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Type-1 fuzzy functions for forecasting: A literature review and bibliometric analysis

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ABSTRACT

Type-1 Fuzzy Functions (T1FFs) have emerged as a rule-free alternative to classical fuzzy inference systems for tackling forecasting problems, especially in the presence of uncertainty and nonlinearity. This study provides a comprehensive literature review and a bibliometric analysis of T1FFs in the context of forecasting. A dataset of 25 articles indexed in the Web of Science Core Collection was examined to assess research trends, author collaboration networks, influential publications, source journals, and key thematic areas. Our review identifies four main components in the design of T1FF-based models: input structure, clustering methods, forecasting models, and objective function optimization. Through citation and co-authorship network analysis, we highlight prominent researchers and collaborations within the field. Source journal analysis reveals publication hotspots, while co-word analysis identifies dominant themes such as "forecasting," "robust regression," and "metaheuristic optimization." The results suggest growing academic interest and methodological diversification in the use of T1FFs, with Turkey leading international contributions. This study serves as a roadmap for researchers aiming to build or extend T1FF-based forecasting systems.

1. Introduction

Fuzzy inference systems (FISs), which are first introduced by Zadeh in 1965, provides a flexible and easy-to-understand framework for making decisions in situations that involve uncertainty or complexity. These systems use fuzzy sets, fuzzy rules, and fuzzy reasoning to map inputs to outputs. FISs typically consist of three parts: fuzzification (turning real inputs into fuzzy sets), a rule base (using if-then rules to relate inputs and outputs), and defuzzification (converting fuzzy outputs into real values).

There are several common types of FISs. The Mamdani Fuzzy Inference System (MFIS), developed by Ebrahim Mamdani in 1975, is one of the first and most commonly used. It uses fuzzy rules with both fuzzy inputs and fuzzy outputs. The Sugeno Fuzzy Inference System (SFIS), introduced by Takagi and Sugeno in 1985, improves on the Mamdani system by expressing the output of rules with mathematical functions instead of fuzzy sets. The Adaptive Neuro-Fuzzy Inference System (ANFIS), developed by Jang in 1993, combines fuzzy logic and neural networks to create systems that can learn from data.

These systems mimic how humans reason, allowing systems to handle vague or imprecise input and make decisions using fuzzy rules. One challenge with FISs is that as the number of inputs increases, creating and managing rules becomes complex, especially since they often rely on expert knowledge. To address these issues, Type-1 Fuzzy Functions (T1FFs) were introduced by Turksen in

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2018 as an alternative form of FIS. T1FFs do not rely on rule bases created by experts. Instead, they use a data-driven approach. The fuzzy c-means (FCM) clustering algorithm is used to generate fuzzy memberships, which are then used to build the model.

The fundamental idea of FFs is to group observations based on the information contained in the variables. For example, suppose we aim to predict car prices using a dataset with 1000 observations and 20 independent variables. By clustering the 1000 observations based on these 20 variables, we can obtain five distinct clusters. These clusters can be labeled, for example, as very high-priced cars, high-priced cars, mid-priced cars, low-priced cars, and very low-priced cars. Once the observations are clustered in this way, the implicit rules are automatically captured. To predict the price of a new car, the FF approach identifies the cluster to which the car is most similar and assigns it the highest membership grade. It also assigns lower membership grades to the second-closest cluster, and so on. Finally, predictions from all clusters are aggregated by weighting them according to these membership grades, thereby producing the final forecast. Unlike classical rule-based fuzzy inference systems, T1FFs handle uncertainty by assigning partial membership of each observation to multiple clusters, rather than relying on crisp rules. In addition, the use of non-linear membership functions and cluster-specific regression models enables T1FFs to capture complex and non-linear relationships in the data, making them a powerful rule-free alternative for forecasting under uncertainty and non-linearity.

Based on the same idea, FFs were applied to forecasting problems by Aladag et al. [1]. In their pioneering study, the inputs of the model were created using lagged values from a time series as covariates, and a linear regression model was applied using least squares estimation. To calculate the membership grades for each cluster, the fuzzy c-means (FCM) clustering algorithm was used. This early work attracted attention to the use of T1FFs in forecasting problems.

The details of FFs for forecasting are given in the following algorithm.

1.1. Type-1 fuzzy functions (T1FF) for forecasting

Türkşen [2] proposed fuzzy functions as an alternative to rule-based fuzzy inference systems. Instead of relying on a rule base, FFs directly generate functional relationships, which is a major advantage. In this study, the Type-1 Fuzzy Functions (T1FF) approach is implemented using the fuzzy C-means (FCM) clustering algorithm (Bezdek, 1981). The procedure can be summarized as follows:

- **Step 1: Clustering of Inputs and Outputs.** Construct the data matrix Z containing lagged variables (inputs) and the output of the time series. Apply FCM clustering:

$$v_i = \frac{\sum_{k=1}^{n} \mu_{ik}^{f} z_k}{\sum_{k=1}^{n} \mu_{ik}^{f}}, \qquad i = 1, 2, \dots, c \tag{1}$$

$$\mu_{ik} = \left[\sum_{j=1}^{c} \left(\frac{d(z_k, v_i)}{d(z_k, v_j)} \right)^{\frac{2}{f-1}} \right]^{-1}, \tag{2}$$

  where f is the fuzziness parameter, $d(z, v) = \|z - v\|$ is the Euclidean distance, z_k is the kth observation, and μ_{ik} is the membership of z_k in cluster i.
- **Step 2: Membership of the Input Space.** For a new input matrix X generated from lagged variables, compute membership values as:

$$\mu_{ik} = \left[\sum_{j=1}^{c} \left(\frac{d(x_k, v_i)}{d(x_k, v_j)} \right)^{\frac{2}{f-1}} \right]^{-1}. \tag{3}$$

