

Application of a New Type-2 Fuzzy Integration Model for the Classification of Inflation and Price Index Time Series: A Case Study of G20 Member Countries

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Abstract. In today's age, one of the main consequences of operating in a globalized environment is the challenge of daily changing conditions, which strongly promote uncertainty in the behavior and processing of information. This, coupled with the complexity that nations face when observing constant and unforeseen changes, necessarily leads to seeking adaptation to daily uncertainty. That is, first, accepting this environmental transformation and selecting alternative strategies to integrate information in a timely and relevant manner. These practices must consider the use of historical records of multiple variables, such as the price index and national inflation. Thus, our contribution focuses on a new proposal for clustering historical results using multiple unsupervised intelligent computing techniques to group data and subsequently using Interval Type-2 fuzzy systems models to integrate the results obtained, considering the uncertainty inherent in the data. Based on a detailed analysis of the experimental results, the advantages of using the proposed fuzzy method to perform time series classification were identified.

Keywords. Clustering, neural networks, time series, fuzzy systems.

1 Introduction

The general idea of a country's political, economic, and social stability refers to its ability to maintain or regain balance when faced with changes or disturbances of various kinds. Among the factors that frequently influence economic instability are inflation, unemployment, national or international crises, and others [1].

In order to strengthen a nation's capacity to withstand the imbalances arising from global

instability, one of the strategies commonly used by governments is to focus their attention on the strategic decision-making process.

Thus, in the case of the financial sector, this phenomenon known as uncertainty accompanies us daily, necessitating the use of multiple technological tools to predict trends [2-4] and integrate or classify economic variables over time [5-7].

Today, it is common for information systems to collect data on the transactions citizens make in their daily lives, primarily for commercial purposes. Having a detailed record of where citizens' economic resources are invested allows consumption trends to be analyzed and compared against the income of individuals in a specific location.

Similarly, countries consider recording their economic indicators to monitor their fluctuations over time. When referring to data recorded throughout history, it is important to keep in mind that creating a time series requires recording chronological data in an orderly and sequential manner over a period.

Time series analysis has remained popular and is frequently performed by entities across multiple sectors [8-10], making it a functional tool that can be applied to strategic decision-making [11-13]. Intelligent computing techniques for data clustering [14] can be used in conjunction with the results obtained during time series analysis, taking advantage of each method's significant strengths [15-17].

Mathematical models are commonly used to integrate results obtained from different methods.

However, for the past couple of decades, models based on fuzzy set theory have emerged among the scientific community. They propose managing perceived uncertainty in the environment by suggesting that, beyond whether an element may or may not belong to a set, it is also possible for that element to partially belong to different sets [18-20].

This proposal differs from other intelligent computing models [21-23] in that it combines multiple clustering methods [24-26] to obtain a variety of results that can be used individually, and general results can also be obtained via fuzzy integration of the clustering results.

Among the advantages of the proposed model are the use of different intelligent computing methods [27-29] to cluster the information [30-32] and the data is subsequently classified using Interval Type-2 fuzzy methods [33]. Therefore, the main contribution of this proposal is to classify the results of time series clustering using a novel Interval Type-2 fuzzy integration model.

This article consists of the following sections: Section 2 provides a summary of the basic concepts of the theory under study; Section 3 refers to the problem description; Section 4 describes the methods used in the proposed model; and Section 5 presents the results obtained through the experimentation. Section 6 summarizes the final reflections on the results obtained, and finally, Section 7 presents the conclusions reached.

2 Basic Concepts

This section briefly presents some of the theory considered in developing our proposal. It primarily covers general topics related to artificial neural networks, intelligent computing techniques, and Interval Type-2 fuzzy systems.

2.1. Clustering intelligent techniques

Competitive neural network is an unsupervised neural network model where only input data are used to form clusters that represent characteristics of the data through classes [34, 35]. K-means (KM) groups similar data points into clusters by minimizing the distance between data points in a

cluster and their centroid [36, 37]. Fuzzy C-Means (FCM) performs clustering by giving each element of the set a degree of belonging to a group based on its degree of membership [38-40].

Once we have identified data, we can facilitate the understanding of the information by detecting patterns and relationships in countless data that do not have previous labels; that is, it does not require supervised training.

2.2 Interval Type-2 Fuzzy systems

Today, a simple way to describe a fuzzy system consists of a knowledge base represented by the fuzzy rules that form the knowledge base; secondly, there is the database that contains the parameters and specifications of the membership functions; and finally, a mechanism is required that performs the calculations to simulate the inference or reasoning process.

In general terms about the theory of fuzzy logic, we can point out that its basic definitions apply to Type-1 and Type-2 fuzzy sets. A Type-2 fuzzy system is integrated with fuzzy if-then rules and membership functions where the antecedent or consequent has Type-2 fuzzy sets that are composed of Type-1 fuzzy sets [41].

The mathematical representation of an Interval Type-2 Fuzzy Set can be expressed as Eq. (1):

$$J_x = \{(x, u) \mid u \in [\mu_A(x), \mu_{\bar{A}}(x)]\}, \quad (1)$$

where $\mu_A(x)$ and $\mu_{\bar{A}}(x)$ correspond to the boundaries of the fuzzy set, usually known as *lower* and *upper* membership functions, respectively.

The mathematical expression of the Footprint of Uncertainty (FOU) is presented as Eq. (2):

$$\text{FOU} \in [\mu_A(x), \mu_{\bar{A}}(x)], \quad (2)$$

where the $\mu_A(x)$ and $\mu_{\bar{A}}(x)$ are the lower and upper membership functions, respectively.

For the rule base and fuzzy inference engine, in an Interval Type-2 Mamdani FIS that performs the same process a Type-1, but for upper and lower rules firing forces respectively. The inference is computed based on the Modus ponens inference (fuzzy logic version), as shown in Eq. (3):

$$R^1 : \text{IF } x_1 \text{ is } \tilde{F}_1^1 \text{ and } \dots \text{ and } x_p \text{ is } \tilde{F}_p^1, \text{ THEN } y \text{ is } \tilde{G}^1, \quad (3)$$

where $l = 1, \dots, M$ [42].

