**00:48:22**	**0.5380**

Table 10. Results integration Mamdani type-3 Trapezoidal Membership functions.

Experiments	Duration	Prediction Error
1	00:42:42	0.4518
2	00:41:23	0.4517
3	00:42:05	0.4517
4	00:47:47	0.4517
5	00:41:00	0.4519
6	00:41:59	0.4518
7	00:41:00	0.4517
8	00:42:01	0.4517
9	00:42:04	0.4517
10	00:42:06	0.4518
AV	**00:43:10**	**0.4517**

Table 9 shows the results of the Mamdani type-3 fuzzy integration using the Generalized Gbell membership function and AV represents the average time and prediction error of 29 experiments using PSO.

Table 10 demonstrates the integration results with the Mamdani type 3 fuzzy system with Trapezoidal MFs, and AV represents the average time and prediction error of 29 experiments using PSO.

Table 11 demonstrates the integration with the Sugeno type-3 fuzzy system with Gaussian MFs, and AV represents the average time and prediction error of 29 experiments using PSO.

Table 12 presents the integration results of the Sugeno Type-3 Fuzzy system Using Generalized Gbell membership functions and AV represents the time and average prediction error of 29 experiments using PSO.

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Table 11. Results integration Sugeno type-3 Gaussian Membership functions

Experiments	Duration	Prediction Error
1	00:00:03	0.0458
2	00:00:03	0.0458
3	00:00:03	0.0458
4	00:00:03	0.0459
5	00:00:03	0.0459
6	00:00:03	0.0458
7	00:00:03	0.0458
8	00:00:03	0.0458
9	00:00:03	0.0458
10	00:00:03	0.0459
AV	**00:00:03**	**0.04581**

Table 12. Results integration type-3 Sugeno Gbell Membership functions

Experiment	Duration	Prediction Error
1	00:00:03	0.0371
2	00:00:03	0.0371
3	00:00:03	0.0372
4	00:00:03	0.0371
5	00:00:03	0.0373
6	00:00:03	0.371
7	00:00:03	0.0371
8	00:00:03	0.0372
9	00:00:03	0.0371
10	00:00:03	0.0372
AV	**00:00:03**	**0.0371**

Table 13. Results integration type-3 Sugeno Triangular Membership functions

Experiment	Duration	Prediction Error
1	00:00:03	0.0527
2	00:00:03	0.0528
3	00:00:03	0.0527
4	00:00:05	0.0527
5	00:00:03	0.0527
6	00:00:07	0.0529
7	00:00:08	0.0528
8	00:00:03	0.0527
9	00:00:03	0.0527
10	00:00:03	0.0527
AV	**00:00:03**	**0.0527**

Table 13 demonstrates the integration with the Sugeno type-3 fuzzy system with Triangular MFs, and AV represents the average time and prediction error of 29 using PSO.

Table 14 presents the integration results of the Sugeno Type-3 Fuzzy system Using Trapezoidal MFs and AV represents the average time and prediction error of 29 experiments using PSO.

Table 15 presents the results of the GA based on 30 experimental runs. However, only the top 10 best results are displayed in the table.

The prediction Error of 0.010501 and shown in row 7. In this table, NM refers to the number layers, NN means the number of neurons, and PE indicates the prediction.

Table 16 represents the results of the Mamdani type-1 fuzzy system with different MFs and AV

Table 14. Results integration type-3 Mamdani Trapezoidal functions

Experiment	Duration	Prediction Error
1	00:00:03	0.0371
2	00:00:03	0.0371
3	00:00:03	0.0372
4	00:00:03	0.0371
5	00:00:03	0.0373
6	00:00:03	0.371
7	00:00:03	0.0371
8	00:00:03	0.0372
9	00:00:03	0.0371
10	00:00:03	0.0372
AV	**00:00:03**	**0.0371**