  An α-cut can be applied: if $\mu_{ik} < \alpha$, then μ_{ik} is set to zero.
- **Step 3: Construction of Fuzzy Functions.** For each cluster i, a regression model is fitted using membership-weighted inputs:

$$Y^{(i)} = X^{(i)} \beta^{(i)} + \varepsilon^{(i)}, \tag{4}$$

  where $X^{(i)}$ and $Y^{(i)}$ include the original inputs and membership values (or transformations such as $\sqrt{\mu_{ik}}, \exp(\mu_{ik}), \ln(1/(1-\mu_{ik}))$).
- **Step 4: Forecasting.** The final prediction is obtained by aggregating the outputs of all clusters, weighted by membership grades:

$$\hat{y}_k = \frac{\sum_{i=1}^{c} \mu_{ik} \hat{y}_k^{(i)}}{\sum_{i=1}^{c} \mu_{ik}}, \qquad k = 1, \dots, n. \tag{5}$$

This study presents a literature review and a bibliometric analysis of how T1FFs have been used in forecasting. Based on the early studies, it is possible to identify four main stages where researchers can contribute to the development of T1FF-based forecasting models:

1. Input selection: Inputs can be selected using autoregressive models or autoregressive moving average (ARMA) models.
2. Clustering algorithm: Various clustering methods can be used to obtain membership grades, such as fuzzy c-means or intuitionistic fuzzy c-means.
3. Forecasting method: Different forecasting techniques can be applied, including linear regression, artificial neural networks (ANN), or adaptive neuro-fuzzy inference systems (ANFIS).

Table 1
Summary of T1FFs forecasting applications.

Reference	Input	Clustering	Model	Optimization
[1]	AR	FCM	Multiple Regression	LSE
[3]	AR	I-FCM	Multiple Regression	LSE
[4]	AR	GK clustering	Multiple Regression	LSE
[5]	ARMA	FCM	Multiple Regression	PSO
[6]	AR	FCM	Robust Regression	M-Estimator
[7]	AR	I-FCM	Robust Regression	M-Estimator
[8]	AR	FCM	Gaussian Process Regression	LSE
[9]	AR	FCM	Elastic-net Regression	Newton-Raphson
[10]	AR	Picture Fuzzy Clustering	Robust Regression	M-Estimator
[11]	AR	Picture Fuzzy Clustering	Multiple Regression	Genetic Algorithm
[12]	AR	I-FCM	Multiple Regression	LSE
[13]	AR	PFCM	Multiple Regression	LSE
[14]	ARMA	I-FCM	Multiple Regression	GWO
[15]	AR	I-FCM	Ridge Regression	MLE
[16]	ARMA	PFCM	Multiple Regression	GWO
[17]	AR	FCM	Multiple Regression	LSE
[18]	AR	FCM	Bootstrap + Multiple Regression	LSE
[19]	AR	FCM	Ridge Regression	MLE
[20]	AR	Picture Fuzzy Clustering	Robust Regression	M-Estimator
[21]	ARMA	FCM	Multiple Regression	MFF + PSO
[22]	ARMA	FCM	Multiple Regression	PSO
[23]	AR	PCM	MARS	SA
[24]	NARMAX	FCM	MARS	Univariate optimization
[25]	AR	FCM	Multiple Regression	LSE
[26]	AR	FCM	WLS-SVM	PSO
[27]	AR	FCM	Dynamic Fuzzy Neural Networks	LSE
[28]	AR	FCM	Ridge Regression	MLE

4. Optimization of the objective function: To estimate the model parameters, techniques like the least squares method or metaheuristic algorithms such as particle swarm optimization (PSO) can be used.

This framework highlights the flexibility of T1FFs and allows researchers to enhance forecasting performance by improving any of the four components. Table 1 presents a literature summary of how T1FFs have been applied across these stages.

Given the growing interest in T1FFs for forecasting tasks and the variety of methods used in their development, it is important to understand how research in this area has evolved over time. To achieve this, we apply a bibliometric analysis focused specifically on the use of T1FFs in forecasting. This approach allows us to quantitatively explore the scientific landscape, identify key contributors, track publication trends, and uncover research hotspots within the field. By analyzing metadata from scientific databases, we aim to provide an overview of the development and impact of T1FFs in forecasting applications.

Bibliometrics or scientometrics is a statistical analysis technique using metadata of scientific articles obtained from databases such as Web of Science (WoS) or Scopus. This statistical method allows the identification of many characteristics of a specific scientific field without the need to read the full articles. It is done by entering keywords into a database (WoS or Scopus) [29]. It should be ensured that all the requested information is retrieved in the listing made with the keyword and that the precision and comprehensiveness levels of the relevant scientific articles are high. The data set to be analyzed includes information such as the title of the articles, author names, journal name, year of publication, institutional information and citations. In the light of these data, the productivity and citation success of authors, institutions and countries can be revealed. Nowadays, bibliometric analysis is widely used in many areas such as the trend of research topics, author collaboration analysis, cluster analysis of research topics, and the development of journals [30–40].