3 Problem Description

Since the beginning of this century, a reality that has kept us alert has opened a significant space for global economic resilience amidst the risks of high public debt and fiscal pressures, among others, that nations face due to volatile market changes and the effects of globalization.

Global decision-makers typically prioritize governance, followed by environmental and social factors [43]. In terms of governance there are differences between developed and developing economies. It should be considering a framework that regulates the preservation of the environment [44].

A global perspective that guides the course of member nations and developing countries is addressed in the G20 international forum, where leaders and central bank governors meet. Its main actions include the implementation of macroeconomic policies that lead to improved long-term growth, debt transparency, and financial stability that contribute to decision-making processes.

The G20 member countries are the economic leaders who concentrate a large part of the energy resources and are also the largest suppliers and importers of energy, promoting stability between energy supply and demand worldwide [45]. Also, these members countries use different financial systems, resulting in the coexistence of diverse economies within the group that promote financial inclusion in broad economic contexts [46].

One of the main tasks of the G20 countries is to maintain a stable global market for raw materials by ensuring the supply of production factors [47]. The search for strategies to achieve an economic balance that includes reducing the income inequality gap among the population is highly complex [48].

Furthermore, a key aspect to consider is the sovereign risk that nations face of not being able to meet their debt obligations within the agreed timeframe [49].



Fig. 1. Member nations of the G20 International Forum

As mentioned earlier, we are facing the current problem from a global and particularly strategic perspective, where the solutions correspond to highly complex and mostly multidimensional models.

Today, uncertainty accompanies daily life; deadlines and commitments are just around the corner.

Therefore, having exploratory analysis tools transforms the decision-making process into an activity that, while not eliminating uncertainty, mitigates the risk of lacking relevant information in most cases.

Coexisting in a globalized environment where hyperconnectivity and transparency allow information to be transmitted from one point to another and where countless aspects governing different population groups are kept in mind leads to an acceptance that, while we are constantly at the mercy of an open world, sometimes the world closes due to countless worries and unexpected events.

In addition to the asymmetries between countries and regions, there are aspects and ramifications of stability, where we cannot ignore that among the elements that make up this globalized scenario, it is inevitable to have different degrees of maturity, where relationships are frequently disparate and in many cases the context is unequal.

For all the above reasons, the use of an intelligent computational model for the

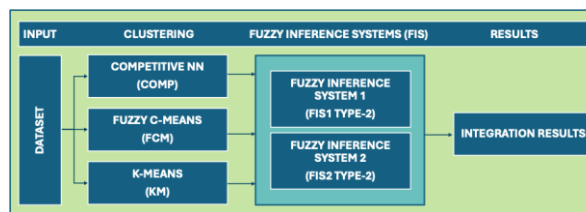


Fig. 2. Proposed method

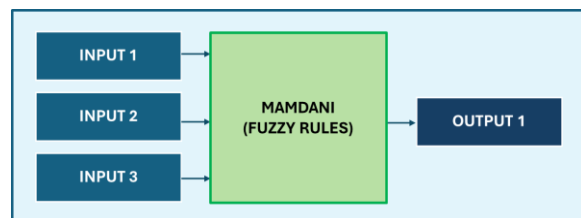


Fig. 3. FIS Description model

classification of economic variables such as inflation and the price index is considered a useful tool in the decision-making process.

For this case study, we used a dataset corresponding to 18 G20 member countries [50]: Australia (AUS), Brazil (BRA), Canada (CAN), China (CHN), France (FRA), Germany (DEU), India (IND), Indonesia (IDN), Italy (ITA), Japan (JPN), Korea, Rep (KOR), Mexico (MEX) Russian Federation (RUS), Saudi Arabia (SAU), South Africa (ZAF), Turkiye (TUR), United Kingdom (GBR), and United States (USA) as shown in Figure 1. This dataset is composed of 18 time series corresponding to the available information on the two-variable series: Inflation and Price Index for the period (1990-2024).

The attributes for each time series are Country Name, Country Code, Series Name and Series Code. Regarding the data used, it is important to mention that this is a collection of statistical data compiled by the World Bank, so it is relevant and of high quality. No preprocessing was required, as the data is available in a format ready for use by interested parties.

4 Methodology

This proposal consists of an intelligent computational model for classifying [51] inflation

and price index time series. This model is first composed of input data (represented by the time series).

As a second step, we will use three unsupervised intelligent computational methods that have proven robust for data clustering tasks: Competitive Neural Networks (COMP), Fuzzy C-Means (FCM), and K-Means (KM). Finally, to perform the classification (result integration), we will use a set of Interval Type-2 fuzzy systems.

The general model is presented in Figure 2, which shows the sections of this proposal.

For the specific case of the design of Interval Type-2 fuzzy systems (FIS) it is important to note that the FIS are of the Mamdani type and are composed of three inputs and one output, 36 fuzzy rules and centroid defuzzification Figure 3.

Next in the Table 1 there are the fuzzy rules where the clustering results corresponding to the identified clusters are considered as antecedents the input 1 (COMP), input 2 (FCM), and input 3 (KM), and finally the output 1 as a consequent of the integration result. The possible values are Cluster 1 (CLT1), Cluster 2 (CLT2), Cluster 3 (CLT3), Cluster 4 (CLT4), and Cluster N (CLTN) for the final result.

