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BUSINESS, ENTREPRENEURSHIP AND SMES
(AIJBES)**www.aijbess.com**A BIBLIOMETRIC ANALYSIS OF THE ARFIMA MODEL
DURING 1993 – 2022**Amirah Hazwani Abdul Rahim^{1*,2}, Mohd Tahir Ismail³, Nurazlina Abdul Rashid⁴¹ Department of Mathematics, Universiti Teknologi Mara, Malaysia

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DOI: 10.35631/AIJBES.725014This work is licensed under [CC BY 4.0](https://creativecommons.org/licenses/by/4.0/)**Abstract:**

The Autoregressive Fractionally Integrated Moving Average (ARFIMA) model is the best choice for the long-term memory data series. In this research, we review and evaluate the literature on ARFIMA models. ARFIMA research activity was examined using a bibliometric technique using a sample of 784 papers from the Scopus database that were published between the years 1993 and 2022. Moreover, we identified the primary research areas, categories of published documents, most significant platforms and sources of ARFIMA publications, widely cited studies, productive authors, author's institutions and countries, as well as evaluated the publication's citation pattern. The titles and keywords, including abstracts of the documents, are also included, as well as their terms and occurrences. Microsoft Excel was used for frequency analysis, Harzing's Publish or Perish for citation analysis and metrics, as well as VOS viewer for data visualisation. The results indicate that there is an increment in the publications' number. The network analysis and statistical analysis revealed that the year 2018 had the most papers issued.

Keywords:

ARFIMA, Long Memory, Forecasting, Time Series, Bibliometric

Introduction

A time series denotes a set of observations made in a specific order, usually at an equally spaced time interval. The unique aspect of time series analysis is that it requires consideration of time order since successive data are rarely independent. At the same time, another statistical theory is mainly affected by random samples of independent observations.

Time series forecasting has long been a focus of study, and it is crucial in the financial time series field. Time series forecasting generates predictions about the future of activity utilizing previous values and related patterns' knowledge. Business, weather, cost and usage of items, electricity demand, stock market and exchange, for example, fuels and electricity, among other areas, are only a few examples of the various applications of time series forecasting and analysis in time series data (Mahalakshmi et al., 2016).

Various forecasting approaches have been studied to obtain accurate forecasting results which use linear and nonlinear models separately or a combination of both. Autoregressive Integrated Moving Average (ARIMA), exponential smoothing, Holt-Winters, linear regression (LR), and other derived techniques, such as Seasonal Autoregressive Integrated Moving Average (SARIMA), are some of the most popular linear model techniques (Huang et al., 2021). However, since they do not accommodate for the long memory characteristic, among the crucial elements in modelling and forecasting the financial markets, these models have not shown positive outcomes in predicting financial markets. The idea of long memory is not new to statistics. It was initially studied in the field of hydrology in the 1950s (Hurst, 1956), who also wrote papers about it in relation to the Nile River's water level in 1951. Ironically, econometricians did not begin applying the long memory theory to the financial field until the 1980s (Baillie, 1996; Ibrahim et al., 2018). According to (Granger & Joyeux, 1980), the ARFIMA (p, d, q) model, also defined as the Autoregressive Fractionally Integrated Moving Average, is a common group of time series models possessing long memory in which p, d, and q are non-negative integers. The ARFIMA model is a popular time series model that allows for long-term dependence in the data, which means that past series values can have a significant effect on future values.

Previous research examined the ARFIMA model and its use in electroencephalography (EEG) (Tokhmpash et al., 2021), climate and financial econometrics (Vera-Valdés, 2020), financial markets (Murialdo et al., 2020), air traffic passengers (Dingari et al., 2019), gold prices (Safitri et al., 2019), crude oil price (Jibrin et al., 2015; Al-Gounmmeen & Ismail, 2021) and air quality (Nimesh et al., 2014). In finance and economics, the ARFIMA model has been used to model and forecast exchange rates, stock prices, and interest rates (Gough et al., 2014; Xie et al., 2015; Ibrahim et al., 2018; Tan et al., 2022). To choose the best predictive model, many authors have recently shown a desire to acquire and predict ARFIMA models. Despite the complexity of the study in these fields, there have only been a few investigations on the ARFIMA research pattern and trend. In order to enlighten researchers regarding the extent of ARFIMA's existence and effect throughout the globe, it is urgently necessary to study the organization's expansion in addition to learning about its latest methodologies. In fact, producing a bibliometric analysis can achieve this. The bibliometrics analysis method is now broadly employed as a research technique to present a study's trends and effects (Sweileh et al., 2017). The most common bibliometric indicators are citation, publication classification, publication impact, authorship, as well as the country (Ahmi et al., 2019).

The objectives of this research in the analysis of the ARFIMA techniques for long memory time series forecasting research using bibliometric methods in trying to identify:

1. An overview of academic research on the application of ARFIMA in time series forecasting.
2. The publication trend.
3. The leading institutions and researchers in terms of publication on the ARFIMA.

This paper presents how the research is carried out in the next section. Subsequently, it describes the overall evolution and dispersion by mentioning the sources, document kinds, document languages, and the number of written research annually. The most prevalent topics that the researchers are interested in are then highlighted using information like co-occurrences as well as keyword frequency. Lastly, it discusses how renowned organisations and academics have promoted ARFIMA research.

Methodology

Database Selection

The analysis of ARFIMA in time series is the main emphasis of the study presented in this paper. All the documents were retrieved from the Scopus database. This database was chosen due to its largest academic database and contained around 22,794 active titles from approximately 11,678 publishers, of which 34,346 are peer-reviewed journals in top-tier subject fields. Furthermore, it also offers a comprehensive outline of the results of scientific research conducted worldwide. Therefore, it is suggested that Scopus be utilised as a useful resource for gathering information about the subject matter of this study.

Inclusion Criteria

Figure 1 illustrates the systematic search strategy used to identify documents relevant to ARFIMA research. The flow diagram presents each step of this search and screening process, including the keyword selection, scope of coverage, inclusion criteria, and final dataset. Throughout the procedure, we identified the relevant documents using a keyword. In this study, the term ARFIMA was used when searching the Scopus database. On October 5, 2022, a search was performed utilising a certain document that had been issued between 1993 to 2022. Scopus found 784 documents in response to our search, and these documents were solely retrieved using the ARFIMA term. The data were exported in CSV and RIS formats as part of the data sets.