The main contributions of this study to the literature can be listed as follows: 1. Providing a bibliometric analysis for all publications on Type-1 Fuzzy Functions (T1-F) and Forecasting in the Web of Science (WoS) Core Collection database indexed in SCI-E (Science Citation Index-Expanded) and Emerging Sources Citation Index (ESCI), 2. It is the first study to analyze in detail the authors and their institutions, author collaboration analysis, and citation counts that contribute to Type-1 Fuzzy Functions and Forecasting research. 3. It also presents the top 10 journals in which Type-1 Fuzzy Functions and Forecasting studies are published, 4. the most cited authors, 5. contributions from different countries, 6. and co-authorship analysis results.

This paper is structured as follows: Section 2 describes the data source and methodology. Section 3 presents the most published journals, the most prolific authors, the most cited authors, the most cited articles, the visual results of the keyword analysis, author-country relationship network analysis. Finally, Section 4 concludes this paper with a discussion of the findings of the study and its future implications.

2. Data collection and methodology

The bibliographic information of the articles was searched from the Web of Science (WoS) database using the terms “Type-1 Fuzzy Functions” OR “Fuzzy Regression Functions” OR “Fuzzy Forecasting Functions” OR “Fuzzy Functions” AND “Forecasting”. The 25

Table 2
Measures of Co-authorship network.

Author(s)	Degree centrality	Betweenness centrality	Closeness centrality
Egrioglu, E	0.5556	0.2516	0.5602
Bas, E	0.2778	0.0131	0.3735
Yolcu, U	0.2222	0.0000	0.3538
Evren, AA	0.2222	0.0098	0.3735
Tak, N	0.2222	0.0768	0.3735
Yolcu, OC	0.1667	0.0153	0.3361
Tez, M	0.1667	0.0114	0.3538
Ghanbari, N	0.1667	0.0000	0.1667
Turksen, IB	0.1667	0.0000	0.1667
Zarandi, MHF	0.1667	0.0000	0.1667
Zarinbal, M	0.1667	0.0000	0.1667
Grosan, C	0.1667	0.0741	0.3361
Chakravarty, S	0.1111	0.0000	0.1111
Demirhan, H	0.1111	0.0000	0.1111
Baser, F	0.1111	0.0000	0.1111

articles that used these terms and were appropriate in terms of content were included in the data set. These articles are indexed in SCI-E or ESCI. 25 articles received 444 citations. While extracting data from the database, information such as author(s), institution(s), title, number of citations, keyword(s) of each article were recorded. The integer counting method was used for numerical calculation. For co-authored articles, one article credit was given to each author. The same was applied for institutions and countries. All analysis were performed in VOSviewer version 1.6.20.

3. Analysis and results

The results of the bibliometric analysis are presented in the sub-section.

3.1. Co-authorship network analysis

Network centrality analysis is a set of methods for measuring how central or influential nodes (e.g. authors, institutions, keywords) are within a network. Network centrality analysis answers the question of which author is most influential in the collaboration network. There are 3 types of centrality used in the determination. These are degree centrality, closeness centrality and betweenness centrality [40,41].

- *Degree Centrality*: It shows how many direct links (edges) a node has, so the nodes with the most links are considered to be "in the center". The more people a writer has a direct connection with, the higher it is.

$$C_D(v) = \deg(v) \tag{6}$$

- *Closeness Centrality*: It is measured by the average distance of a node from all other nodes in the network. Shorter distances are more centralized.

$$C_C(v) = \frac{1}{\sum_{u \neq v} d(v,u)} \tag{7}$$

- *Betweenness Centrality*: It looks at how often a node is located on the shortest paths between other nodes. It reveals critical nodes for information flow.

$$C_B(v) = \frac{\sigma_{st}(v)}{\sum_{s \neq v \neq t} \sigma_{st}} \tag{8}$$

where:
σ_{st} is the number of shortest paths between nodes s and t.
$\sigma_{st}(v)$ indicates how many of these paths pass through node v.
Degree Centrality, Closeness Centrality and Betweenness Centrality results calculated from bibliometric data are given in Table 2. According to Table 2:

1. **Egrioglu, E - Network Centrality Figure:**
   Degree Centrality (0.56): He is directly connected to 56 % of the nodes (i.e., authors) in the network. This makes him the most collaborative person in the network.
   Betweenness Centrality (0.25): Acts as a "bridge" in the flow of information between different authors. In other words, this author is a transit point for indirect collaborations between others.
   Closeness Centrality (0.56): The author with the shortest access distance to other authors. Information or interaction can spread very quickly from this person.

