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Research Article

Implementing ANFIS with Three-Layer Architecture for Time Series

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Abstract: The complex time addiction and randomness of multivariate time series make it necessary to apply time series analysis to these variables. So, it is important to produce methods that can be used appropriately for time series system identification. Time series are generally handled as a single-layer architecture consisting of only the observed data processing layer. In this study, a hybrid method has three-layer adapted and evaluated using an adaptive neuro-fuzzy inference system (ANFIS). The main motivation of this study is to learn the errors produced by ANFIS method and to use them as new information. For this purpose, proposed method was evaluated using real-time serial data sets obtained from different fields. Due to the three-layer architecture, the errors caused by the results produced by ANFIS are reused. As a result, the method of learning from errors has been realized and better results have been produced com-pared to traditional single-layer architecture.

Keywords: time series; ANFIS; neuro-fuzzy; eurostat; streamflow

Araştırma Makalesi

Zaman Serileri için Üç-Katmanlı Mimari ile ANFIS'in Uygulanması

Özet: Çok değişkenli zaman serilerinin karmaşık zaman bağımlılığı ve rastgeleliği, bu değişkenlere zaman serisi analizinin uygulanmasını gerekli kılar. Bu nedenle, zaman serisi sistemi tanımlaması için uygun şekilde kullanılabilecek yöntemler üretmek önemlidir. Zaman serileri genellikle yalnızca gözlenen veri işleme katmanından oluşan tek katmanlı bir mimari olarak ele alınır. Bu çalışmada, üç katmanlı bir hibrit yöntem uyarlanmış ve adaptif ağ tabanlı bulanık mantık çıkarım sistemi (ANFIS) kullanılarak değerlendirilmiştir. Bu çalışmanın temel motivasyonu, ANFIS yöntemi tarafından üretilen hataları öğrenmek ve bunları yeni bilgi olarak kullanmaktır. Bu amaçla, önerilen yöntem farklı alanlardan elde edilen gerçek zamanlı seri veri kümeleri kullanılarak değerlendirilmiştir. Üç katmanlı mimari nedeniyle, ANFIS tarafından üretilen sonuçların neden olduğu hatalar yeniden kullanılmaktadır. Sonuç olarak, hatalardan öğrenme yöntemi gerçekleştirilmiş ve geleneksel tek katmanlı mimariye kıyasla daha iyi sonuçlar üretilmiştir.

Anahtar Kelimeler: zaman serileri; ANFIS; sinirsel-bulanık; eurostat; nehir akış

1. Introduction

Forecasting has always been an important component of decision-making and planning. The uncertainty of the future is both exciting and challenging for someone and/or organizations trying to minimize potential risks and maximize public services [1]. Forecasting based on historical data can assist policy-makers in identifying the potential of forward-looking movements such as planning, investment, and development. Predictability is important for long-term and high-budget investments that countries will make in areas such as population, health, transportation, energy, infrastructure, and economy.

Air transport demand forecasting is gaining increasing attention, especially because of the inherent challenges and practical applications. Air passenger counts are an important indicator for air transport. However, air passenger time series usually have complex behavior due to their high volatility, irregularity, and seasonality [2]. Also, air transportation is a type of transportation that is complex and has high budgets, in which many processes such as aircraft, airport, air traffic, and flight routes must be considered. For this reason, the accuracy of forward-looking passenger demand forecasts gains importance in critical matters such as new airport construction, flight and route arrangement, and ticket price determination for airline companies [3].

Mortality rates are an indicator that closely concerns many sectors, including countries. It is one of the important indicators used by countries to determine the policy to be applied by companies on issues such as future workforce, health and population planning, and life and pension insurance [4].

Migration is one of the most unpredictable demographic processes. Also, even if reliable explanations of earlier migration flows were available, their principles would be difficult to predict in the future – thus, most formal forecasting models rely on time-series analysis [2].

Epidemics are large-scale infectious diseases that greatly increase morbidity and mortality over a wide geographical area and cause significant economic, social, and political breakdown [4]. In the last two years, with the entry of the pandemic into our lives, studies on mortality rates after covid-19 disease have been increasing. COVID-19, a highly contagious viral disease triggered by a novel coronavirus named SARS-CoV-2, emerged in December 2019 in Wuhan, China. After rapid transmission from one country to another, on 12 March 2020, the World Health Organization (WHO) declared COVID-19 a global epidemic [5].

Water is one of the important resources that directly and indirectly affect humans. In addition to being directly consumed by living things, it is also linked to many areas such as climate, energy, agriculture, and economy [5]. Getting the maximum benefit from valuable and limited water resources requires appropriate planning and management. Thanks to the estimation of the rivers' streamflow, which are one of the water resources, they can provide insight to decision-makers in realizing works such as electricity generation, and agricultural irrigation at more affordable costs [6-8] and in preventing disasters such as floods, droughts, or ecological imbalances [9, 10]. There can be continuous variability in the basic features of river flows due to human-induced events such as wild irrigation, ecological change, climate change, drought, and excessive precipitation. In this case, the equations created by adhering to the basic properties may not be successful in sufficient prediction. Today, data-based methods such as artificial neural networks and deep learning can learn these changes and produce more successful results compared to traditional methods.