Data Analysis and Tools

As a method of research, bibliometric analysis was applied to this research. The quantitative study of bibliographic materials, known as bibliometric analysis, gives an overall image of a particular research field that may be categorised by journals, authors, as well as papers. To get comprehensive answers to address all of the research questions, we employed a variety of technologies. For example, we utilised VOSviewer to create bibliometric connections and depict them, Microsoft Excel 2019 to determine the proportion and frequency of every publication, in addition to creating pertinent charts and graphs, as well as Harzing's Publish and Perish software to determine the citation metrics.

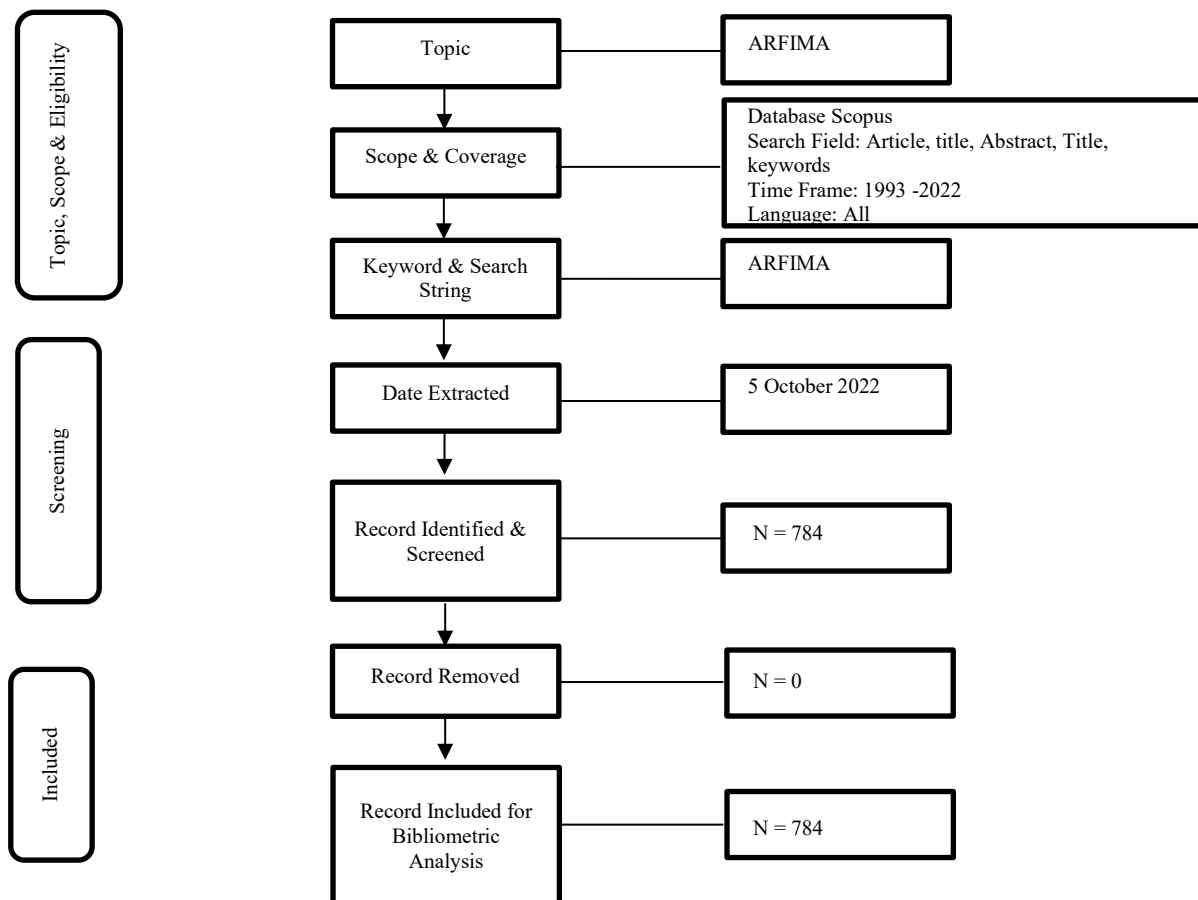


Figure 1: The Search Strategy's Flow Diagram

Results and Findings

Annual Growth of Publication

Comprehensive information on ARFIMA research publications from 1993 to 2022 is shown in Table 1, which demonstrates an increase in the publications' number. The scholar can understand the topic's development over time by analysing the document's publication year (Ahmi et al., 2019). ARFIMA was first published and indexed by Scopus in 1993, having three documents. Note that there were fewer than 20 documents published from 1994 to 2005. In 2006, the number of documents published rose to 33 documents. Nevertheless, the number of publications keeps increasing slowly from 2015 to 2021, with more than 40 documents. A total of 52 documents were published in 2018, which is the largest number recorded.

Table 1: Growth of Publication by Year

| Year | TP | (%) | NCP | TC | C/P | C/CP | h | g |
|------|----|-------|-----|-----|-------|-------|----|----|
| 2022 | 33 | 4.21% | 6 | 9 | 0.27 | 1.50 | 2 | 2 |
| 2021 | 44 | 5.61% | 27 | 87 | 1.98 | 3.22 | 5 | 6 |
| 2020 | 47 | 5.99% | 31 | 429 | 9.13 | 13.84 | 9 | 20 |
| 2019 | 45 | 5.74% | 36 | 271 | 6.02 | 7.53 | 7 | 15 |
| 2018 | 52 | 6.63% | 44 | 423 | 8.13 | 9.61 | 10 | 18 |
| 2017 | 48 | 6.12% | 46 | 620 | 12.92 | 13.48 | 13 | 23 |