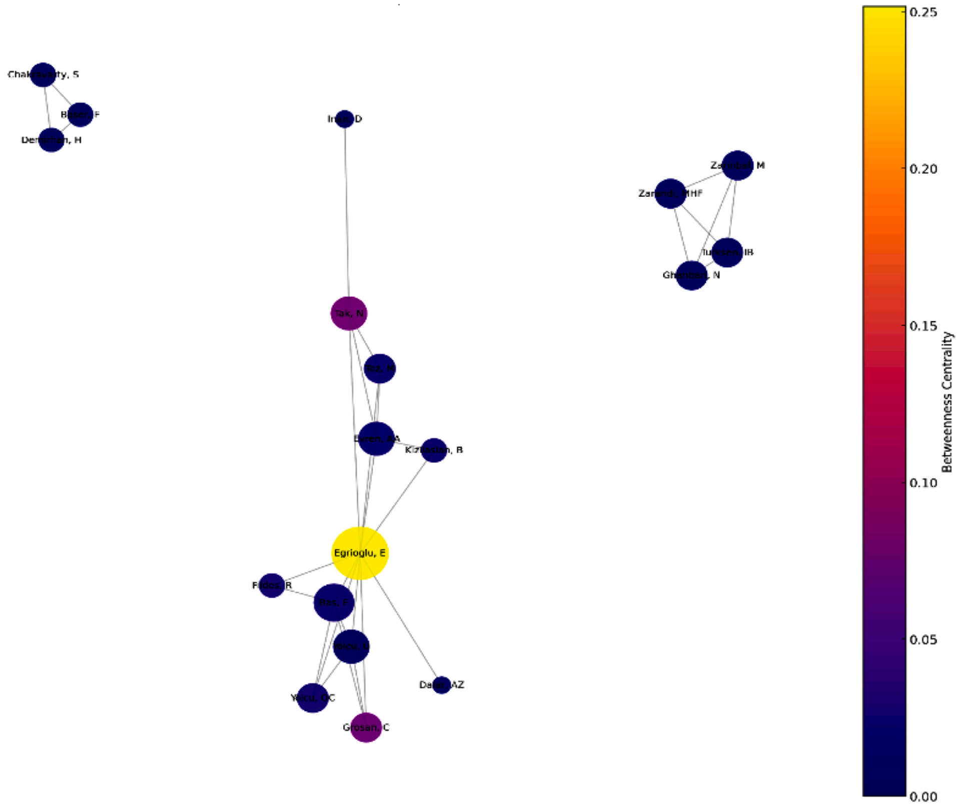


Fig. 1. Co-authorship network (Node size: degree centrality, color: betwenness centrality).

2. **Bas, E - Active**
   High degree value indicates that he/she works with many people. However, the betweenness is low, meaning it is not the central connection point. Closeness is medium, placing it relatively close to the network.
3. **Tak, N - Strategic Partner**
   Degree is lower, but betweenness is relatively high (0.0768). This suggests that although he works with fewer people, he acts as a bridge between the two groups.
4. **Evren, AA and Yolcu, U - Secondary Actors**
   These authors also worked with a few people, but not at the center of the network. Passenger, U has a betweenness value of zero, which positions him as an individual within a group, with no transitional role between networks.

In conclusion, according to this table, Egrioglu, E is both the most collaborative and the key to inter-author relationships at the center of the network. Tak, N functions as a strategic bridge with fewer connections. The other authors appear to be peripheral supporting actors. Author collaboration network visualization is given in Fig. 1.

3.2. *Citation analysis*

Citation analysis plays a role in determining academic impact by looking at which articles, authors, journals or institutions receive more citations. It also enables the comparison of scientific productivity and impact levels between authors or countries. When the top 10 most cited authors are listed, Erol E is in the first place and the most cited publication is Baser, F; Demirhan, H:A fuzzy regression with support vector machine approach to the estimation of horizontal global solar radiation. The 10 most cited authors and the most cited publications are given in Fig. 2 and Table 3.

Author co-citation analysis is an important citation analysis method and was first proposed in 1981 [42]. Scientific research can be guided by co-citation relationships between authors in the literature [30,43,44]. Accordingly, the author co-citation map on Type-1 Fuzzy Functions research is given in Fig. 3. This analysis associates authors who are co-cited in the same articles in a network structure. The nodes in this network represent the authors and the edges represent the cases in which these authors are co-cited.

Those with a high centrality value play critical roles in terms of linking different research clusters and disseminating knowledge. The author with the highest centrality value is 'Egrioglu, Erol', who appears to play an important bridging role between the publications analyzed. The following authors such as 'Grosan, Crina', 'Tak, Nihat' and 'Yolcu, Ozge Cagcag' are also located at important