Table 1. FIS fuzzy rules (three inputs-one output)

Fuzzy rules	Antecedents			Consequent
	Input1 (COMP)	Input2 (FCM)	Input3 (KM)	Ouput1 (CLTN)
1	CLT1	CLT1	CLT1	CLT1
2	CLT1	CLT1	CLT2	CLT1
3	CLT1	CLT1	CLT3	CLT2
4	CLT1	CLT1	CLT4	CLT2
5	CLT1	CLT2	CLT1	CLT1
6	CLT1	CLT3	CLT1	CLT2
7	CLT1	CLT4	CLT1	CLT2
8	CLT2	CLT1	CLT1	CLT1
9	CLT2	CLT2	CLT1	CLT2
10	CLT2	CLT2	CLT2	CLT2
11	CLT2	CLT2	CLT3	CLT2
12	CLT2	CLT2	CLT4	CLT3
13	CLT2	CLT3	CLT2	CLT2

14	CLT2	CLT4	CLT2	CLT3
15	CLT2	CLT3	CLT3	CLT3
16	CLT2	CLT4	CLT4	CLT3
17	CLT3	CLT1	CLT1	CLT2
18	CLT3	CLT3	CLT1	CLT2
19	CLT3	CLT3	CLT3	CLT3
20	CLT3	CLT2	CLT2	CLT2
21	CLT3	CLT3	CLT2	CLT3
22	CLT3	CLT3	CLT4	CLT3
23	CLT3	CLT2	CLT3	CLT3
24	CLT3	CLT4	CLT3	CLT3
25	CLT3	CLT4	CLT4	CLT4
26	CLT4	CLT1	CLT1	CLT2
27	CLT4	CLT4	CLT1	CLT3
28	CLT4	CLT2	CLT2	CLT3
29	CLT4	CLT4	CLT2	CLT3
30	CLT4	CLT3	CLT3	CLT3
31	CLT4	CLT4	CLT3	CLT4
32	CLT4	CLT2	CLT4	CLT3
33	CLT4	CLT3	CLT4	CLT4
34	CLT4	CLT4	CLT4	CLT4
35	CLT1	CLT4	CLT4	CLT3
36	CLT4	CLT1	CLT4	CLT3

Regarding the membership functions (MF), we exclusively use the triangular type, and the linguistic values correspond to the identified clusters Cluster 1 (CLT1), Cluster 2 (CLT2), Cluster 3 (CLT3) and Cluster 4 (CLT4) respectively as shown in Figures 4 and 5. For both Type-1 and Interval Type-2 systems, the MF parameters and rules were manually tested until obtaining these values.

5 Experimental Results

It is important to highlight that these results were obtained from 30 executions of each method. Also, we can mention that as part of the clustering experiment in Tables [2-3] we can note that for the inflation variant three clusters were identified using COMP and four clusters using FCM and KM.

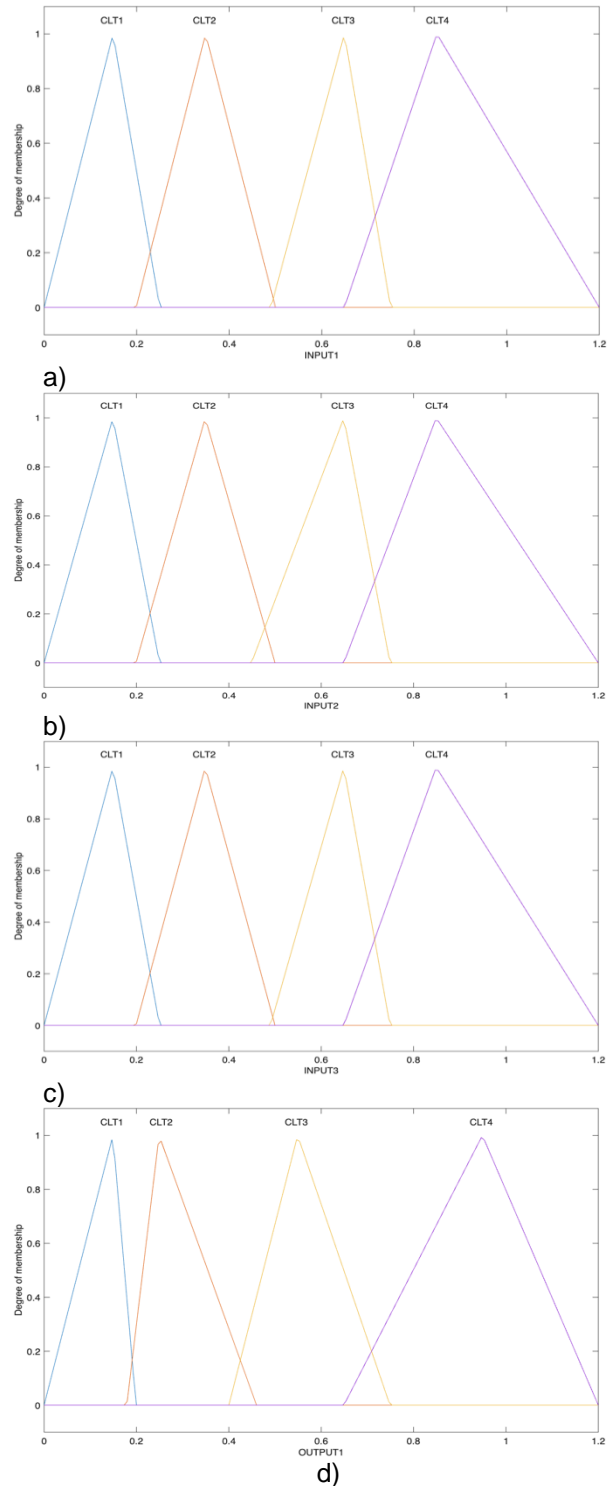


Fig. 4. Type-1 FIS Membership function a) Input 1 b) Input 2 c) Input 3 d) Output 1