| | | | | | | | | |
|------|----|-------|----|------|--------|--------|----|----|
| 2016 | 43 | 5.48% | 38 | 376 | 8.74 | 9.89 | 9 | 17 |
| 2015 | 42 | 5.36% | 38 | 317 | 7.55 | 8.34 | 11 | 15 |
| 2014 | 35 | 4.46% | 31 | 422 | 12.06 | 13.61 | 11 | 19 |
| 2013 | 44 | 5.61% | 37 | 436 | 9.91 | 11.78 | 11 | 19 |
| 2012 | 45 | 5.74% | 34 | 553 | 12.29 | 16.26 | 12 | 22 |
| 2011 | 22 | 2.81% | 20 | 487 | 22.14 | 24.35 | 10 | 20 |
| 2010 | 21 | 2.68% | 19 | 147 | 7.00 | 7.74 | 6 | 11 |
| 2009 | 36 | 4.59% | 34 | 417 | 11.58 | 12.26 | 13 | 19 |
| 2008 | 26 | 3.32% | 22 | 510 | 19.62 | 23.18 | 9 | 22 |
| 2007 | 24 | 3.06% | 19 | 559 | 23.29 | 29.42 | 13 | 19 |
| 2006 | 33 | 4.21% | 29 | 461 | 13.97 | 15.90 | 12 | 20 |
| 2005 | 17 | 2.17% | 15 | 138 | 8.12 | 9.20 | 6 | 11 |
| 2004 | 17 | 2.17% | 17 | 419 | 24.65 | 24.65 | 11 | 17 |
| 2003 | 17 | 2.17% | 17 | 473 | 27.82 | 27.82 | 12 | 17 |
| 2002 | 18 | 2.30% | 18 | 528 | 29.33 | 29.33 | 11 | 18 |
| 2001 | 11 | 1.40% | 11 | 199 | 18.09 | 18.09 | 7 | 11 |
| 2000 | 8 | 1.02% | 7 | 292 | 36.50 | 41.71 | 6 | 8 |
| 1999 | 13 | 1.66% | 12 | 395 | 30.38 | 32.92 | 10 | 12 |
| 1998 | 7 | 0.89% | 7 | 652 | 93.14 | 93.14 | 7 | 7 |
| 1997 | 11 | 1.40% | 10 | 166 | 15.09 | 16.60 | 6 | 10 |
| 1996 | 13 | 1.66% | 11 | 1840 | 141.54 | 167.27 | 9 | 11 |
| 1995 | 2 | 0.26% | 2 | 13 | 6.50 | 6.50 | 2 | 2 |
| 1994 | 7 | 0.89% | 7 | 282 | 40.29 | 40.29 | 5 | 7 |
| 1993 | 3 | 0.38% | 3 | 335 | 111.67 | 111.67 | 3 | 3 |

Notes: NCP = number of cited publications; TP = total number of publications; TC = total citations; C/CP = average citations per cited publication; C/P = average citations per publication; g = g-index; h = h-index

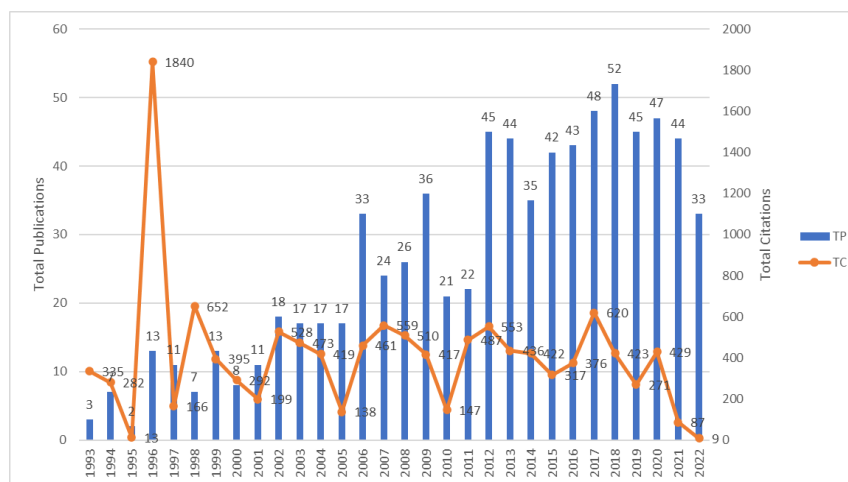


Figure 2: Total Publications and Citations by Year

The overall publications' number is rising, as seen in Figure 2, while the total number of citations is fluctuating. The highest citations' number was in the year 1996, with 1840, while the largest publications' number was 52 in the year 2018.

Document and Source Type

The types of sources and documents where the research on ARFIMA was released were examined in further detail. The percentage and number for every category of document type are depicted in Table 2. From the table, the largest number of publications on ARFIMA research is an article (82.4%), followed by conference paper (12.76%), book chapters (2.17%), reviews (1.4%) and other types of documents, for example, book, data paper, note, editorial, conference review, erratum and letter represented less than 1%.

Table 2 : Types of Document

| Types Of Documents | Total Publications | (%) |
|---------------------------|---------------------------|------------|
| Article | 646 | 82.40% |
| Conference Paper | 100 | 12.76% |
| Book Chapter | 17 | 2.17% |
| Review | 11 | 1.40% |
| Note | 3 | 0.38% |
| Conference Review | 2 | 0.26% |
| Book | 1 | 0.13% |
| Data Paper | 1 | 0.13% |
| Editorial | 1 | 0.13% |
| Erratum | 1 | 0.13% |
| Letter | 1 | 0.13% |

Table 3 : Sources Type

| Sources Type | Total Publication | (%) |
|-----------------------|--------------------------|------------|
| Journal | 667 | 85.08% |
| Conference Proceeding | 80 | 10.20% |
| Book Series | 25 | 3.19% |
| Book | 11 | 1.40% |
| Trade Journal | 1 | 0.13% |

While there are a variety of document types for the articles that have been published on ARFIMA, there are also a variety of categories of source types that have been found in this research. To determine where the ARFIMA documents have been published, statistics are shown in Table 3 according to the various types of document sources. The majority of the sources, or (n=667, 85.08%) of the total, were journals. The total numbers for book series (n=25, 3.19%) and conference proceedings (n=80, 10.20%) are presented afterward.

Languages of Documents

Eight different languages were used to write the research papers for ARFIMA. With 96.16% of all ARFIMA publications being in English, it was the most frequently utilised language, as presented in Table 4. Portuguese was applied second most often, with 1.14% of the total. The remaining six languages, which accounted for less than 1% of the total publication, were Chinese, Russian, Spanish, French, Bosnian, and Malay.