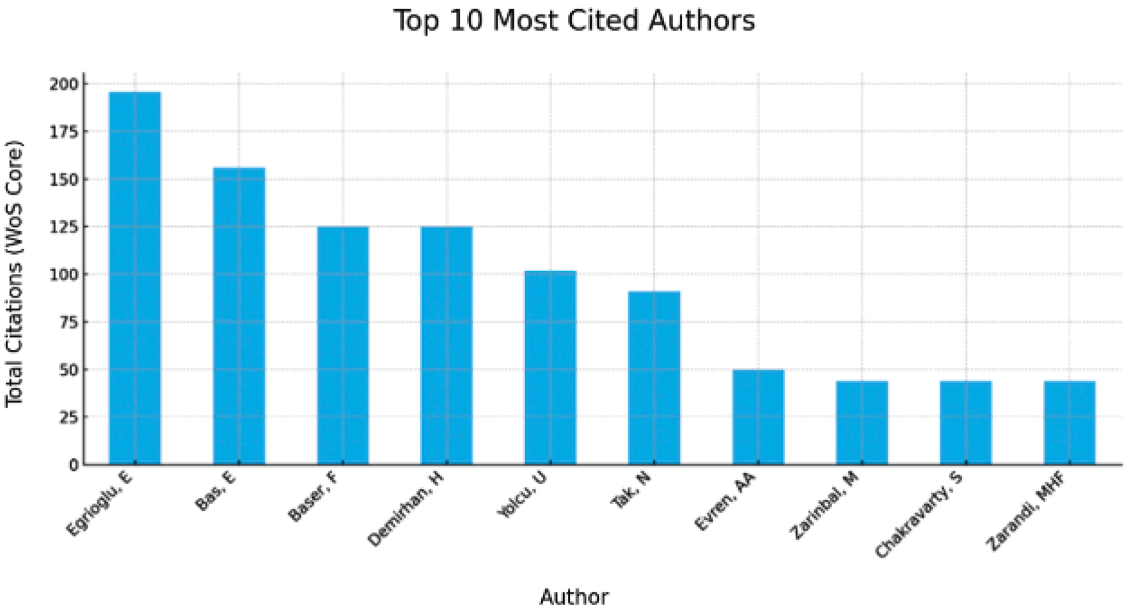


Fig. 2. Top 10 most cited authors.

Table 3
Most cited publications.

Author(s)	Manuscript title	Number of cited (WoS core)
Baser, F; Demirhan, H	A fuzzy regression with support vector machine approach to the estimation of horizontal global solar radiation	81
Zarandi, MHF; Zarinbal, M; Ghanbari, N; Turksen, IB	A new fuzzy functions model tuned by hybridizing imperialist competitive algorithm and simulated annealing Application: Stock price prediction	44
Bas, E; Yolcu, U; Egrioglu, E	Intuitionistic fuzzy time series functions approach for time series forecasting	42
Tak, N; Evren, AA; Tez, M; Egrioglu, E	Recurrent type-1 fuzzy functions approach for time series forecasting	35
Chakravarty, S; Demirhan, H; Baser, F	Fuzzy regression functions with a noise cluster and the impact of outliers on mainstream machine learning methods in the regression setting	29
Bas, E; Egrioglu, E; Yolcu, U; Grosan, C	Type 1 fuzzy function approach based on ridge regression for forecasting	20
Egrioglu, E; Fildes, R; Bas, E	Recurrent fuzzy time series functions approaches for forecasting	20
Bas, E; Yolcu, U; Egrioglu, E	Picture fuzzy regression functions approach for financial time series based on ridge regression and genetic algorithm	20
Yolcu, OC; Bas, E; Egrioglu, E; Yolcu, U	A new intuitionistic fuzzy functions approach based on hesitation margin for time-series prediction	18
Tak, N	Meta fuzzy functions: Application of recurrent type-1 fuzzy functions	17

points in the network. In particular, 'Tak, Nihat' both appears in a large number of publications and stands out as a central and influential figure in areas where Turkish researchers are concentrated (Table 4).

3.3. Source journal analysis

In bibliometric analysis, source journal analysis identifies the main platforms from which scientific literature is produced and plays a critical role in understanding the structure of research fields. This type of analysis allows for the identification of the journals with the most publications, the most citations or the most influential journals. Total number of publications, the total number of citations and citation/publication ratio are used to determine the journals that contribute the most to the field. The h-index is used to visualize this impact according to the results of the source journal analysis, the top 15 impact journals in the field of Type-1 Fuzzy Functions and Forecasting and the number of publications are given in Table 5.

Information Sciences has the highest number of contributions with 5 publications and is also one of the most influential journals with an h-index of 4. Granular Computing has the highest average citation (27.3) with a total of 82 citations in 3 publications. Applied