Table 15. GA results for the ERNN for Ethereum Time Serie

Pm	Pc	NM	NL	NN	PE
0.05	1	2	3	9,13,24,9,13,24	0.010542
0.08	1	2	1	12,12	0.010545
0.02	0.04	2	2	18,15,18,15	0.010514
0.06	0.9	2	2	20,15,20,15	0.010533
0.8	0.9	2	3	20,1,28, 30,1,26	0.010516
0.3	0.9	2	1	19,19	0.10522
0.03	0.5	2	2	2,8,4,19	0.10501
0.09	0.5	2	3	28,1.21, 28,1,21	0.010498
0.01	1	2	2	10,5,10,5	00.010531
0.07	0.9	2	2	29,24, 29,24	0.010523

Table 16. Results of type-1 fuzzy Integration (GA)

Gaussian	Bell Generalized	Triangular	Trapezoidal
0.2715	0.2469	0.2562	0.2603
0.2715	0.2469	0.2562	0.2603
0.2698	0.2458	0.2562	0.2603
0.2698	0.2458	0.2562	0.2603
0.2716	0.2470	0.2563	0.2603
0.2716	0.2470	0.2563	0.2603
0.2716	0.2470	0.2562	0.2603
0.2697	0.2458	0.2554	0.2599
0.2716	0.2458	0.2563	0.2603
0.2698	0.2458	0.2556	0.2599
0.2708	**0.2464**	**0.2561**	**0.2602**

represents the average time and prediction error of 29 experiments using a GA.

Table 17 represents the Sugeno type-1 fuzzy system results with different MFs and AV represents the average time and prediction error of 29 experiments using a GA.

Table 18 presents the results of the Mamdani type-2 fuzzy system with various MFs, where AV indicates the average time and prediction error from 29 experiments conducted using a Genetic Algorithm.

Table 19 displays the results of the Sugeno type-2 fuzzy system with various MFs, where AV

Table 17. Results of type-1 Sugeno fuzzy Integration

Gaussian	Bell Generalized	Triangular	Trapezoidal
0.1322	0.1440	0.0588	0.1583
0.1322	0.1440	0.0589	0.1584
0.1323	0.1439	0.0589	0.1585
0.1324	0.1439	0.0589	0.1583
0.1325	0.1440	0.0588	0.1583
0.1322	0.1440	0.0589	0.1582
0.1322	0.1440	0.0589	0.1583
0.1325	0.1439	0.0589	0.1583
0.1325	0.1440	0.0589	0.1583
0.1325	0.1439	0.0587	0.1583
0.1323	**0.1439**	**0.0588**	**0.1583**

Table 18. Results of type-2 fuzzy Integration (GA)

Gaussian	Bell Generalized	Triangular	Trapezoidal
0.4152	0.4734	0.3995	0.4996
0.4153	0.4733	0.3999	0.4997
0.4152	0.4732	0.3999	0.4997
0.4152	0.4733	0.3998	0.4997
0.4151	0.4733	0.3998	0.4996
0.4151	0.4732	0.3997	0.4996
0.4152	0.4733	0.3997	0.4996
0.4152	0.4733	0.3997	0.4996
0.4153	0.4733	0.3997	0.4997
0.4152	0.4734	0.3998	0.4997
0.4152	**0.47899**	**0.3997**	**0.4996**

Table 19. Results of type-2 fuzzy Integration (GA)

Gaussian	Bell Generalized	Triangular	Trapezoidal
0.5668	0.6061	0.6506	0.6213
0.5667	0.6061	0.6503	0.6210
0.5666	0.6062	0.6526	0.6227
0.5666	0.6062	0.6526	0.6277
0.5666	0.6062	0.6503	0.6210
0.5566	0.6063	0.6503	0.6210
0.5667	0.6062	0.6503	0.6211
0.5670	0.6061	0.6540	0.6240
0.5669	0.6062	0.6503	0.6210
0.5669	0.6062	0.6536	0.6237
0.5656	**0.6061**	**0.6514**	**0.6224**

indicates the average prediction error from 29 experiments conducted using a Genetic Algorithm.