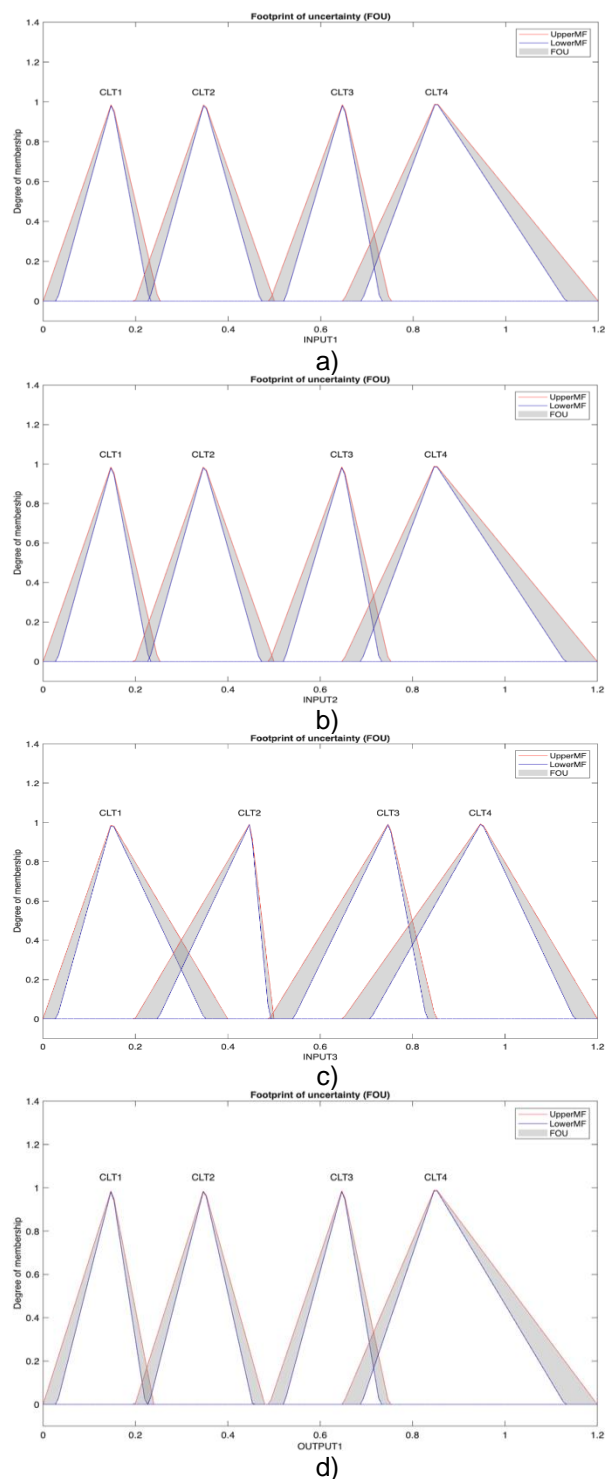


Fig. 5. Type-2 FIS Membership functions. a) Input 1 b) Input 2 c) Input3 d) Output 1

Table 2. Clustering results of Inflation time series

CLUSTER (CLT)	COMP	FCM	KM
CLT1	16	15	15
CLT2	1	1	1
CLT3	1	1	1
CLT4	0	1	1

Table 3. Clustering results of Inflation time series by country

CLUSTER (CLT)	COMP	FCM	KM
CLT1	AUS	AUS	AUS
	CAN	CAN	CAN
	CHN	CHN	CHN
	FRA	FRA	FRA
	DEU	DEU	DEU
	IND	IND	IND
	IDN	IDN	IDN
	ITA	ITA	ITA
	JPN	JPN	JPN
	KOR	KOR	KOR
	MEX	MEX	MEX
	SAU	SAU	SAU
	ZAF	ZAF	ZAF
	TUR	GBR	GBR
GBR	USA	USA	
USA	-	-	
CLT2	BRA	BRA	BRA
CLT3	RUS	RUS	RUS
CLT4	-	TUR	TUR

It is noteworthy to point out in Figure 6 that at least 83% of the total number of elements were concentrated in Cluster 1 (CLT1).

In the case of the price index variable, Tables [4-5] show that four clusters were identified using COMP and FCM, and only three clusters for the KM method.

Table 4. Clustering results of Price index time series

CLUSTER (CLT)	COMP	FCM	KM
CLT1	11	11	11
CLT2	2	4	6
CLT3	4	2	0
CLT4	1	1	1

Table 5. Clustering results of Price index time series by country

CLUSTER (CLT)	COMP	FCM	KM
CLT1	AUS	AUS	AUS
	CAN	CAN	CAN
	CHN	CHN	CHN
	FRA	FRA	FRA
	DEU	DEU	DEU
	ITA	ITA	ITA
	JPN	JPN	JPN
	KOR	KOR	KOR
	SAU	SAU	SAU
	GBR	GBR	GBR
CLT2	USA	USA	USA
	BRA	BRA	BRA
	IND	IND	IND
	-	RUS	IDN
	-	ZAF	MEX
	-	-	RUS
	-	-	ZAF
CLT3	IDN	IDN	-
	MEX	MEX	-
	RUS	-	-
	ZAF	-	-
CLT4	TUR	TUR	TUR

It is noteworthy that, unlike the inflation variable, 61% of the elements were in Cluster 1 (CLT1) as is shown in Figure 7.

Before beginning the presentation of the fuzzy classification results, we consider it pertinent to mention that uncertainty can also be represented by incomplete or uncertain data, which resembles the reality of our environment.

Through the following results we can facilitate the visualization and interpretation of the behavior of fuzzy classification models that consider variables inflation and price index.

So, the results obtained for the inflation time series by using the fuzzy systems are presented in Table 6 and Figure 8, where it can be observed that only clusters 1, 2 and 4 contain elements and that using Interval Type-2 fuzzy integration it was possible to identify the greatest number of elements belonging to cluster 4, as opposed to Type-1 FIS.

Table 6. FIS Classification results for Inflation time series

CLUSTER (CLT)	Type-1 FIS	Interval Type-2 FIS
CLT1	15	15
CLT2	2	1
CLT3	0	0
CLT4	1	2

Similarly, in Table 7 and Figure 9 we can observe that for the Price index time series the three clusters are maintained and again Interval Type-2 FIS presents better results in the classification of Cluster 4 compared to Type-1 FIS.