In summary, the main contributions of this paper are the following: Using the difference between the predicted value and the actual value produced by the model as an input. Revealing the pattern of the used time series and parameterizing the basic variables (depth, lag, cluster). Measuring the performance of the model with the ANFIS method using datasets gathering from different fields such as Air transport, Mortality rates, Migration, Epidemics and Water. It can assist decision makers in the development of airport components such as runways, roads, aprons, boarding and landing areas, and waiting halls.

Thanks to the study, airport construction and maintenance work, which have an impact on many important issues such as economy, health, and tourism, which are important for countries, regulations to be made in the field of health, drinking water, irrigation and electricity production facilities, proactive studies to be made about the spread of diseases and migration events. It is predicted that it will provide a healthier foresight to decision makers. Thus, both countries and relevant institutions will be able to manage existing resources more efficiently and more economically.

This paper has been divided into five main sections: introduction, material and method, experimental results, summary and conclusions, and future directions. In the introduction section, information about time series estimation, estimation fields and related literature are given. In the material and method section, the main structure and procedure of the three-layer architecture, a short introduction of the ANFIS model, performance measurement method, and the feature information of the datasets used in the paper are presented. In the experimental results section, firstly, the results produced by the single-layer architecture and the three-layer architecture are presented separately. Then the results of the two architectures are compared. In the summary and conclusions section, the results obtained are evaluated and the achievements obtained according to previous studies are given as examples. In the section on future directions, information on how the study and the contribution to the literature can be developed and advanced are given.

2. Related Works

In time series estimation studies, AR (Autoregression), MA (Moving Average), ARMA (Autoregressive Moving Average), ARIMA (Autoregressive Integrated Moving Average Method), SARIMA (Seasonal Autoregressive Integrated Moving Average Method), MSARIMA (Multiplicative Seasonal Autoregressive Integrated Moving Average Method)) and other traditional methods such as daily maximum temperature [11], rain regimes [12], actual ip network traffic density [13], drought [14], battery health [15], bus arrival time estimation [16], etc. It is used in different areas and successful results are obtained. In [17], lip landmark movements were tracked using MediaPipe Face Mesh technology and forecasted with ARIMA and SARIMA models. This study highlights the potential of traditional methods in time series forecasting based on facial analysis for innovative applications in healthcare, security, and augmented reality. In the last two decades, machine learning methods have come to the forefront in the field of time series prediction due to their simplicity, clearness, and rapid progress in data mining [18, 19]. Many machine learning methods such as SVR [20], ANN [21], LSTM [22], Random Forest [23], etc. have produced more successful results than traditional methods. In addition, the number of hybrid methods that include traditional methods and machine learning methods and obtain successful results is increasing in the literature [24, 25]. The study by [26] presents an innovative framework utilizing pre-trained Large Language Models (LLMs) for multivariate time series forecasting. The work aims to address the challenge of large data requirements by leveraging the learning capabilities of LLMs. Challenges arise in integrating time series data with LLMs, particularly due to data structure differences and multi-scale temporal information processing. To overcome these, the authors propose LLM4TS, a two-stage fine-tuning strategy (time series alignment and prediction fine-tuning) and a two-level aggregation method to integrate multi-scale temporal data. Experiments on seven datasets demonstrate that LLM4TS outperforms fully trained models in both full and low-data scenarios and is more effective than unsupervised representation learning approaches. Ablation studies further emphasize the importance of the framework's components and pre-trained weights. Additionally, [27] introduces an innovative approach to enhance the effectiveness of Transformer models for time series forecasting. While the channel-independent (CI) strategy improves training robustness, it may limit forecasting performance by neglecting inter-channel correlations. To address this, the authors propose CARD (Channel Aligned Robust Blend Transformer), which includes: first, a channel-aligned attention mechanism capturing temporal correlations between signals and multivariate dynamic dependencies; second, a token mixture module generating tokens at different resolutions to efficiently utilize multi-scale information; and third, a robust loss function based on prediction uncertainties, prioritizing finite-horizon forecasts to reduce overfitting. Tests on long- and short-term time series datasets indicate that CARD outperforms state-of-the-art forecasting methods. Addressing the challenges of large data requirements and real-world constraints, such as missing labels, Klopries et al. (2024) focus on generating synthetic time series data while preserving its characteristics and ensuring interpretability. The study proposes two interpretable synthetic data generation methods using features from continuous function candidates. The first method manipulates features of a deep autoencoder to generate synthetic data while preserving core components, while the second employs generative adversarial learning (GAN) to create synthetic data guided by the main characteristics of the source dataset. The proposed methods produce indistinguishable data patterns across multiple datasets, offering full control over each time series component and ensuring interpretability of