Table 4: Languages Used for Publications

| Language | Total Publications | (%) |
|-----------------|---------------------------|------------|
| English | 758 | 96.19% |
| Portuguese | 9 | 1.14% |
| Chinese | 7 | 0.89% |
| Russian | 5 | 0.63% |
| Spanish | 5 | 0.63% |
| French | 2 | 0.25% |
| Bosnian | 1 | 0.13% |
| Malay | 1 | 0.13% |

Subject Area**Table 5: Subject Area**

| Subject area | Total Publications | (%) |
|--|---------------------------|------------|
| Agricultural and Biological Sciences | 19 | 2.42% |
| Arts and Humanities | 10 | 1.28% |
| Biochemistry, Genetics and Molecular Biology | 10 | 1.28% |
| Business, Management and Accounting | 104 | 13.27% |
| Chemical Engineering | 3 | 0.38% |
| Chemistry | 5 | 0.64% |
| Computer Science | 142 | 18.11% |
| Decision Sciences | 118 | 15.05% |
| Earth and Planetary Sciences | 18 | 2.30% |
| Economics, Econometrics and Finance | 280 | 35.71% |
| Energy | 17 | 2.17% |
| Engineering | 97 | 12.37% |
| Environmental Science | 31 | 3.95% |
| Health Professions | 2 | 0.26% |
| Immunology and Microbiology | 1 | 0.13% |
| Materials Science | 12 | 1.53% |
| Mathematics | 310 | 39.54% |
| Medicine | 17 | 2.17% |
| Multidisciplinary | 9 | 1.15% |
| Neuroscience | 6 | 0.77% |
| Physics and Astronomy | 90 | 11.48% |
| Psychology | 9 | 1.15% |
| Social Sciences | 78 | 9.95% |

Table 5 provides the result of the publication based on 23 subject areas. The highest subject area is Mathematics, with 39.54% of publications. This is followed by Economics, Econometrics and Finance (35.71%), Computer Science (18.11%), Decision Sciences (15.05%), Engineering (12.37%), and Physics and Astronomy (11.48%). Less than 10% of the total articles were in other subject areas.

Publications By Countries

Table 6 : Total Publication By Country

| Country | TP | NCP | TC | C/P | C/CP | h | g |
|----------------|-----|-----|------|-------|-------|----|----|
| United States | 149 | 138 | 4839 | 32.48 | 35.07 | 33 | 66 |
| China | 119 | 87 | 1222 | 10.27 | 14.05 | 17 | 32 |
| United Kingdom | 72 | 66 | 1307 | 18.15 | 19.80 | 20 | 33 |
| Brazil | 50 | 42 | 449 | 8.98 | 10.69 | 13 | 19 |
| France | 47 | 38 | 793 | 16.87 | 20.87 | 13 | 27 |
| Spain | 36 | 32 | 576 | 16.00 | 18.00 | 10 | 23 |
| Germany | 30 | 29 | 495 | 16.50 | 17.07 | 14 | 21 |
| India | 29 | 19 | 97 | 3.34 | 5.11 | 6 | 8 |
| Italy | 27 | 23 | 365 | 13.52 | 15.87 | 10 | 18 |
| Malaysia | 27 | 16 | 90 | 3.33 | 5.63 | 6 | 8 |
| Poland | 27 | 25 | 245 | 9.07 | 9.80 | 8 | 14 |
| Taiwan | 26 | 25 | 484 | 18.62 | 19.36 | 11 | 21 |
| Australia | 25 | 25 | 199 | 7.96 | 7.96 | 7 | 13 |
| Greece | 21 | 18 | 368 | 17.52 | 20.44 | 9 | 18 |
| South Korea | 21 | 18 | 329 | 15.67 | 18.28 | 9 | 18 |
| Portugal | 20 | 20 | 202 | 10.10 | 10.10 | 9 | 13 |
| Canada | 17 | 15 | 195 | 11.47 | 13.00 | 7 | 13 |
| Turkey | 17 | 17 | 167 | 9.82 | 9.82 | 8 | 12 |
| Netherlands | 15 | 14 | 592 | 39.47 | 42.29 | 9 | 14 |
| Hong Kong | 14 | 14 | 380 | 27.14 | 27.14 | 9 | 14 |

Notes: NCP = number of cited publications; TP = total number of publications; TC = total citations; C/CP = average citations per cited publication; C/P = average citations per publication; g = g-index; h = h-index

This research also describes which countries published the most documents on ARFIMA. The country was determined based on the writers' affiliation. Table 6 illustrates the 20 most productive countries publishing papers on ARFIMA models. With 149 articles, the United States has contributed the most to the area of ARFIMA research, followed by China with 119 and the United Kingdom with 72. The remainder of the country included below 50 articles, including France, Spain, Germany, India, Italy, Malaysia, Poland, Taiwan, Australia, Greece, South Korea, Portugal, Canada, Turkey, Netherlands and Hong Kong. As can be seen, ARFIMA serves a vital role in a broad range of places around the world.

Authorship Analysis

This research also illustrates the most active authors who contributed to research on ARFIMA. Data top 10 authors were identified as depicted in Table 7. The most productive author is Shang, P., with 16 articles on ARFIMA, whose work received 155 citations, followed by Reisen, V.A., with 15 articles. Baillie R.T. has the highest citations, with 1795 citations and 11 published articles.

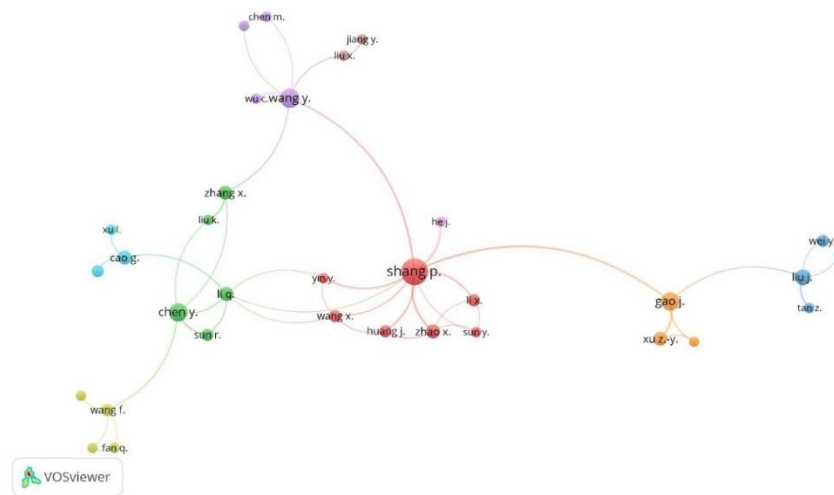


Figure 3: The Co-Authorships Network Visualisation Map Based on the Authors

Figure 3 displays the network visualisation map of the co-authorship based on the collaboration of authors having a minimum of two citations and at least two documents on ARFIMA using the fractional counting technique. This study uses a VOSviewer to analyse author collaboration. Specific elements like circle size, colour, text size, as well as thickness intensify the authors' relationship. The use of the same colour denotes that associated authors are commonly grouped together. For instance, the above figure exhibits how closely Shang P., Huang J., Li X., Sun Y., Wang X., Yin Y. and Zhao X. collaborated.