Table 7. Classification FIS results for Price index time series

CLUSTER (CLT)	Type-1 FIS	Interval Type-2 FIS
CLT1	10	11
CLT2	6	2
CLT3	0	0
CLT4	2	5

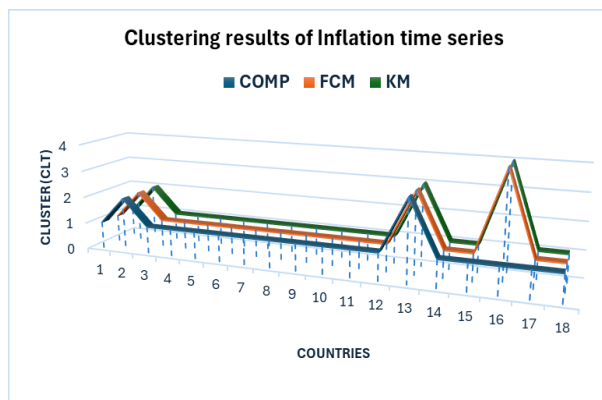


Fig. 6. Clustering results of Inflation time series

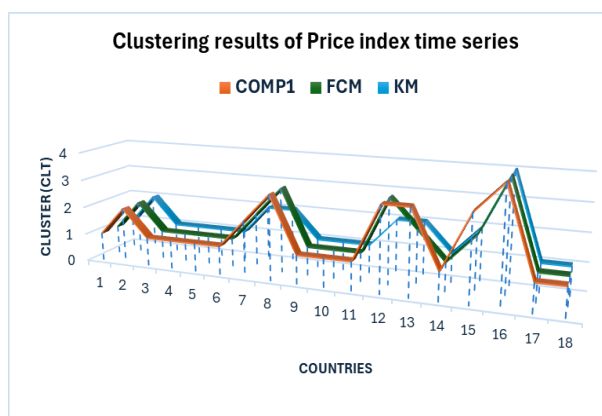


Fig. 7. Clustering results of Price Index time series

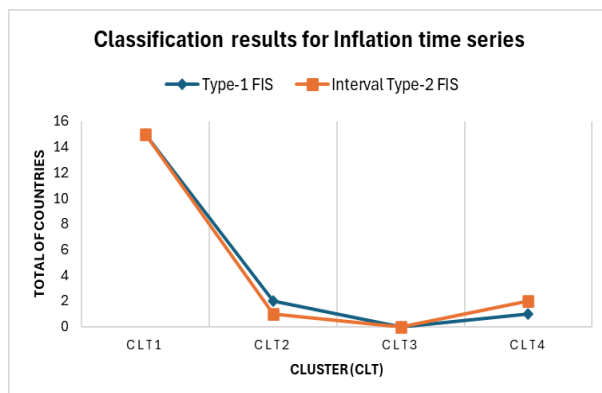


Fig. 8. Classification results for Inflation time series

Finally, we compared the results obtained using the proposed model with an Interval Type-2 FIS (IT2 FIS) of Sugeno Type (where we can observe in Table 8 and Figures [10-11] that for both methods the same results were obtained for the

inflation variable. However, for the price index variable, the cluster CLT1 remains similar with 11 elements for each one, but the cluster CLT2 has two elements for Sugeno and four elements for Mamdani and CLT4 has five elements for Mamdani and 3 elements for Sugeno respectively. In both cases the cluster CLT3 remains without elements.

Table 8. Comparison of Interval Type-2 FIS results

Variable	Inflation		Price index	
	Mamdani IT2 FIS	Sugeno IT2 FIS	Mamdani IT2 FIS	Sugeno IT2 FIS
CLT1	15	15	11	11
CLT2	1	1	2	4
CLT3	0	0	0	0
CLT4	2	2	5	3

6 Discussion of Results

Based on the results obtained from the experimentation carried out, we noted that it is possible to use different unsupervised intelligent methods to perform clustering, considering four classes that were subsequently combined using fuzzy integration where the scope ranges of an Interval Type-2 FIS allow the aggregation to consider the uncertainty inherent in the data.

The advantages of using the proposed model are that it is possible to simultaneously obtain multiple results for the clustering of the time series and at that stage it is possible to choose the most appropriate result, or it is also possible to subsequently integrate the results with a Interval Type-2 fuzzy system if it is chosen to obtain a robust result.

We also note that because a sample of countries that were previously grouped based on their global indicators was used, it was a factor that influenced the fuzzy classification of Cluster 1 (CLT1) to have the largest number of elements; however, if we look at it from the other side, this factor makes it possible to identify which countries are separated from Cluster 1 (CLT1) and that were distributed in the rest of the groups.

It is considered necessary to test the proposed model with a group of elements with different

characteristics and evaluate its behavior when there is no prior classification or categorization of the elements.

Regarding the integration phase, because as mentioned above the elements of the sample presented previous similarity due to the nature of their origin, the difference between the results obtained using Interval Type-2 fuzzy systems was slightly better than Type-1 for inflation variable, so we consider that for similar samples Type-1 fuzzy systems may possibly work better if the priority is to counteract the effect of the computational cost of using Type-2 fuzzy systems.

However, if the aim is to have a refined integration as the case of price index variable where it considers the minimum difference between the integration results obtained, choosing Interval Type-2 fuzzy systems would surely be the option for this type of case.

7 Conclusions

The simulation results demonstrated that it is possible to use Interval Type-2 Fuzzy systems to integrate results obtained through different intelligent computing methods and neural networks. Compared to Type-1 fuzzy systems, for this work Interval Type-2 fuzzy systems performed better for the variables used.

Furthermore, it was observed that by using multiple Type-1 and Type-2 fuzzy systems, it is possible to classify elements based on their characteristics and integrate the results obtained, with the goal of serving as a support tool for strategic decision-making.

This proposal differs from other intelligent computing models in that it combines multiple clustering methods to obtain a variety of results that can be used individually, and general results can also be obtained via fuzzy integration of the clustering results.

Among the advantages of the proposed model are the use of different intelligent computing methods to cluster the information and the data is subsequently classified using Interval Type-2 fuzzy methods.

As future work, we contemplate using optimization methods applied to fuzzy rules optimization and subsequently focusing on tuning

the parameters of the membership functions. We also consider using intelligent hybrid techniques to