features in both source and target datasets. Tests on multiple industrial datasets demonstrate the method's qualitative and quantitative superiority over existing approaches [28]. ANFIS (adaptive neuro-fuzzy inference system) [29] is applied universally as it has shown successful results in many existing implementations. Moreover, since it is a flexible model, it can detect nonlinearity in time series and combine both ANN (Artificial Neural Network) and fuzzy logic systems [30]. Due to these reasons and its extra properties, studies on its use in the time series problems have begun to increase in recent years. [31]. In [32], EEG-based methods combined with the Adaptive Neuro-Fuzzy Inference System (ANFIS) and genetic algorithms (GA) are investigated for depression diagnosis. A 21-channel EEG setup, arranged according to the international 10-20 system, analyzes brain wave patterns to detect neural abnormalities associated with mental health conditions. Notably, alpha, beta, and delta frequency bands have proven effective in classifying depression with high accuracy. The hybrid ANFIS-GA system enhances diagnostic accuracy by processing multimodal data, emerging as a promising tool in mental health technology. The study underscores the potential of neuroscience-based diagnostic tools to improve patient outcomes. In [33], the integration of ANFIS and a Hybrid Optimization method is examined for rainfall-runoff modeling in the Banjar River Basin, Moraya Pradesh, India. The proposed model developed using daily rainfall and runoff data from 2001–2015, employs the GIS-based Thiessen Polygon method to analyze the spatial distribution of rainfall. Comparative results indicate that the proposed method, combining the Hybrid Optimization (Least Squares Estimator and Gradient Descent) outperforms Backpropagation and SCS-CN methods in accuracy. The model effectively predicts outcomes using five input parameters (current and previous two-time steps' rainfall and runoff) with minimal data. Performance comparisons using the coefficient of determination (R^2) confirm the superiority of the ANFIS Hybrid Optimization method. The study also suggests future research directions, including applying the methodology to other river basins, comparing it with models like SWAT, SWMM, and HEC-HMS, and exploring different membership functions. Xiao et al. (2014) proposes a hybrid approach named HSAI (hybrid SSA–ANFIS–IPSO) for short-time-interval air travel density estimation. A hybrid approach is proposed using single spectrum analysis (SSA) to determine the trend and seasonality of air transport demand, and enhanced particle swarm optimization (IPSO) and ANFIS to deal with demand irregularity and variability. According to the results of the experimental study conducted with the data of Hong Kong, it is stated that the hybrid approach is a successful alternative [2].

In the study by [34] on Covid-19, a new model based on the combination of ANFIS and mutation-based Bee Algorithm (mBA) has been proposed. In order to increase the performance of ANFIS, Four types of mutations were applied to the Meta-Heuristic Bees Algorithm (BA) and its parameters were optimized. As a result of the experimental study, the model used for the prediction of Covid-19 cases in India and the USA achieved successful results. In another recent study [35], a model named FPASSA-ANFIS, which combines Flower Pollination Algorithm (FPA), Salp Swarm Algorithm (SSA), and ANFIS method, is proposed. The proposed model was evaluated using Chinese Covid-19 data and the results were compared with different hybrid models. Considering the results, it was stated that the proposed model was more successful in the RMSE, MAE, MAPE, and R^2 criteria.

2.1. Motivation and Background

If a person cannot reach the expected result in an activity, he/she performs, he/she can find the part where he/she is wrong and learn to correct it and not to do it again. In this way, it can achieve better results every time. This process, which is valid for humans, may be valid for computers. This basic motivation approach, for the study can be stated as "To reach the best estimate by using the differences between the estimate made and the actual estimate". The success rate is tried to be increased by using the difference between the estimation and the actual value in the three-layer architecture created with this basic approach. In addition, some basic variables are parameterized, and variables are determined according to the pattern specific to the time series used.

3. Materials and Methods

In this section, the main structure of the proposed three-layer architecture and the definitions of the mathematical equations used in its layers are given. In the next step, the definition of the ANFIS method used in the three-layer architecture is made. Besides, the values of the parameters of the ANFIS method

are presented in the experimental study. In the last part, information about the statistical method used as a performance measurement method and the mathematical equation is given.

3.1. Data Collection

The Euphrates and Seyhan Rivers are in Turkey and have Turkey's highest productivity and water potential. In this study, the four different flow measurement stations (FMSs) belonging to the Euphrates and Seyhan Rivers are used to evaluate the forecasting performance of the proposed method. The ***Zamanti*** and ***Körkün*** FMSs located in the upper part of the Seyhan River Basin, in addition ***Kilayak*** and ***Akyazi*** FMSs of the Euphrates River are selected according to the conditions of being on different branches of both rivers. These differences will be useful in prediction of river flow regimes. The long-term flow values between October 2000 and September 2011 are used as sample data. The number of measurements, the continuity of the data among the measurements and the homogeneous distribution of the data were the determining factors in using the flow data of these stations in the study.

Covid-19 data set consisting of the number of confirmed covid-19 infected individuals in the UK between 2020 and 2021 was used. Taken from the official website of John Hopkins University and Medicine.

Three datasets belonging to Eurostat were used. The data sets were taken from the open access electronic database of Eurostat. The European Statistical Office, or Eurostat in short, is an organization that compiles and publicly presents the statistical data obtained in European Union member countries, candidate countries and European Free Trade Association member countries [36]. Eurostat datasets can be downloaded from "https://ec.europa.eu/eurostat/" using the online data code information. All datasets are real-life time series data.

Death: It gives the total number of deaths in Germany between 2001 and 2021 on a weekly basis (online data code: DEMO_R_MWK_TS).

Air passenger: It gives monthly the number of passengers who preferred the airway as transportation between 2002 and 2021 in Germany (online data code: AVIA_PAOC).

Asylum: The number of applications for citizenship (asylum and first-time asylum applicants) made in Germany between 2008 and 2021 is given monthly (online data code: TPS00189).