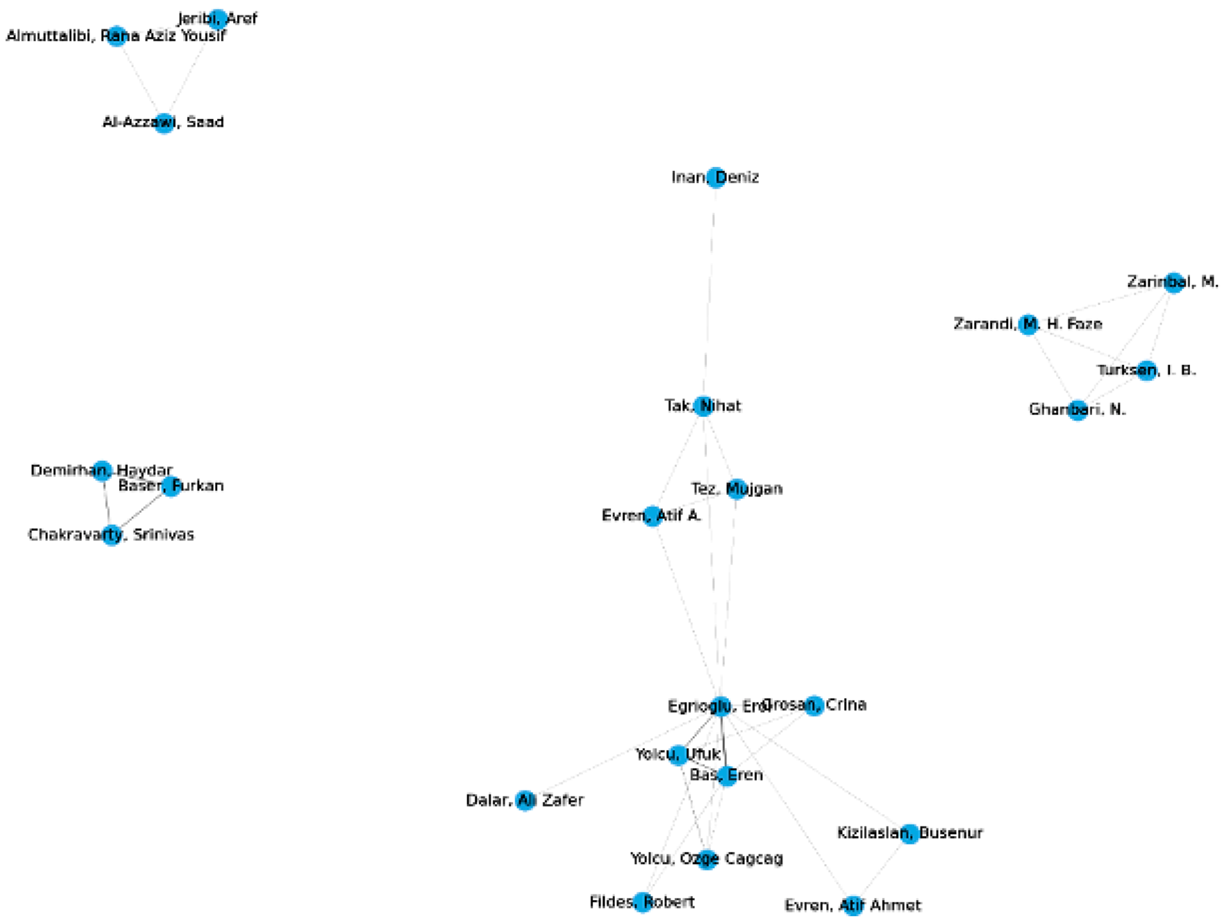


Fig. 3. Author co-citation map.

Table 4
The top 10 people with the highest centrality value according to author co-citation analysis.

Author name	Betweenness
Egrioglu, Erol	0.2208
Grosan, Crina	0.0548
Tak, Nihat	0.0476
Yolcu, Ozge Cagcag	0.0115
Fildes, Robert	0.0115
Bas, Eren	0.0087
Inan, Deniz	0.0000
Dalar, Ali Zafer	0.0000
Evren, Atif A.	0.0000
Tez, Mujgan	0.0000

Intelligence seems to be quite influential with 35 citations in a single publication. Energy is also noteworthy with 81 citations in only one publication. These results are important to understand which journals are more visible and influential in Type-1 Fuzzy Functions and Forecasting or similar topics when determining a publication strategy. The heat map showing the fields of study in the top 15 journals is given in Fig. 4.

According to the heat map, journals such as "Information Sciences, Expert Systems with Applications, Granular Computing, Applied Soft Computing" mostly publish fuzzy logic in the field of computer science, while Computational Economics and Energy journals publish publications on the use of fuzzy logic and artificial intelligence methods in economic modeling.

Table 5
The top 15 impact journals in the field of Type-1 Fuzzy Functions and Forecasting and the number of publications.

Journal	Total publication (TP)	Total citation (TC)	Citation/publication	h-index
Information Sciences	5	80	16.00	4
Expert Systems with Applications	3	32	10.67	3
Granular Computing	3	82	27.33	3
Applied Soft Computing	2	46	23.00	2
Computational Economics	2	5	2.50	2
Journal of Computational and Applied Mathematics	2	32	16.00	2
Applied Intelligence	1	35	35.00	1
Communications in Statistics-Simulation and Computation	1	15	15.00	1
Energy	1	81	81.00	1
Energy Conversion and Management	1	7	7.00	1
Energy Conversion and Management-X	1	0	0.00	0
Engineering Applications of Artificial Intelligence	1	0	0.00	0
International Journal of Uncertainty Fuzziness and Knowledge-Based Systems	1	0	0.00	0
Soft Computing	1	18	18.00	1