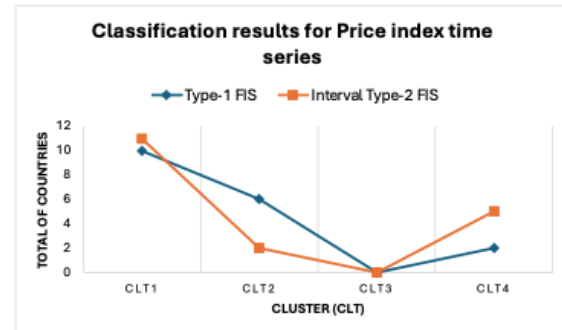


Fig. 9. Classification results for Price Index time series

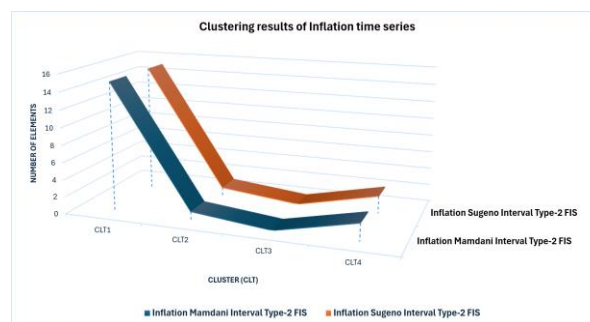


Fig. 10. Classification Interval Type-2 FIS results for Inflation time series

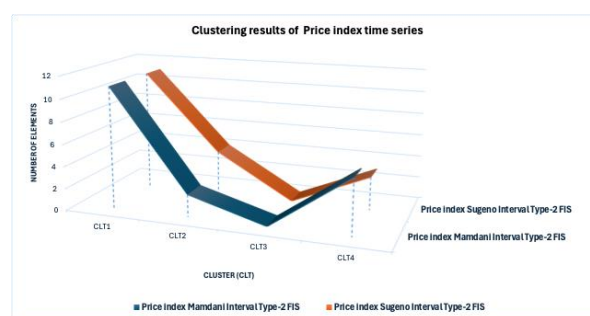


Fig. 11. Classification Interval Type-2 FIS results for Prices index time series

work with time series forecasting in addition to fuzzy classification.

It is also true that the more variables are considered, the more complex it is for a single model to offer satisfactory results, so other

strategies must be considered to refine the overall visualization gap without neglecting the level of detail of the data.

The central idea is that once new data is available, it will be possible to compare the evolution in the formation of clusters and whether the similarity attributes remain or move away from the elements of the assigned group.

Regarding the decision-making process, it is possible to consider that fuzzy integration presents a proposal that helps to make responses to social, economic or environmental problems, among others, faster. As future work, we could optimize the system with metaheuristics, as in [52].

References

- Ramírez, M., Melin, P. (2025).** Application of a New Approach for the Prediction of Inflation, Exchange Rate and Gross National Income in North American Countries Using Supervised Neural Networks. *Modern Artificial Intelligence Based on Soft Computing Techniques. Studies in Computational Intelligence*, Vol 1204, pp 77–87. doi: 10.1007/978-3-031-88279-1_5.
- Tsague, C.B.N., Seutche, J.C.N., Djeusu, L.N. (2024).** Application of Neural Networks to Predict Indoor Air Temperature in a Building with Artificial Ventilation: Impact of Early Stopping. *Springer* doi: 10.1007/s41870-024-02023-5.
- Kamsing, P., Cao, C., Boonpook, W. (2025).** Artificial Neural Network for Air Pollutant Concentration Predictions Based on Aircraft Trajectories over Suvarnabhumi International Airport. *Atmosphere*, Vol. 16, No. 4, pp. 366. doi: 10.3390/atmos16040366.
- Toba, L., Kulkarni, S., Khallouli, W. (2025).** Long-Term Traffic Prediction Using Dee Learning Long Short-Term Memory. *Smart Cities*, Vol. 8, No. 4, pp. 126. doi: 10.3390/smartcities8040126.
- Stržinar, Ž., Škrjanc, I., Pratama, M. (2025).** Evolving Clustering of Time Series for Unsupervised Analysis of Industrial Data Streams. *Computers & Industrial Engineering*. doi: 10.1016/j.cie.2025.111508.
- Ramirez, M., Melin, P. (2024).** Modular Perspective for Population and Gross National Income Time Series Prediction Using a Neural Network Model: A Case Study of OECD Member Countries. *New Directions on Hybrid Intelligent Systems Based on Neural Networks, Fuzzy Logic, and Optimization Algorithms*. Vol 1146, pp 63–71. doi: 10.1007/978-3-031-53713-4_6.
- Madanchian, M., Taherdoost, H. (2025).** Applications of Multi-Criteria Decision Making in Information Systems for Strategic and Operational Decisions. *Computers*, Vol. 14, No. 6, pp. 208. doi: 10.3390/computers14060208.
- Nery, S.B.M., Araújo, S.M., Magalhães, B.G. (2024).** Parkinson's Disease Severity Index Based on Non-Motor Symptoms by Self-Organizing Maps. *Electronics*. Vol. 13, No. 8, pp. 1523. doi: 10.3390/electronics13081523.
- Bulus, H. N. (2024).** Adaptive Neuro-Fuzzy Inference System and Artificial Neural Network Models for Predicting Time-Dependent Moisture Levels in Hazelnut Shells (*Corylus avellana* L.) and Prina (*Oleae europaeae* L.). *Processes*, Vol. 12, No. 8, pp. 1703. doi: 10.3390/pr12081703.
- Zhan, J., Huang, X., Qian, Y. (2024).** A Fuzzy C-Means Clustering-Based Hybrid Multivariate Time Series Prediction Framework with Feature Selection, in *IEEE Transactions on Fuzzy Systems*, Vol. 32, No. 8, pp. 4270–4284, doi: 10.1109/TFUZZ.2024.3393622.
- Manzoor, S., Mustafa, S., Gulzar, K. (2024).** MultiFuzzTOPS: A Fuzzy Multi-Criteria Decision-Making Model Using Type-2 Soft Sets and TOPSIS. *Symmetry*, Vol. 16, No. 6, pp. 655. doi: 10.3390/sym16060655.
- Sharma, P., Mehlawat, M.K., Gupta, P. (2025).** Cluster-Based Decision Making: A Novel Approach for Handling Large-Scale Alternatives in Rooftop Solar PV Site Selection. *Artificial Intelligence Review*, Vol. 58, No. 113. doi: 10.1007/s10462-024-11097-3.
- Chen, L., Liu, W., Zhang, J. (2025).** An Interval Type-2 Fuzzy Multi-Criteria Decision-Making Approach for Patient Bed Allocation. *Scientific Reports*, Vol. 15, pp. 1–32. doi: 10.1038/s41598-025-09199-1.
- Singh, J., Singh, D. (2024).** A Comprehensive Review of Clustering Techniques in Artificial