3.2. Adaptive Neuro-Fuzzy Inference System (ANFIS)

Adaptive neuro-fuzzy inference system (ANFIS) is an artificial system developed based on the Takagi-Sugeno fuzzy model [37]. The back propagation learning capabilities of neural networks and the inference features of fuzzy logic are combined in the ANFIS structure. It generates output by mapping input data through membership functions and applying fuzzy rules across the network. Since this process provides inference capability to the ANFIS model, this integration of inference capability enhances ANFIS's performance, particularly for complex problems.

ANFIS operates with two types of parameters: premise parameters and consequent parameters. The training of the model is provided by optimizing these parameters. The ANFIS architecture basically comprises five layers. These layers are the fuzzification layer, the rule layer, the normalization layer, the defuzzification layer, and the sum layer, respectively. Figure 1. Illustrates the basic ANFIS structure, which includes two inputs and one output.

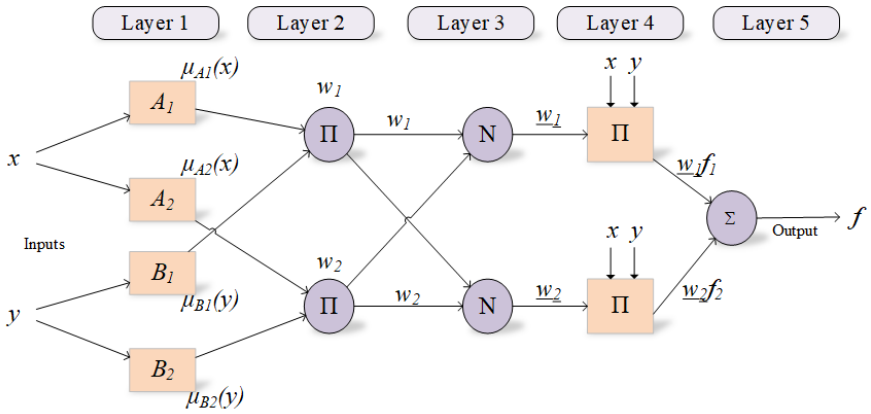


Figure 1. Basic structure of ANFIS

Fuzzy systems facilitate the learning and adaptation process. Also, neural networks are successful in nonlinear problems by distributing control parameters over the network [29,30]. These characteristic behaviors give great advantage to the ANFIS architecture, which is a neuro-fuzzy network model. The purpose of training the ANFIS model is to produce optimal values for the parameters depending on the input and output values.

3.3. The Three-Layer Architecture

Time series estimation is traditionally thought of as a single-layer architecture, as shown in Figure 2. The observed data is given as input to the data processing layer, which is the only layer of the architecture, and the result is produced. They propose a three-layer architecture that outperforms the single-layer architecture, with results obtained using both traditional methods [16] and machine learning methods [38]. The layers and features of the three-layer architecture, the basic structure of which is shown in Figure 3, are as follows:

1. In the first layer, which is the actual data prediction layer, the measured data is processed, and the next value is estimated using the ANFIS method.

2. In the second layer, which is the residuals prediction layer, the residuals are processed using the ANFIS method. It is then predicted along the specified depth according to the values of the parameterized variables.

3. In the third layer, which is the residuals procession layer, the predicted data and residuals are evaluated using the mean smoothing method, mean residual method, sum smooth method, and sum residual method and the final result is produced.

Smooth data returns a moving average of the objects of a vector using a fixed heuristic determined window length. The window slides down the length of the vector and calculates an average value over the values in each window.



Figure 2. Single-layer architecture

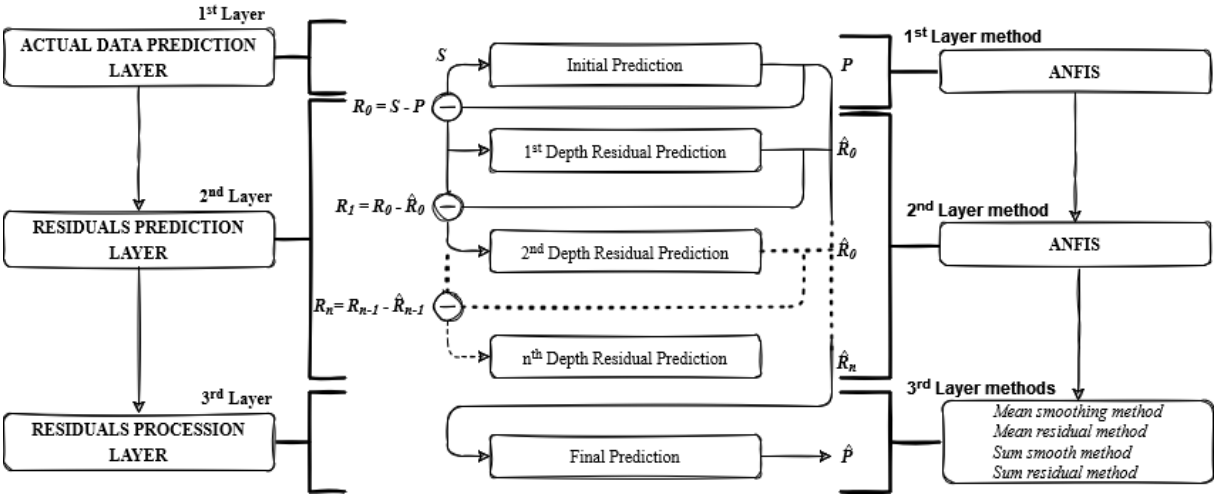


Figure 3. The three-layer architecture

The variables used in the equations for the three-layer architecture are defined as follow:

S represents the measured values of the time series, *P* denotes the initial predicted values of *S*, $\mathbf{R_0}$ represents the residuals, or the differences, between *S* and *P*, while $\widehat{\boldsymbol{R}}_{\mathbf{0}}$ stands for the predicted values of $\mathbf{R_0}$. Similarly, $\boldsymbol{R_d}$ denotes the residuals calculated at depth *d*, and $\widehat{\boldsymbol{R}}_{\boldsymbol{d}}$ represents the predicted values of $\boldsymbol{R_d}$. Finally, $\widehat{\boldsymbol{P}}$ refers to the final (target) prediction.

4. Experimental Results

The model, which was created by combining the three-layer architecture and the ANFIS method, was applied to the total eight streams data sets of air passenger (orange), covid-19 (red), asylum (purple), death (brown), Zamanti FSM (pink), Korkun FSM (gray), Kilayak FSM (blue) and Akyazi FSM (turquoise). The best combination values were determined by giving values between 0 and 10 for the depth, cluster and lag parameters used in the model.

The ANFIS control parameters used in simulations, fuzzy rule generation method at the first layer is used to create the ANFIS models. Because with this method, ANFIS and FCM work as a whole. A gaussian function (*gaussmf*) is used for the type of membership function in the current system. Back propagation (BP) algorithm is used to train the ANFIS parameters. The learning rate for the BP algorithm was set to 0.2 and the momentum coefficient was set to 0.4. In addition, the number of iterations for BP is given as 1000. The MAPE (Mean Absolute Percent Error) performance measure represented by Equation 4.1 was used to evaluate the estimation results.

$$\boldsymbol{MAPE} = \left(\frac{\mathbf{1}}{\boldsymbol{n}}\sum_{\boldsymbol{t}=\mathbf{1}}^{\boldsymbol{n}}\frac{|\boldsymbol{Y_t}-\widehat{\boldsymbol{Y}}_{\boldsymbol{t}}|}{\boldsymbol{Y_t}}\right) * \mathbf{100} \tag{4.1}$$

4.1. The results of single-layer architecture

In this subsection, the best MAPE values were obtained by applying four distinct methods which are the mean smooth method, the total smooth method, the average residuals method, and the total residuals method to air passenger (orange), covid-19 (red), asylum (purple), death (brown), Zamanti FSM (pink), Korkun FSM (gray), Kilayak FSM (blue) and Akyazi FSM (turquoise) data on a -layer architecture. In addition, the three configuration values of the depth, cluster, and lag parameters of the MAPE values are presented in Figure 4.

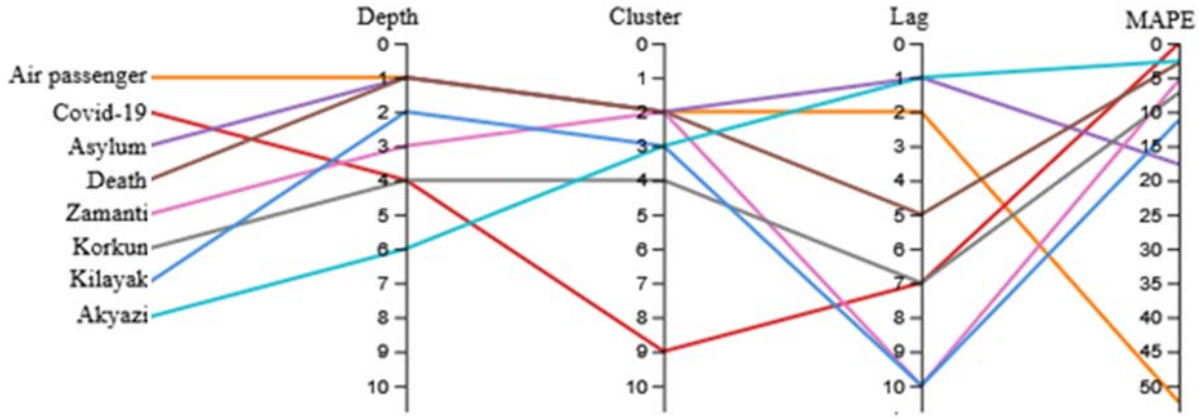


Figure 4. The MAPE values of the best results for each dataset according to the single-layer architecture

The best MAPE value of 0.045 belongs to Covid-19 (red) dataset. Besides, the configuration values of depth, cluster, and lag parameters are 4, 9, and 7, respectively. The highest MAPE value obtained in single-layer architecture, on the other hand, belongs to the air passenger (orange) dataset with 52.408 MAPE.

4.2. The results of three-layer results with ANFIS

In this subsection, the results of the air passenger (orange), covid-19 (red), asylum (purple), death (brown), Zamanti FSM (pink), Korkun FSM (gray), Kilayak FSM (blue), and Akyazi FSM (turquoise) datasets using the three-layer architecture with the ANFIS method are explained. The values obtained by the datasets are illustrated separately according to the methods used in the last layer.