Table 20 shows the integration results of the Mamdani Type-3 Fuzzy system using Gaussian MFs, with AV representing the average time and prediction error from 29 experiments conducted with a Genetic Algorithm. Table 21 presents the integration results of the Mamdani Type-3 Fuzzy system Using Generalized Bell membership functions and AV represents the average time and prediction error of 29 experiments using a Genetic Algorithm. Table 22 presents the integration results of the Mamdani Type-3 Fuzzy system Using Trapezoidal MFs and AV represents the average time and prediction error of 29 experiments using a Genetic Algorithm. Table 23 presents the integration results of the Mamdani Type-3 Fuzzy system Using Trapezoidal MFs and AV represents the average time and prediction error of 29 experiments using a Genetic Algorithm.

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Table 19. Results of type-2 fuzzy Integration (GA)

Gaussian	Bell Generalized	Triangular	Trapezoidal
0.5668	0.6061	0.6506	0.6213
0.5667	0.6061	0.6503	0.6210
0.5666	0.6062	0.6526	0.6227
0.5666	0.6062	0.6526	0.6277
0.5666	0.6062	0.6503	0.6210
0.5566	0.6063	0.6503	0.6210
0.5667	0.6062	0.6503	0.6211
0.5670	0.6061	0.6540	0.6240
0.5669	0.6062	0.6503	0.6210
0.5669	0.6062	0.6536	0.6237
0.5656	**0.6061**	**0.6514**	**0.6224**

Table 20. Results integration type-3 Mamdani Gaussian Membership functions (GA)

Experiment	Duration	Prediction Error
1	00:04:07	0.3752
2	00:04:07	0.3751
3	00:03:58	0.3752
4	00:04:02	0.3752
5	00:04:01	0.3752
6	00:04:01	0.3752
7	00:03:57	0.3752
8	00:04:05	0.3758
9	00:04:00	0.3753
10	00:04:03	0.3751
AV	**00:03:59**	**0.37525**

Table 21. Results integration type-3 Mamdani Gbell Membership functions (GA)

Experiment	Duration	Prediction Error
1	00:05:58	0.9472
2	00:06:03	0.9473
3	00:06:03	0.9473
4	00:06:06	0.9473
5	00:06:01	0.9472
6	00:06:02	0.9472
7	00:06:06	0.9473
8	00:05:58	0.9472
9	00:05:42	0.9473
10	00:05:46	0.9472
AV	**00:05:42**	**0.9472**

Table 22. Results integration type-3 Mamdani Triangular Membership functions (GA)

Experiment	Duration	Prediction Error
1	01:21:13	0.5472
2	01:20:30	0.5471
3	01:20:30	0.5472
4	01:21:32	0.5473
5	01:19:09	0.5471
6	01:19:06	0.5472
7	01:18:28	0.5472
8	01:20:00	0.5472
9	01:20:47	0.5472
10	01:19:00	0.5473
AV	**01:19:56**	**0.5471**

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Table 23. Results integration type-3 Mamdani Trapezoidal Membership functions (GA)

Experiment	Duration	Prediction Error
1	00:47:10	0.5041
2	00:47:06	0.5041
3	00:47:05	0.5041
4	00:47:26	0.5041
5	00:47:19	0.5042
6	00:47:25	0.5041
7	00:47:49	0.5042
8	00:46:31	0.5040
9	00:48:27	0.5042
10	00:46:18	0.5041
AV	**00:46:58**	**0.5041**

Table 24. Results integration type-3 Sugeno Gaussian membership functions GA

Experiment	Duration	Prediction Error
1	00:00:03	0.0606
2	00:00:03	0.0607
3	00:00:03	0.0607
4	00:00:03	0.0606
5	00:00:03	0.0607
6	00:00:03	0.0606
7	00:00:03	0.0605
8	00:00:03	0.0606
9	00:00:03	0.0605
10	00:00:03	0.0608
AV	**00:00:06**	**0.06062**