- Intelligence for Knowledge Discovery: Taxonomy, Challenges, Applications and Future Prospects, *Advanced Engineering Informatics*, Vol. 62. doi: 10.1016/j.aei.2024.102799.
15. **Enriquez-Loja, J., Castillo-Pérez, B., Serrano-Guerrero, X. (2025).** Performance Evaluation Method for Different Clustering Techniques, *Computers and Electrical Engineering*, Vol. 123. doi: 10.1016/j.compeleceng.2025.110132.
 16. **Demirhan, H. (2025).** Mixed Fuzzy C-Means Clustering, *Information Sciences*, Vol. 690. doi: 10.1016/j.ins.2024.121528.
 17. **Li, X., Ding, D., Wang, X. (2025).** Integration of Self-Organizing Map and Monte Carlo Simulation for Ecological Risk Prediction of Heavy Metal Attenuation in Groundwater, *Ecotoxicology and Environmental Safety*, Vol. 302. doi: 10.1016/j.ecoenv.2025.118761.
 18. **Poma, Y., Melin, P. (2025).** Momentum Adaptation in Convolutional Neural Networks Using a Fuzzy Gravitational Algorithm, *Intelligent System Design Based on Soft Computing Models*, *Studies in Computational Intelligence*, Vol. 1223, pp. 91–101. doi: 10.1007/978-3-031-97309-3_8.
 19. **Cordero-Martínez, R., Sánchez, D., Castillo, O. (2025).** Estimation of Filter Number for Convolutional Neural Networks with Fuzzy Logic for Diabetic Retinopathy Classification, *Hybrid Intelligent Systems. Lecture Notes in Networks and Systems*, Vol. 1223. doi: 10.1007/9783-031-78922-9_9.
 20. **Miramontes, I., Melin, P. (2025).** Enhancing Nocturnal Blood Pressure Detection Through Interval Type-2 Fuzzy Classification Systems, *Artificial Intelligence and Quantum Computing: Early Innovations. Studies in Computational Intelligence*, Vol. 1, pp. 45–56. doi: 10.1007/978-3-031-85614-3_3.
 21. **Huang, Z., Yang, Z., Wu, Y. (2025).** Improving a Prediction Model for Tunnel Water Inflow Estimation Using LSTM and Bayesian Optimization. *Water*, Vol. 17, No. 21, pp. 3045. doi: 10.3390/w17213045.
 22. **Hayat, M.T., Allawi, Y.M., Alamro, W. (2025).** A Hybrid Convolutional Neural Network–Long Short-Term Memory (CNN–LSTM)–Attention Model Architecture for Precise Medical Image Analysis and Disease Diagnosis. *Diagnostics*, Vol. 15, No. 21, pp. 2673. doi: 10.3390/diagnostics15212673.
 23. **Gowda, S., Kunjar, V., Gupta, A. (2024).** Prediction of the Subgrade Soil California Bearing Ratio Using Machine Learning and Neuro-Fuzzy Inference System Techniques: A Sustainable Approach in Urban Infrastructure Development, *Urban Science*, Vol. 8, No. 1, pp. 1–18. doi: 10.3390/urbansci8010004.
 24. **Nery, S.B.M., Araújo, S.M., Magalhães, B.G. (2024).** Parkinson's Disease Severity Index Based on Non-Motor Symptoms by Self-Organizing Maps, *Electronics*, Vol. 13, No. 8. doi: 10.3390/electronics13081523.
 25. **Nakhaeepishkesh, M., Peng, W., Lin, H. (2024).** A Self-Organizing Map Artificial Neural Network to Improve the K-Means Algorithm on the Classification of Different Cancers, *Engineering Proceedings*, Vol. 76, No. 1, pp. 1–9. doi: 10.3390/engproc2024076067.
 26. **Fan, X., Zhang, S., Xue, X. (2025).** An Improved Self-Organizing Map (SOM) Based on Virtual Winning Neurons, *Symmetry*, Vol. 17, No. 3, pp. 1–22. doi: 10.3390/sym17030449.
 27. **Amézquita, L., Cortes-Antonio, P., Soria, J. (2024).** A New Interval Type-2 Fuzzy Logic Variant of the Multiverse Optimizer Algorithm, *Intelligent and Fuzzy Systems*, Vol. 1090, pp. 549–557. doi: 10.1007/978-3-031-67192-0_62.
 28. **Polanco-Martagón, S., Hernández-Mier, Y., Nuño-Maganda, M.A. (2025).** Comparison of Deep Neural Networks for the Classification of Adventitious Lung Sounds, *Journal of Clinical Medicine*, Vol. 14, No. 20, pp. 1–13. doi: 10.3390/jcm14207427.
 29. **Mohammadi, N., Naujokaitis, D., Kairaitis, G. (2025).** Hybrid Hourly Solar Energy Forecasting Using BiLSTM Networks with Attention Mechanism, *General Type-2 Fuzzy Logic Approach: A Comparative Study of Seasonal Variability in Lithuania*, *Applied Sciences*, Vol. 15, No. 17, pp. 1–13. doi: 10.3390/app15179672.
 30. **Mónica, J.C., Melin, P., Sánchez, D. (2025).** Self-Organizing Maps as Neural Models for Different Unsupervised Clustering Problems,