The results measured using the mean smooth residual method are illustrated in Figure 5. The best MAPE value produced by the mean smooth residual method from data sets belongs to the covid-19 data set (red) at 0.02. In the configuration where the best MAPE value is obtained with 0.02, the depth parameter value is 1, the cluster parameter value is 9, and the lag parameter value is 7. The highest value obtained by using the mean smooth residual method belongs to the air passenger dataset (orange) with 48.842 MAPE. Among all the methods implemented in the proposed architecture, the mean smooth residual method produced the best MAPE for the Korkun FSM (grey) and asylum (purple) datasets. The MAPE produced for Korkun FSM (grey) is 6.498 and the depth, cluster, and lag parameter values are 4, 3, and 7, respectively. The MAPE 17.352 and depth, cluster, and lag parameter values produced for asylum (purple) are 1, 2, and 1, respectively.

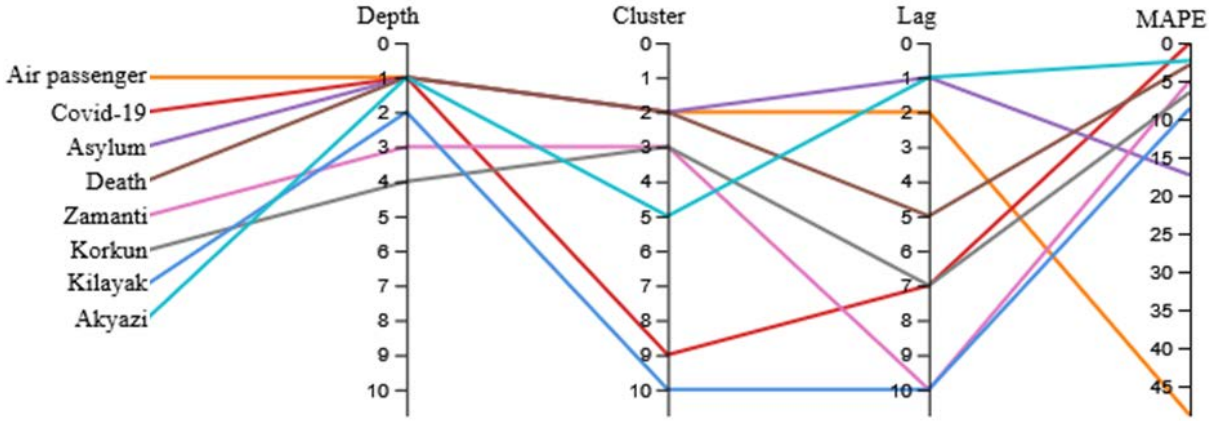


Figure 5. The MAPE values of the best results for each dataset according to the mean smooth residual method

The results measured using the sum smooth residual method are illustrated in Figure 6. The best MAPE value produced by the sum smooth residual method from data sets belongs to the covid-19 data set (red) at 0.026. In the configuration where the best MAPE value is obtained with 0.026, the depth parameter value is 9, the cluster parameter value is 7, and the lag parameter value is 7. The highest value obtained by using the sum smooth residual method belongs to the air passenger dataset (orange) with 46.001 MAPE. Among all the methods implemented in the proposed architecture, the sum smooth residual method produced the best MAPE for the asylum (purple), death (brown), Zamanti FSM (pink), Kilayak FSM (blue), and Akyazi FSM (turquoise) datasets. The MAPE produced for asylum (purple) is 17.352 and the depth, cluster, and lag parameter values are 1, 2, and 1, respectively. The MAPE 2.861 and depth, cluster, and lag parameter values produced for death (brown) are 9, 7, and 5, respectively. The MAPE produced for the Zamanti FSM (pink) is 4.3 and the depth, cluster, and lag parameter values are 10, 9, and 5, respectively. The MAPE produced for the Kilayak FSM (blue) is 7.305 and the depth, cluster, and lag parameter values are 8, 2, and 5, respectively. The MAPE produced for the Akyazi FSM (turquoise) is 2.293 and the depth, cluster, and lag parameter values are 10, 3, and 1, respectively.

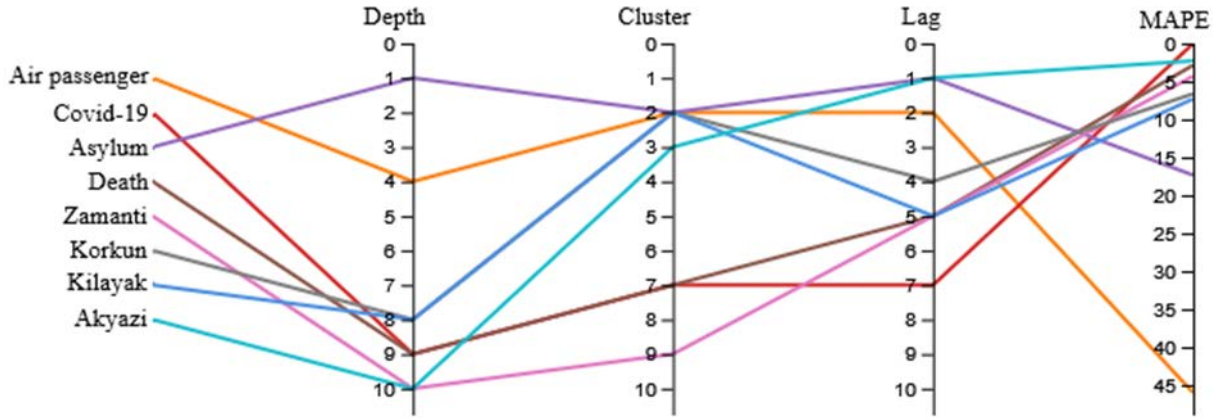


Figure 6. The MAPE values of the best results for each dataset according to the sum smooth residual method