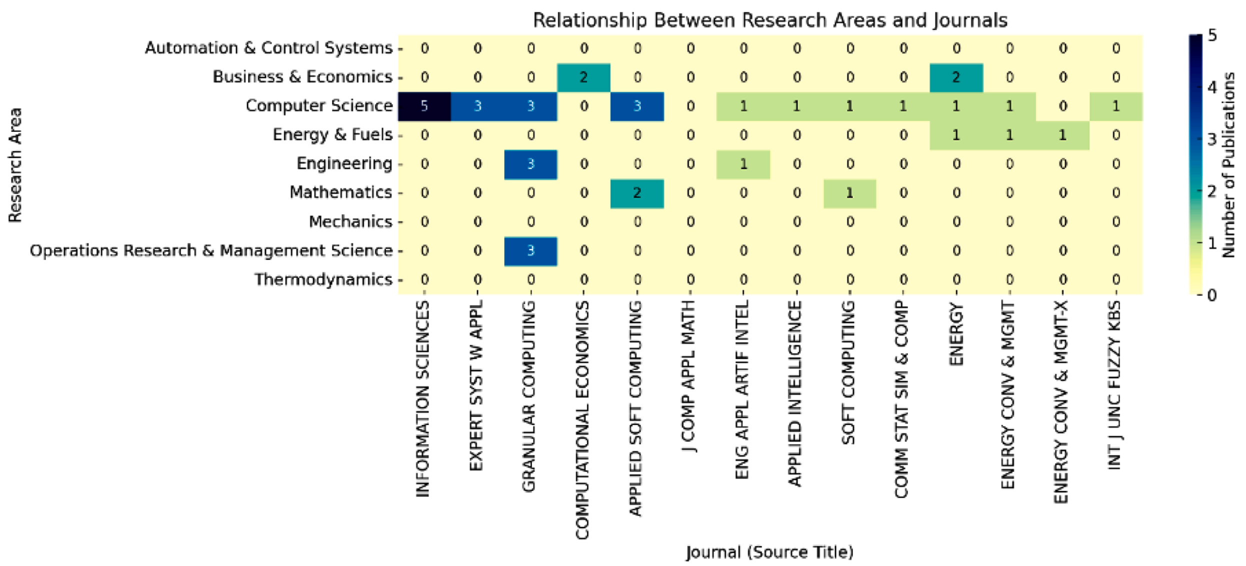


Fig. 4. Heatmap of top 15 journals.

3.4. Keyword co-word analysis

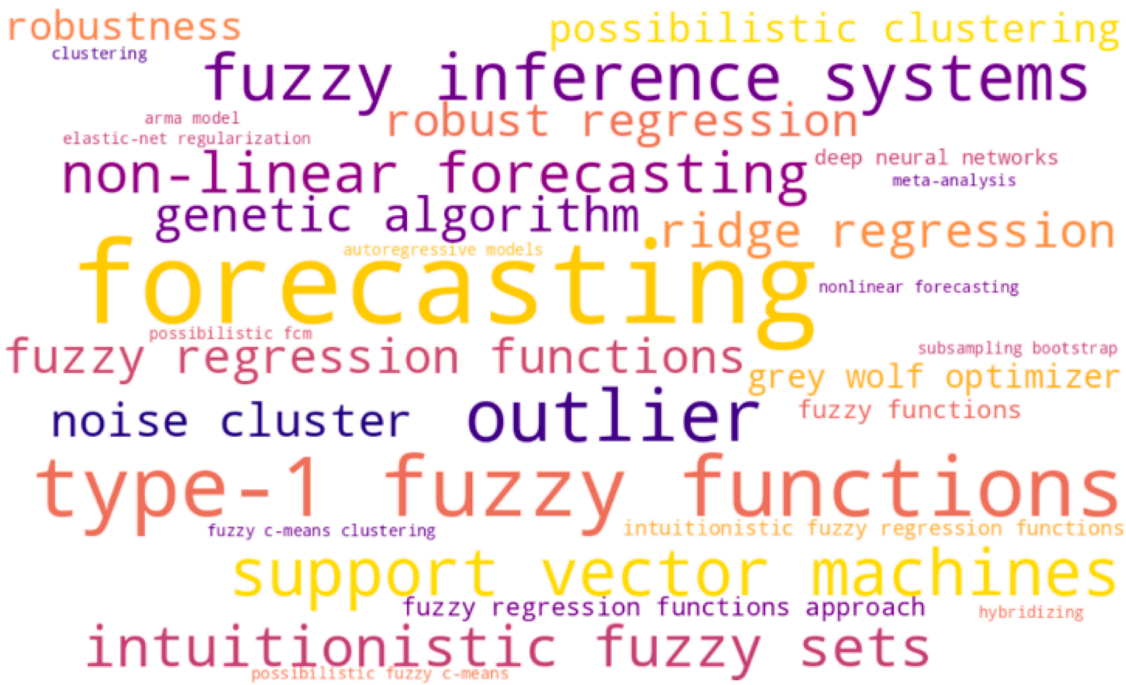
It can be said that keywords are the soul of scientific articles. Keyword analysis identifies research topics and provides a summary of what the article is about [45,46]. Each of the 25 studies evaluated in the Wos database has at least 3 keywords.

According to the keyword cloud, words that are written more dominant (larger) are the most frequently used words. For example: “forecasting”, “Type-1 Fuzzy Functions”, “outlier”, “Fuzzy Inference Systems” are frequently used keywords.

3.5. Author-country relationship network analysis

It is a type of bibliometric analysis that visualizes and analyzes the relationship of authors with their countries and international collaborations in the process of scientific production. In Fig. 5, orange nodes represent countries and blue nodes represent authors. In the research area of Type-1 Fuzzy Functions and Forecasting, Turkey, the UK, Romania, Australia, Iran, Canada and Iraq are overlaid on the map, with Turkey occupying the most central position. This shows that Turkish authors are both highly contributing to the field and active in international collaborations.

In the network map, if an author is connected to more than one country, it means either joint projects or multiple institutional affiliations of the author. Accordingly, names like Grosan, Crina and Egrioglu, Erol act as a bridge between Romania, England and Turkey. Fildes, Robert is linked to both England and Turkey, suggesting cooperation between the countries. Furthermore, authors such as Zarandi, M. H. Faze, Turksen, I. B., Ghanbari, N. are clustered around Iran and Canada (Fig. 6).