Table 7: Authorship Analysis

| Author Name | TP | % | Affiliation | Country | NCP | TC | C/P | C/CP | h | g |
|-----------------|----|-------|--|---------------|-----|------|--------|--------|----|----|
| Shang, P. | 16 | 2.04% | Beijing Jiaotong University | China | 15 | 155 | 9.69 | 10.33 | 6 | 12 |
| Reisen, V.A. | 15 | 1.91% | Federal University of Espirito Santo | Brazil | 14 | 205 | 13.67 | 14.64 | 10 | 14 |
| Baillie, R.T. | 11 | 1.40% | Michigan State University | United States | 10 | 1795 | 163.18 | 179.50 | 10 | 10 |
| Palma, W. | 10 | 1.28% | Instituto Milenio de Astrofisica | Chile | 10 | 186 | 18.60 | 18.60 | 8 | 10 |
| Rocha, A.P. | 10 | 1.28% | Universidade do Porto | Portugal | 10 | 60 | 6.00 | 6.00 | 5 | 7 |
| Silva, M.E. | 10 | 1.28% | Universidade do Porto | Portugal | 10 | 60 | 6.00 | 6.00 | 5 | 7 |
| Andrysiak, T. | 9 | 1.15% | Bydgoszcz University of Science and Technology | Poland | 8 | 52 | 5.78 | 6.50 | 4 | 7 |
| Leite, A. | 9 | 1.15% | University of Trás-os-Montes and Alto Douro | Portugal | 9 | 70 | 7.78 | 7.78 | 4 | 8 |
| Gil-Alana, L.A. | 8 | 1.02% | Universidad de Navarra | Spain | 7 | 79 | 9.88 | 11.29 | 5 | 7 |
| Crato, N. | 7 | 0.89% | Universidade de Lisboa | Portugal | 7 | 553 | 79.00 | 79.00 | 6 | 7 |

According to the fractional counting method, Figure 4 shows the network visualisation map of co-authorship based on affiliation with at least five citations and five documents. Based on the analysis, authors from the United States and China collaborated the most. The findings also presented that the United States has a tight connection with Canada, China, Denmark, Hong Kong, Taiwan, and Thailand. At the same time, Malaysia seems to have worked closely with Indonesia, Jordan and Nigeria.

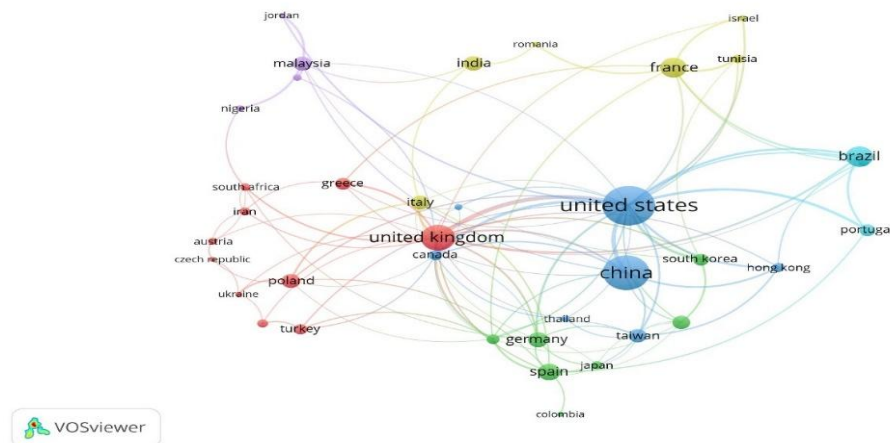


Figure 4: The Co-Authorships Network Visualisation Map Based on Countries

Most Active Institutions

This section analyses the present situation with respect to the most impactful institutions in publishing ARFIMA articles. Beijing Jiaotong University and the Federal University of Espirito Santo are the most productive institution in ARFIMA research, with 17 publications. This is consistent with the most productive author since they belong to that institution. Meanwhile, the third place is followed by Michigan State University, with 15 publications. The remaining institution is presented in Table 8. This information can benefit early-career researchers and students looking for postgraduate programmes in this field.

Table 8: Most Active Institutions

| Institution | TP | % | Country | NCP | TC | C/P | C/CP | h | g |
|--|-----------|----------|----------------|------------|-----------|------------|-------------|----------|----------|
| Beijing Jiaotong University | 17 | 2.17% | China | 16 | 162 | 9.53 | 10.13 | 6 | 12 |
| Federal University of Espirito Santo | 17 | 2.17% | Brazil | 16 | 247 | 14.5 | 15.44 | 11 | 15 |
| Michigan State University | 15 | 1.91% | USA | 13 | 1929 | 129 | 148.4 | 11 | 13 |
| Universidade do Porto | 12 | 1.53% | Portugal | 12 | 97 | 8.08 | 8.08 | 5 | 9 |
| University of Trás-os-Montes and Alto Douro | 10 | 1.28% | Portugal | 10 | 78 | 7.8 | 7.8 | 5 | 8 |
| Pontificia Universidad Católica de Chile | 10 | 1.28% | Chile | 10 | 175 | 17.5 | 17.5 | 7 | 10 |
| Bydgoszcz University of Science and Technology | 9 | 1.15% | Poland | 8 | 52 | 5.78 | 6.5 | 4 | 7 |