The results measured using the mean residual method are illustrated in Figure 7. The best MAPE value produced by the mean residual method from data sets belongs to the covid-19 data set (red) at 0.028. In the configuration where the best MAPE value is obtained with 0.028, the depth parameter value is 1, the cluster parameter value is 9, and the lag parameter value is 7. The highest value obtained by using the mean residual method belongs to the air passenger dataset (orange) with 45.262 MAPE. Among all the methods implemented in the proposed architecture, the mean residual method produced the best MAPE for the air passenger (orange) dataset. The MAPE produced for air passengers (orange) is 45.262 and the depth, cluster, and lag parameter values are 1, 2, and 1, respectively.

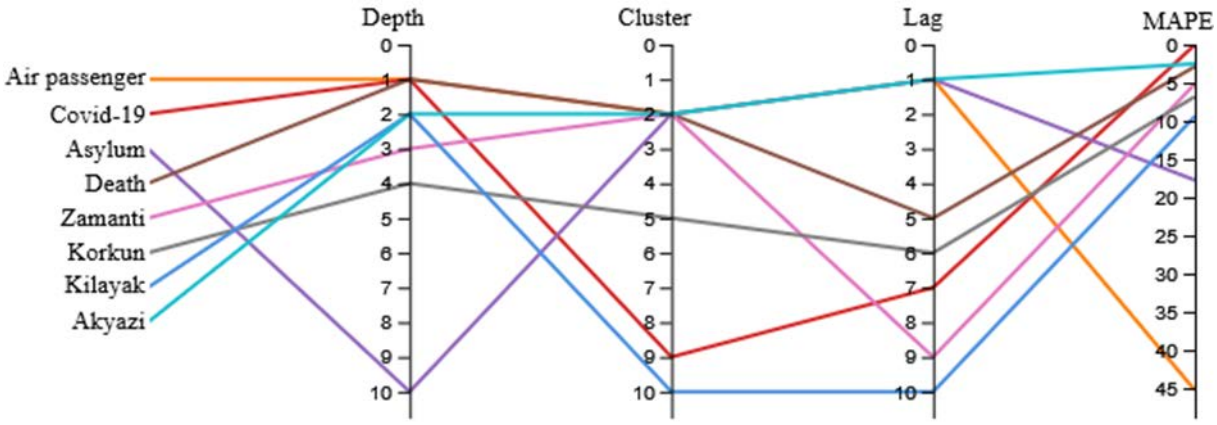


Figure 7. The MAPE values of the best results for each dataset according to the mean residual method

The results measured using the sum residual method are illustrated in Figure 8. The best MAPE value produced by the sum residual method from data sets belongs to the covid-19 data set (red) at 0.027. In the configuration where the best MAPE value is obtained with 0.027, the depth parameter value is 10, the cluster parameter value is 7, and the lag parameter value is 7. The highest value obtained by using the mean residual method belongs to the air passenger dataset (orange) with 45.262 MAPE again. Among all the methods implemented in the proposed architecture, the sum residual method produced the best MAPE for the air passenger (orange) dataset. The MAPE produced for air passengers (orange) is 45.262 and the depth, cluster, and lag parameter values are 1, 2, and 1, respectively.

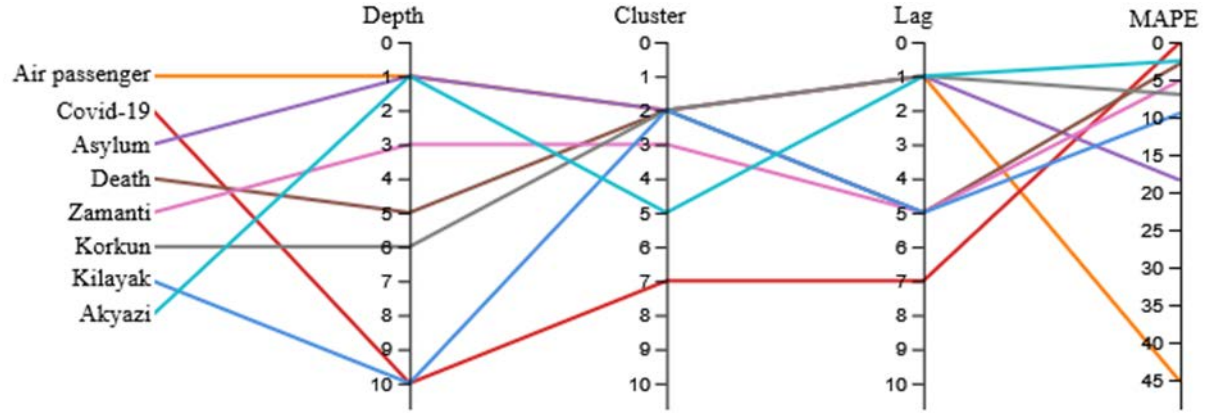


Figure 8. The MAPE values of the best results for each dataset according to the sum residual method

4.3. Comparison between single-layer architecture and three-layer architecture

The three-layer architecture produced more successful results than single-layer architecture in all dataset results. The values produced by the single-layer architecture (blue) and the values produced by the mean smooth residual method (yellow), the sum smooth residual method (red), the mean residual method (turquoise), and the sum residual method (green) used in the three-layer architecture are shown in Figure 9. The results obtained are explained separately according to the datasets below.