Table 25. Results integration type-3 Sugeno Gbell membership functions GA

Experiment	Duration	Prediction Error
1	00:00:04	0.0405
2	00:00:07	0.0405
3	00:00:11	0.0405
4	00:00:03	0.0406
5	00:00:07	0.0407
6	00:00:03	0.0406
7	00:00:07	0.0407
8	00:00:04	0.0405
9	00:00:07	0.0405
10	00:00:11	0.0405
AV	**00:00:06**	**0.0405**

Table 26. Results integration type-3 Sugeno Trapezoidal GA

Experiment	Duration	Prediction Error
1	00:00:04	0.0589
2	00:00:08	0.0589
3	00:00:12	0.0590
4	00:00:08	0.0589
5	00:00:03	0.0589
6	00:00:04	0.0589
7	00:00:07	0.0588
8	00:00:03	0.0588
9	00:00:07	0.0588
10	00:00:11	0.0589
AV	**00:00:07**	**0.05887**

Table 24 presents the integration results of the Sugeno Type-3 Fuzzy system using Gaussian membership functions (MFs), where AV denotes the average time and prediction error from 29 experiments conducted using a Genetic Algorithm.

Table 27. Results integration of type-3 Sugeno Trapezoidal GA

Experiment	Duration	Prediction Error
1	00:00:03	0.0422
2	00:00:06	0.0423
3	00:00:03	0.0422
4	00:00:10	0.0422
5	00:00:07	0.0422
6	00:00:08	0.0423
7	00:00:07	0.0422
8	00:00:07	0.0423
9	00:00:07	0.0424
10	00:00:07	0.0423
AV	**00:00:09**	**0.0422**

Table 28. Test for Ethereum Time Series for Type-1 Mamdani

FuzzyType System	Mean	Standard deviation	Mean Error	P Value
Gaussian PSO	0.2716345	0.0000484	0.0000090	0.000
Gaussian GA	0.270886	0.000887	0.00016	
Generalized Bell PSO	0.2470103	0.0000310	0.00000058	0.000
Generalizad Bell GA	0.246400	0.000591	0.00011	
Triangular PSO	0.256197	0.000211	0.000039	0.192
Triangular GA	0.256107	0.000298	0.000055	
Trapezoidal PSO	0.2598103	0.0000557	0.000010	0.000
Trapezoidal GA	0.260231	0.000154	0.000029	

Table 29. Test for Ethereum Time Series for Type-1 Sugeno.

Fuzzy Type System	Mean	Standard deviation	Mean Error	P Value
Gaussian PSO	0.1385690	0.0000660	0.000012	0.000
Gaussian GA	0.132345	0.00138	0.000026	
Generalized Bell PSO	0.0606006	0.0000025	0.00000048	0.000
Generalizad Bell GA	0.1439621	0.0000494	0.00000092	
Triangular PSO	0.1483172	0.0000468	0.00000087	0.266
Triangular GA	0.11	0.164	0.031	
Trapezoidal PSO	0.1483310	0.0000930	0.000017	0.000
Trapezoidal GA	0.1583207	0.0000774	0.000014	

Table 30. t-statistical test for Ethereum Time Series for Mamdani Type-2

Fuzzy Type System	Mean	Standard deviation	Mean Error	P Value
Gaussian PSO	0.4207	0.0292	0.0055	0.328
Gaussian GA	0.4151964	0.0000637	0.00012	
Generalized Bell PSO	0.4386	0.0275	0.0051	0.000
Generalized Bell GA	0.4732966	0.0000325	0.0000060	
Triangular PSO	0.398914	0.000210	0.000039	0.000
Triangular GA	0.399748	0.000115	0.000021	
Trapezoidal PSO	0.459676	0.000162	0.000030	0.000
Trapezoidal GA	0.4996483	0.0000509	0.0000094	

Table 25 presents the integration results of the Sugeno Type-3 Fuzzy system Using Generalized Gbell membership functions and AV represents the average time and prediction error of 29 experiments for the Ethereum time series with a genetic algorithm.