| | | | | | | | | | |
|--|---|-------|----------|---|-----|------|-------|---|---|
| CNRS Centre National de la Recherche Scientifique | 9 | 1.15% | France | 5 | 18 | 2 | 3.6 | 3 | 4 |
| Wrocław University of Science and Technology | 9 | 1.15% | Poland | 9 | 90 | 10 | 10 | 6 | 9 |
| Universidade Federal do Rio Grande do Sul | 8 | 1.02% | Brazil | 8 | 96 | 12 | 12 | 5 | 8 |
| Tianjin University | 8 | 1.02% | China | 5 | 36 | 4.5 | 7.2 | 3 | 5 |
| ICAR - Indian Agricultural Statistics Research Institute, New Delhi | 8 | 1.02% | India | 5 | 23 | 2.88 | 4.6 | 3 | 4 |
| Academia Sinica Taiwan | 7 | 0.89% | China | 7 | 150 | 21.4 | 21.43 | 6 | 7 |
| Universidade Federal de Minas Gerais | 7 | 0.89% | Brazil | 6 | 118 | 16.9 | 19.67 | 5 | 6 |
| Universidad de Navarra | 7 | 0.89% | Spain | 6 | 55 | 7.86 | 9.17 | 5 | 6 |
| Faculdade de Economia da Universidade do Porto | 7 | 0.89% | Portugal | 7 | 52 | 7.43 | 7.43 | 4 | 7 |
| Wirtschaftsuniversität Wien | 6 | 0.77% | Austria | 6 | 108 | 18 | 18 | 5 | 6 |
| Universiti Sains Malaysia | 6 | 0.77% | Malaysia | 4 | 5 | 0.83 | 1.25 | 1 | 1 |
| Chinese University of Hong Kong | 6 | 0.77% | China | 6 | 95 | 15.8 | 15.83 | 5 | 6 |
| Universidade de São Paulo | 6 | 0.77% | Brazil | 4 | 30 | 5 | 7.5 | 3 | 4 |
| Université Paris Nanterre | 6 | 0.77% | France | 6 | 37 | 6.17 | 6.17 | 3 | 6 |

Keywords Analysis

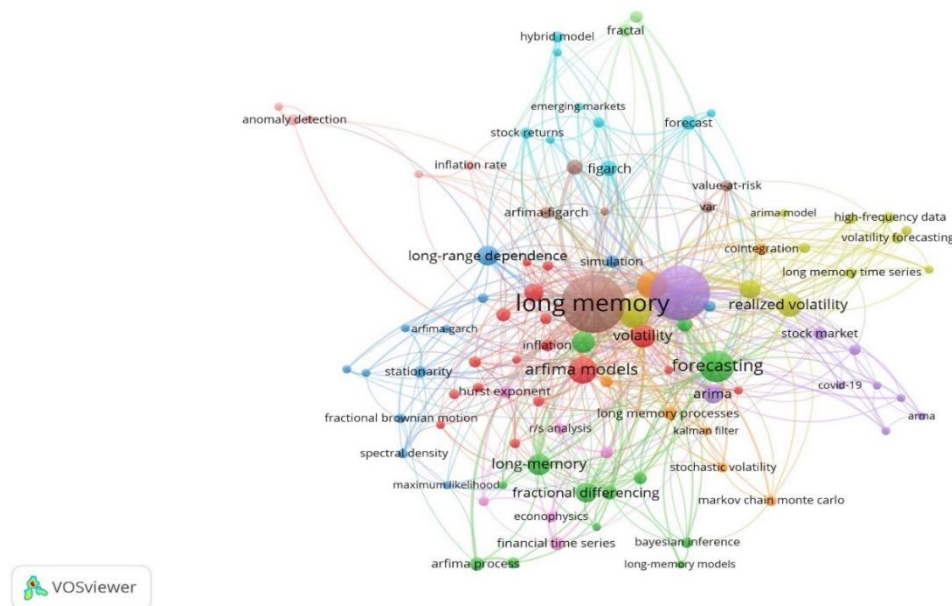


Figure 5: Network Visualisation Map of The Author Keywords

Figure 5 illustrates the visualisation of keywords in research publications produced by VOSviewer. Note that the crucial component of any article is the keyword. The Scopus articles were used to retrieve the keyword dataset. Here, 784 papers were included for analysis, with 1768 keywords in the entire dataset. The minimum number of keyword occurrences was set at 4. As a result, 98 keywords met the requirement. Apart from that, the co-occurrence indicates the relationship between the topics and aids in determining the conceptual framework and foundational ideas covered by the area. The analysis shows eleven clusters in the ARFIMA publication, given that the number of documents containing the keyword increases with the node's size. We can observe that long memory is the biggest node in the brown cluster. Another large cluster, the purple one, is dominated by the keyword ARFIMA. Similar-coloured keywords frequently co-occur and are typically connected to one another. Table 9 records the top 20 keywords from the ARFIMA research in the Scopus database so that the authors' keywords can be examined in further detail. The primary search terms, such as long memory, ARFIMA, forecasting, and time series, are among those that occur more than 10% of the time

Table 9: Top 20 Author Keywords

| Author Keywords | Frequency | % |
|------------------------|-----------|--------|
| Long Memory | 194 | 24.74% |
| ARFIMA | 152 | 19.39% |
| Forecasting | 110 | 14.03% |
| Time Series | 89 | 11.35% |
| Time Series Analysis | 71 | 9.06% |
| ARFIMA Models | 55 | 7.02% |
| ARFIMA Model | 48 | 6.12% |
| Fractional Integration | 42 | 5.36% |
| Commerce | 33 | 4.21% |

| | | |
|----------------------|----|-------|
| Realised Volatility | 32 | 4.08% |
| Stochastic Systems | 32 | 4.08% |
| Parameter Estimation | 29 | 3.70% |
| Auto-regressive | 28 | 3.57% |
| Long-memory | 28 | 3.57% |
| Moving Averages | 28 | 3.57% |
| Regression Analysis | 28 | 3.57% |
| Volatility | 28 | 3.57% |
| Financial Markets | 27 | 3.44% |
| Mathematical Models | 26 | 3.32% |
| Computer Simulation | 25 | 3.19% |

Citation Analysis

Table 10 presents information on top-cited articles in ARFIMA research. The document entitled "Long memory processes and fractional integration in econometrics" by (Baillie, 1996) has accumulated the largest citations' number (1093 citations or an average of 42.04 citations annually). The second highest citation was also written by (Baillie et al., 1996) with 365 citations, followed by (Breidt et al., 1998) with 364 citations. However, based on citations per year, (Bukhari et al., 2020) are the most influential, receiving 65 citations annually.