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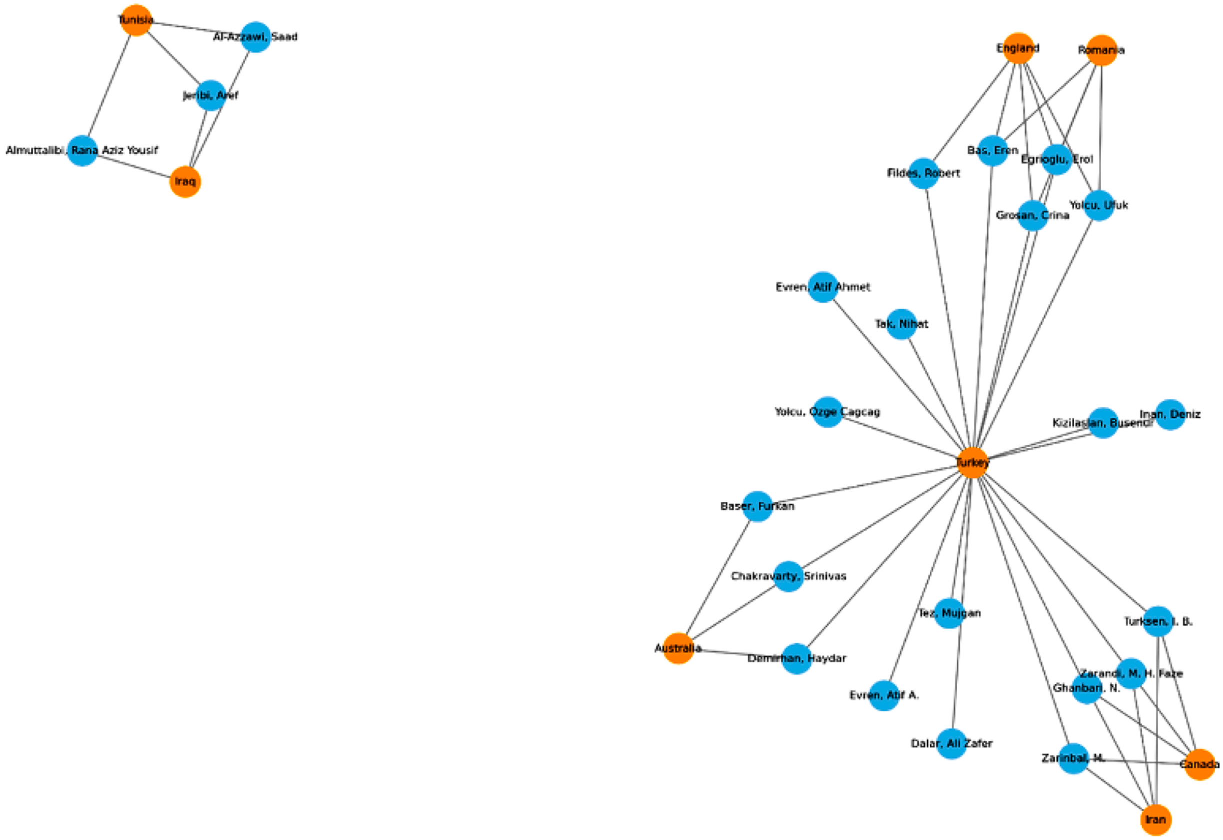

Fig. 6. Author-country relationship network.

4. Discussion

The bibliometric results demonstrate that Type-1 Fuzzy Functions have gained traction in the forecasting literature due to their rule-free, modular structure and their capacity to integrate different modeling and optimization techniques. Among the 25 studies evaluated, various clustering strategies (e.g., FCM, I-FCM, GK) and regression approaches (e.g., linear, robust, Gaussian process, ridge) have been tested, confirming the adaptability of the T1FF framework.

Our co-authorship network analysis revealed that Turkish researchers, particularly Egrioglu, E., Bas, E., and Tak, N., have played a central role in the development and dissemination of T1FF applications. These authors often act as bridges in the research network, fostering collaboration and knowledge flow. The author-country relationship analysis also confirmed Turkey's dominant role in this area, supported by contributions from countries such as the UK, Romania, and Iran.

Citation analysis identified influential publications that have helped shape the direction of the field. For instance, studies incorporating hybrid models (e.g., fuzzy regression with support vector machines, MARS, or PSO optimization) tend to receive higher citations, pointing to a demand for hybrid and computationally efficient methods.

Journal analysis shows that venues such as *Information Sciences*, *Granular Computing*, and *Applied Soft Computing* are key outlets for research in this area, particularly in domains combining fuzzy logic, AI, and forecasting. Co-word analysis suggests emerging interest in robust estimation methods and uncertainty-aware clustering.

Collectively, these findings reflect a maturing field with growing methodological diversity, institutional collaboration, and interdisciplinary potential.

CRediT authorship contribution statement

Aysegul Yabaci Tak: Writing – review & editing, Writing – original draft, Formal analysis, Data curation; **Nihat Tak:** Writing – review & editing, Writing – original draft, Conceptualization.

Data availability

Data will be made available on request.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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During the preparation of this work, the authors used [ChatGPT 4.0] in order to improve language and readability. After using this service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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