Table 26 displays the integration results of the Sugeno Type-3 Fuzzy system using triangular MFs, with AV representing the average time and prediction error from 29 experiments conducted using a Genetic Algorithm.

Table 31. t statistical test for Ethereum Time Series for Sugeno Type-2

Fuzy Type System	Mean	Standarddeviation	MeanError	P Value
Gaussian PSO	0.5587	0.0275	0.0051	0.187
Gaussian GA	0.56568	0.003147	0.00058	
Generalized Bell PSO	0.6025	0.0275	0.0051	0.477
Generalizad Bell PSO	0.606179	0.000062	0.000012	
Triangular PSO	0.6302	0.0275	.0051	0.000
Triangular GA	0.65142	0.00145	0.00027	
Trapezoidal PSO	0.5816	0.0275	0.0051	0.000
Trapezoidal GA	0.62241	0.00214	0.00040	

Table 32. t statistical test for Ethereum Time Series for Type-3 Mamdani

Fuzzy Type ¿System	Mean	Standard deviation	Mean Error	P Value
Gaussian PSO	0.3825	0.0106	0.0020	0.001
Gaussian GA	0.000196	0.000196	0.00036	
Generalized Bell PSO	0.4517483	0.0000688	0.000013	0.000
Generalizad Bell GA	0.9472517	0.0000509	0.0000094	
Triangular PSO	0.538041	0.000148	0.000027	0.000
Triangular GA	0.54711966	0.0000626	0.000013	
Trapezoidal PSO	0.3462	0.0102	0.0019	0.000
Trapezoidal GA	0.5041207	0.0000620	0.000012	

Table 33. t statistical test for Ethereum Time Series for Type-3 Sugeno

Fuzy Type System	Mean	Standard deviation	Mean Error	P Value
Gaussian PSO	0.0458276	0.0000455	0.0000084	0.000
Gaussian GA	0.0606241	0.0000872	0.000016	
Generalized Bell PSO	0.0527414	0.0000682	0.000013	0.000
Generalizad Bell GA	0.0405621	0.0000820	0.000015	
Triangular PSO	0.0437000	0.0000655	0.000012	0.000
Triangular GA	0.0588793	0.0000620	0.000012	
Trapezoidal PSO	0.0371483	0.0000688	0.000013	0.000
Trapezoidal GA	0.0405621	0.0000820	0.000015	

Table 27 presents the integration results of the Sugeno Type-3 Fuzzy system using Trapezoidal MFs and AV represents the average time and prediction error of 29 experiments using a Genetic Algorithm.

4.1. Comparison of results

This subsection shows the comparisons between particle optimization algorithms and the genetic algorithm are also shown, statistical tests were performed with the results of two fuzzy systems type-1, type-2, and type-3 of Mamdani and Sugeno type, also using the different Gaussian, generalized bell and triangular systems.

4.1.1. Mamdani Type-1 with PSO and GA

To compare the results of two Mamdani type-1 fuzzy systems using the two optimization algorithms, PSO and GA for the prediction of Ethereum time series, the statistical t test was used, in which Gaussian membership functions were used, Generalized Bell, Triangular and Trapezoidal we can deduce that there is substantial evidence supporting the relationship between the MandaniType-1 PSO fuzzy system and the Mamdani Type-1 GA System, in the statistical tests using the Gaussian MF with the GA, in the generalized bell function the GA was also better, with the Triangular membership function it was also GA and with the Trapezoidal membership function it was PSO, a 95% confidence interval was used, and the results of each of these tests are shown in the Table 28.