Table 10: Top Cited Articles in ARFIMA Research

| Authors | Title | Year | TC | C/Y |
|------------------------------|---|------|------|-------|
| (Baillie, 1996) | Long memory processes and fractional integration in econometrics | 1996 | 1093 | 42.04 |
| (Baillie et al., 1996) | Analysing inflation by the fractionally integrated Arfima-Garch Model | 1996 | 365 | 14.04 |
| (Breidt et al., 1998) | The detection and estimation of long memory in stochastic volatility | 1998 | 364 | 15.17 |
| (Cheung, 1993) | Long memory in foreign exchange rates | 1993 | 208 | 7.17 |
| (Koopman et al., 2007) | Periodic seasonal reg-ARFIMA_GARCH models for daily electricity spot prices | 2007 | 172 | 11.47 |
| (Li et al., 2002) | Recent theoretical results for time series models with GARCH errors | 2002 | 169 | 8.45 |
| (Pong et al., 2004) | Forecasting currency volatility: A comparison of implied volatilities and AR(FI)MA models | 2004 | 156 | 8.67 |
| (Bukhari et al., 2020) | Fractional neuro-sequential ARFIMA-LSTM for financial market forecasting | 2020 | 130 | 65 |
| (Baillie & Bollerslev, 1994) | The long memory of the forward premium | 1994 | 130 | 4.64 |

(Podobnik et al., 2008) Modelling long-range cross-correlations in two-component ARFIMA and FIARCH processes.

Publication by Source Title

Table 11 demonstrates the most active source title in ARFIMA. The most significant number of publications on ARFIMA is a journal called Physica A Statistical Mechanics And Its Applications (n = 38). This was followed by the Journal of Forecasting, Journal of Econometrics, Journal of Time Series Analysis, Applied Economics, and International Journal of Forecasting, with more than 15 total publications. Journal of Econometrics has the highest number of citations, with 1862.

Table 11: Most Active Source Title

| Source Title | TP | % | Publisher | Cite Score | SJR 2021 | SNIP 2021 | NCP | TC | C/P | C/CP |
|--|----|-------|------------------------------|------------|-------------|-------------|-----|------|--------|-------|
| Physica A Statistical Mechanics And Its Applications | 38 | 4.85% | Elsevier | 7.1 | 0.891 | 1.208 | 36 | 737 | 19.39 | 20.47 |
| Journal Of Forecasting | 18 | 2.30% | Wiley-Blackwell | 3.7 | 0.594 | 0.984 | 18 | 252 | 14 | 14 |
| Journal Of Econometrics | 17 | 2.17% | Elsevier | 4.1 | 3.523 | 2.475 | 17 | 1862 | 109.53 | 109.5 |
| Journal Of Time Series Analysis | 16 | 2.04% | Wiley-Blackwell | 1.8 | 0.875 | 1.366 | 14 | 365 | 22.81 | 26.07 |
| Applied Economics | 15 | 1.91% | Taylor & Francis | 2.8 | 0.563 | 1.086 | 15 | 186 | 12.4 | 12.4 |
| International Journal Of Forecasting | 15 | 1.91% | Elsevier | 7.9 | 1.99 | 2.792 | 15 | 320 | 21.33 | 21.33 |
| Computational Statistics And Data Analysis | 12 | 1.53% | Elsevier | 2.9 | 1.016 | 1.523 | 12 | 234 | 19.5 | 19.5 |
| Applied Financial Economics | 10 | 1.28% | Taylor & Francis (1991-2014) | 1.0(2015) | 0.371(2017) | 1.322(2017) | 10 | 189 | 18.9 | 18.9 |
| Economics Letters | 10 | 1.28% | Elsevier | 3.2 | 0.683 | 1.085 | 10 | 199 | 19.9 | 19.9 |
| Empirical Economics | 9 | 1.15% | Springer Nature | 2.5 | 0.535 | 1.056 | 8 | 196 | 21.78 | 24.5 |

| | | | | | | | | | | |
|---|---|-------|------------------|-----|-------|-------|---|-----|-------|-------|
| Journal Of Statistical Computation And Simulation | 9 | 1.15% | Taylor & Francis | 2.1 | 0.588 | 1.261 | 7 | 69 | 7.67 | 9.86 |
| Journal Of Statistical Planning And Inference | 9 | 1.15% | Elsevier | 1.6 | 0.688 | 1.205 | 8 | 163 | 18.11 | 20.38 |

Notes: TC = total citations; CiteScore = average citations received per document published in the source title; TP = total number of publications; SIGKDD = special interest group on knowledge discovery in data; SNIP = source normalised impact per paper measures actual citations received relative to citations expected for the source title's subject field; SJR = SCImago Journal Rank measures weighted citations received by the source title

Title And Abstract Analysis

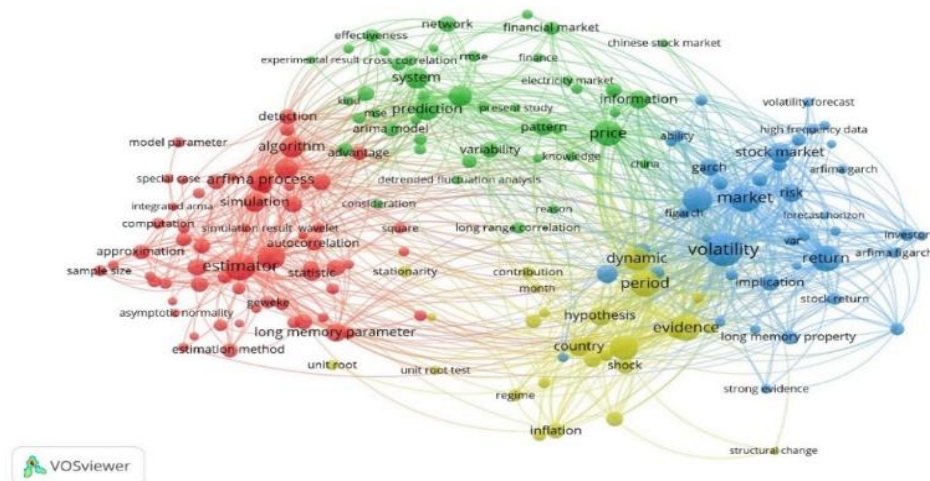


Figure 6: VOSviewer Visualisation of A Term Co-Occurrence Network Based on Title and Abstract Fields

The documents' titles and abstracts were analysed employing the VOS viewer software. The co-occurrences network was analysed in this research using the binary counting method. According to (van Eck & Waltman, 2014), the developers of VOS viewer, utilising a binary counting methodology, indicates that it is irrelevant how many times a noun phrase appears in a publication's title or abstract. A term co-occurrence network with ten or more minimum occurrences is visualised in Figure 6, relying on the title and abstract fields. The intensity of the occurrences is shown by the size of the nodes, whilst the strength of the connection is indicated by the thickness of the lines between nodes. Other than that, comparable words are often found together and are identified by a similar colour. For instance, the diagram depicts that the ARFIMA process, long memory parameter, estimator, simulation, autocorrelation, and model parameter, including all other terms which are red in colour, are closely related and occur together. From the analysis, four different colours were made to represent four important groups.