- Modern Artificial Intelligence Based on Soft Computing Techniques, Vol. 1204, pp. 63–76. doi: 10.1007/978-3-031-88279-1_4.
31. **Nakhaeepishkesh, M., Peng, W., Lin, H. (2024).** A Self-Organizing Map Artificial Neural Network to Improve the K-Means Algorithm on the Classification of Different Cancers, *Engineering Proceedings*, Vol. 76, No. 1, pp. 1–9. doi: 10.3390/engproc2024076067.
 32. **Li, X., Yang, Q., Wei, G. (2024).** Risk Assessment of Renewable Energy Investment Based on Fuzzy C-Means Clustering Algorithm, In *International Conference on Electrical, Mechanical and Computer Engineering*, pp. 46–50. doi: 10.1109/ICEMCE64157.2024.10861985.
 33. **Huang, C., Lei, H., Chen, Y. (2024).** Interval Type-2 Enhanced Possibilistic Fuzzy C-means Noisy Image Segmentation Algorithm Amalgamating Weighted Local Information, *Engineering Applications of Artificial Intelligence*, Vol. 137, pp. 1–21. doi: 10.1016/j.engappai.2024.109135.
 34. **Hao, C., Wang, B., Tang, D. (2024).** Finite-Time and Fixed-Time Function Projective Synchronization of Competitive Neural Networks with Noise Perturbation, *Neural Computing and Applications*, Vol. 36, pp. 16527–16543. doi: 10.1007/s00521-024-09885-7.
 35. **Ramírez, M., Melin, P., Castillo, O. (2024).** A New Hybrid Approach for Clustering, Classification, and Prediction of World Development Indicators Combining General Type-2 Fuzzy Systems and Neural Networks, *Axioms*, Vol. 13, No. 6, pp. 1–16. doi: 10.3390/axioms13060368.
 36. **Miraftebzadeh, S.M., Colombo, C.G., Longo, M. (2023).** K-Means and Alternative Clustering Methods in Modern Power Systems, in *IEEE Access*, Vol. 11, pp. 119596–119633, doi: 10.1109/ACCESS.2023.3327640.
 37. **Chen, Y., Tan, P., Li, M. (2024).** K-Means Clustering Method Based on Nearest-Neighbor Density Matrix for Customer Electricity Behavior Analysis, *International Journal of Electrical Power & Energy Systems*, Vol. 161, pp. 1–19. doi: 10.1016/j.ijepes.2024.110165.
 38. **Wu, C., Gao, Y. (2025).** Generalized Multiplicative Interval Type-2 Fuzzy Partition C-Means Clustering, *Information Sciences*, Vol. 718, pp. 1–30. doi: 10.1016/j.ins.2025.122356.
 39. **Zhang, H., Huang, S-L. (2025).** Improved Fuzzy C-Means Clustering Algorithm Based on Fuzzy Particle Swarm Optimization for Solving Data Clustering Problems, *Mathematics and Computers in Simulation*, Vol. 233, pp. 311–329, doi: 10.1016/j.matcom.2025.02.012.
 40. **Zhang, S., Quan, L., Zhao, Y. (2025).** Model and Method for Comprehensive Evaluation of Investment Benefits of Power Grid Based on FCM Algorithm, *Procedia Computer Science*, Vol. 261, pp. 1072–1078. doi: 10.1016/j.procs.2025.04.687.
 41. **Castillo, O., Melin, P., Valdez, F (2025).** A Review on the Role of Fuzzy Logic in Hybrid Intelligent Systems, *Computación y Sistemas*, Vol. 29, No. 3, pp. 1723–1740. doi: 10.13053/cys-29-3-5897.
 42. **Ramírez, M., Melin, P. (2023).** A New Interval Type-2 Fuzzy Aggregation Approach for Combining Multiple Neural Networks in Clustering and Prediction of Time Series, *International Journal Fuzzy Systems*, Vol. 25, pp. 1077–1104, doi: 10.1007/s40815-022-01426-5.
 43. **Elfarra, B., Yasmeen, R., Shah, W.U.H. (2025).** Role of Governance Indicators and Natural Resources Reserves on Energy Efficiency and Productivity Change: Evidence from Developed and Developing G20 Countries, *Sustainable Futures*, Vol. 10, pp.1–21. doi: 10.1016/j.sftr.2025.101314.
 44. **de Souza, J.M., Martins, O.S., De Carvalho, P.L. (2025).** The Relationship between Corporate Performance and ESG Disclosure and Performance: Evidence from G20 Countries, *International Review of Applied Economics*, pp.1–21. doi: 10.1080/02692171.2025.2531756.
 45. **Yan, Q., Wang, Y., Zhang, X. (2025).** Energy Import Dependence, Renewable Energy Deployment, and Carbon Emissions in G20 Countries, In *Natural Resources Forum*, Vol. 49, No. 2, pp. 1996–2024. doi: 10.1111/1477-8947.12480.

46. **Nurhaliza, S., Hidayat, A., Rohima, S. (2024).** The Relationship between Financial Inclusion and Financial Stability Banking Industry in G20 Emerging Market Countries: A Panel Data Evidence, *Economic Studies*, Vol. 33, No. 6. URL: <https://www.ceeol.com/search/article-detail?id=1251404>.
47. **Rahmouni, O., Kahtani, D.A. (2025).** The Impact of Oil Prices Fluctuations on Industrial Production in G20 Countries, *International Journal of Energy Economics and Policy*, Vol. 15, No. 3, pp. 2–18. doi: 10.32479/ijep.18819.
48. **Subekti, M.J.M., Sari, D.W. (2024).** The Influence of Economic Complexity Index on Income Inequality in G20 Forum Countries, *Jurnal Ilmu Ekonomi Terapan*, Vol. 9, No. 1, pp. 137–150, doi: 10.20473/jiet.v9i1.57677.
49. **Chen, Z., Shi, G., Sun, B. (2024).** Cross-Border Spillovers in G20 Sovereign CDS Markets: Cluster Analysis Based on K-means Machine Learning Algorithm and TVP–VAR Models, *Empirical Economics*, Vol. 67, No. 6, pp. 2463–2502. doi: 10.1007/s00181-024-02628-6.
50. **The World Bank Data: World Development Indicators (2025).** Available online: <https://datatopics.worldbank.org/world-development-indicators/> (accessed on 5 June 2025).
51. **Gonzalez, C.I. (2025).** Designing Optimal CNNs Architectures Using Metaheuristic Algorithms Applied to the Classification of Alzheimer's Disease, *Computación y Sistemas*, Vol. 29, No. 1, pp. 179–189. doi: 10.13053/CyS-29-1-5512.
52. **Sanchez, D., Melin, P., Castillo O. (2020).** Comparison of Particle Swarm Optimization Variants with Fuzzy Dynamic Parameter Adaptation for Modular Granular Neural Networks for Human Recognition, *Journal of Intelligent & Fuzzy Systems*, Vol. 38, No. 3, pp. 3229–3252. doi: 10.3233/JIFS-191198.

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