4.1.2. Type-1 Sugeno with PSO and GA

To compare the results of two Sugeno type-1 fuzzy systems using the two optimization algorithms, PSO and GA for the prediction of Ethereum time series, the statistical t test was used, in which Gaussian membership functions were used, Generalized Bell, Triangular and Trapezoidal we can conclude that there is significant evidence between the Sugeno Type-1 PSO fuzzy system and the Sugeno Type-1 GA System, in the statistical tests using the Gaussian MF with the GA, in the generalized bell function the PSO was also better, with the Triangular membership function it was also GA and with the Trapezoidal membership function it was PSO, a 95% confidence interval was used, and the results of each of these tests are shown in the Table 29.

4.1.3. Mamdani Type-2 with PSO and GA

To compare the results of two Mamdani type-2 fuzzy systems using the two optimization algorithms, PSO and GA for the prediction of Ethereum time series, the statistical t test was used, in which Gaussian membership functions were used, Generalized Bell, Triangular and Trapezoidal we can conclude that there is significant evidence between the MamdaniType-2 PSO fuzzy system and the Mamdani Type-2 GA System, in the statistical tests using the Gaussian MF with the GA, in the generalized bell function the PSO was also better, with the Triangular membership function it was also PSO and with the Trapezoidal membership function it was PSO, a 95% confidence interval was used, and the results of each of these tests are shown in the Table 30.

4.1.4. Sugeno Type-2 with PSO and GA

To compare the results of two Sugeno type-2 fuzzy systems using the two optimization algorithms, PSO and GA for the prediction of Ethereum time series, the statistical t test was used, in which Gaussian membership functions were used, Generalized Bell, Triangular and Trapezoidal we can conclude that there is significant evidence between the Sugeno Type-2 PSO fuzzy system and the Sugeno Type-2 GA System, in the statistical tests using the Gaussian MF with the PSO, in the generalized bell function the PSO was also better, with the Triangular membership function it was also PSO and with the Trapezoidal membership function it was PSO, a 95% confidence interval was used, and the results of each of these tests are shown in the Table 31.

4.1.5. Mamdani Type-3 with PSO and GA

To compare the results of two Mamdani Type-3 fuzzy systems using the two optimization algorithms, PSO and GA for the prediction of Ethereum time series, the statistical t test was used, in which Gaussian membership functions were used, Generalized Bell, Triangular and Trapezoidal we can conclude that there is significant evidence between the Mamdani Type-3 PSO fuzzy system and the Mamdani Type-3 GA System, in the statistical tests using the Gaussian MF with the GA, in the generalized bell function the PSO was also better, with the Triangular membership function it was also PSO and with the Trapezoidal membership function it was PSO, a 95% confidence interval was used, and the results of each of these tests are shown in the Table 32.

4.1.6. Sugeno Type-3 with PSO and GA

To compare the results of two Sugeno type-2 fuzzy systems using the two optimization algorithms, PSO and GA for the prediction of Ethereum time series, the statistical t test was used, in which Gaussian membership functions were used, Generalized Bell, Triangular and Trapezoidal we can conclude that there is significant evidence between the Sugeno Type-2 PSO fuzzy system and the Sugeno Type-2 GA System, in the statistical tests using the Gaussian MF with the PSO, in the generalized bell function the GA was also better, with the Triangular membership function it was also PSO and with the Trapezoidal membership function it was PSO, a 95% confidence interval was used, and the results of each of these tests are shown in the Table 33.

5. Conclusions

This article tested two optimization algorithms to obtain the best network architecture, the responses of this network were integrated with type-3 fuzzy systems, with different types of Gaussian, generalized bell, trapezoidal and triangular MFs to obtain the best prediction error. To compare the optimization algorithms using particles and the genetic algorithm, statistical tests were performed with the results of two fuzzy systems type-1, type-2 and type-3 of Mamdani and

Sugeno type, also using the different Gaussian, generalized bell, triangular and trapezoidal member functions for each type of system. We can conclude that in most cases the best was the optimization algorithm using particles. As future work, it is necessary to carry out tests with this method using other time series and also change the optimization of ensemble neural network method.

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