Instead of combining the documents' titles and abstracts, this study also investigates co-occurrences relying on the document titles (refer to Figure 7). There are 4 clusters, and the VOSviewer created 17 items depending on the seven required minimum occurrences. Cluster 1 consists of the ARFIMA model, fractional integration, long memory parameter, long memory process, and maximum likelihood estimator. Cluster 2 consists of a long memory time series, prediction, time series and time series model. Meanwhile, Cluster 3 involves return, stock market, stock return and volatility. Cluster 4 has three items, which are the ARFIMA process, modelling and structural break.

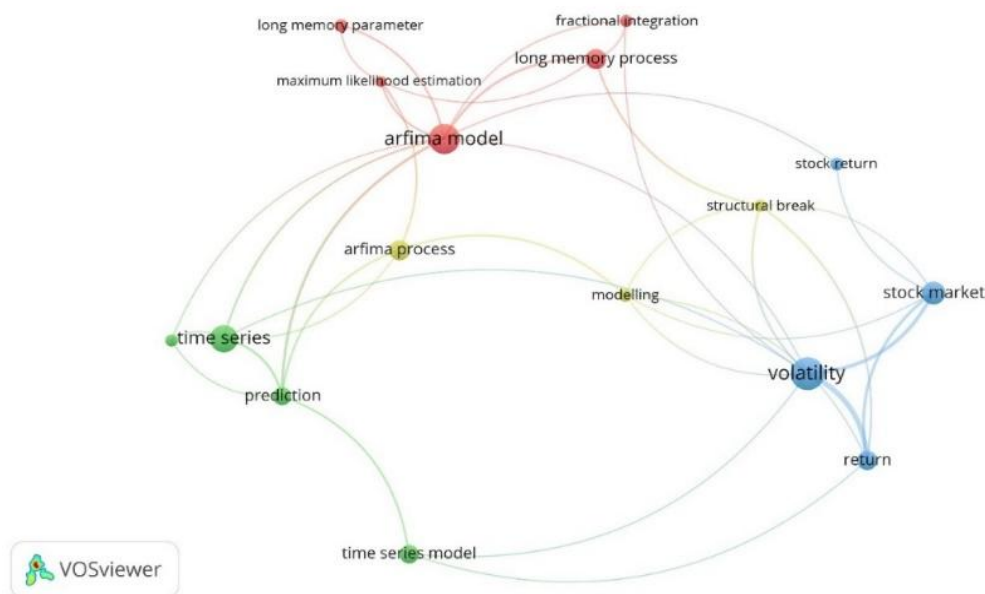


Figure 7: VOSviewer Visualisation of A Term Co-Occurrence Network Based on The Title

Discussions And Conclusion

This research utilised bibliometric analysis to investigate the research trend on ARFIMA. Bibliometric analysis, which considers the document types, number of publications by year, keyword analysis, language, the most active source title, the countries that contributed the most to the ARFIMA research, the most active institution, as well as the number of citations, may be employed to evaluate the performance of publication and research in a specific field. The findings of the bibliometric analysis can assist academicians in producing relevant and up-to-date research, as the results will highlight the significant area that must be addressed (Ellegaard & Wallin, 2015).

This study analyses 784 articles published between 1993- 2022 on ARFIMA for time series forecasting using Scopus database. The bibliometric analysis was carried out using VOSviewer software, which examined and visualised a number of attributes of publications, including the 'co-occurrences' of author keywords. The results of this research suggest that although the number of overall publications' number is rising, the total citations' number is fluctuating. Note that the maximum number of publications was 52 in the year 2018, whereas the greatest number of citations was 1840 in the year 1996. Nearly all publications were produced in English, and

85.08% were published in academic journals. Apart from that, over 20 countries publish ARFIMA. This means that ARFIMA publications are still relevant worldwide, despite their slow progress in publications. The results also indicate that ARFIMA research publication spread significantly in many disciplines such as Mathematics, Economics, Econometrics and Finance, Computer Sciences and others.

The study that has received the most citation is "Long memory processes and fractional integration in econometrics" by (Baillie, 1996). However, depending on citations annually, the author's document with the title "Fractional neuro-sequential ARFIMA-LSTM of financial market forecasting" (Bukhari et al., 2020) is the most influential, receiving 65 citations per year. On the other hand, the most productive author is Shang, P. from Beijing Jiaotong University, with 16 articles on ARFIMA, whose work received 155 citations. In addition, the most effective universities in ARFIMA are Beijing Jiaotong University, China, followed by the Federal University of Espirito Santo, Brazil and Michigan University, USA. Additionally, the majority of the study to date has been conducted in the United Kingdom, China, and the USA.

Due to the lack of studies on ARFIMA, it is thought that there are still several opportunities for a study connected to ARFIMA that may be conducted in the additional investigation. Apart from that, since our study did not cover a performance comparison of different techniques, future research should compare the performance of the different methods in forecasting. The study has certain limitations, which use only the Scopus database. Upcoming studies may utilise numerous databases, for instance, Google Scholar and Web of Science, to perform searches. By presenting a thorough trend analysis of ARFIMA-related papers issued in the Scopus database from 1993 until 2022, the research's outcomes potentially add to the body of knowledge and guide future studies to develop this field of study.

This bibliometric analysis contributes to the academic field, the industrial field and national development. In the academic field, this study can be a basic reference for identifying prolific authors, high-impact journals and emerging themes in the field of long memory modeling. In the industrial sector, especially in finance and forecasting, this study shows the importance of the ARFIMA model in capturing long memory patterns in time series data. Policymakers and funding agencies can use productivity trends and patterns to plan investments and encourage collaboration of high impact research that contribute to national growth.

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