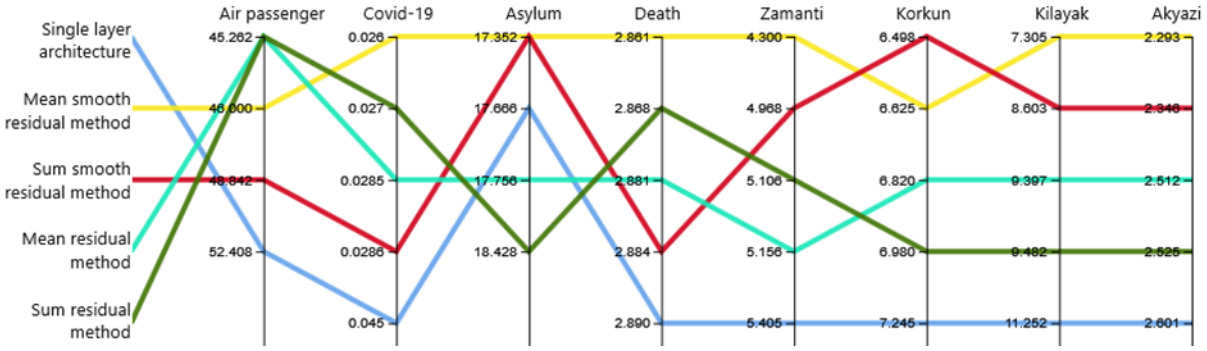


Figure 9. The MAPE values of the best results obtained for the methods used for each dataset

Air passenger: For the data set in which the single-layer architecture produces 52.408 MAPE values, the mean residual method and the sum residual method have achieved the best results with 45.262 MAPEs in the three-layer architecture. The sum smooth residual method and mean smooth residual method produced MAPE values of 46.001 and 48.842, respectively.

Covid-19: For the data set, where the single-layer architecture produces 0.045 MAPE, the sum smooth residual method achieved the best result with 0.026 MAPE in the three-layer architecture. The sum residual method, mean residual method, and mean smooth residual method produced MAPE values of 0.027, 0.028, and 0.029, respectively.

Asylum: The mean smooth residual method and the sum smooth residual method achieved the best results with 17.352 MAPE in the three-layer architecture for the data set where the single-layer architecture produced 17.666 MAPE values. The mean residual method and the sum residual method produced MAPE values of 17.756 and 18.428, respectively.

Death: For the data set where single-layer architecture produces 2.890 MAPE values, sum smooth residual method achieved the best result with 2.861 MAPE in three-layer architecture. The sum residual method, mean residual method and mean smooth residual produced MAPE values of 2.868, 2.881 and 2.884, respectively.

Zamanti: For the data set in which the single-layer architecture produces 5.405 MAPE values, the sum smooth residual method achieved the best result with 4.3 MAPE in the three-layer architecture. The mean smooth residual, sum residual method, and mean residual method produced MAPE values of 4.968, 5.106, and 5.156, respectively.

Korkun: The mean smooth residual method has achieved the best result with 6.498 MAPE in the three-layer architecture for the data set in which the single-layer architecture produces 7.245 MAPE values. The sum smooth residual, mean residual method, and sum residual method produced MAPE values of 6.625, 6.82, and 6.98, respectively.

Kilayak: For the data set in which single-layer architecture produces 11.252 MAPE values, sum smooth residual method achieved the best result with 7.305 MAPE in three-layer architecture. The mean smooth residual, mean residual method, and sum residual method produced MAPE values of 8.603, 9.397 and 9.482, respectively.

Akyazi: The sum smooth residual method achieved the best result with 2.293 MAPE in the three-layer architecture for the data set in which the single-layer architecture produced 2.601 MAPE values. The mean smooth residual, mean residual method and sum residual method produced MAPE values of 2.346, 2.512 and 2.525, respectively.

5. Summary and Conclusion

Some of the variables affecting the time series can be shown as a trend, seasonal, cyclical, and random fluctuations. The effect of these fluctuations may vary according to the area, time, or method in which the series is obtained. For this reason, while time series estimation methods can produce acceptable results in some areas, they cannot achieve sufficient success in some areas. In the study, the idea of using the ANFIS method, which is one of the methods with the ability to learn by using the past time series, was applied to the three-layer architecture by implementing it. The basic approach in the three-

layer architecture is to use the difference between the prediction value made in the first layer and the actual value as an input again in the second layer. The main aim here is to understand the pattern specific to the time series data set and to enable the model to learn by using the error obtained. The proposed architecture is the data gathered from Zamanti FSM and Korkun FSM belonging to Seyhan river with high water flow in Turkey, Kilayak FSM, and Akyazi FSM belonging to Euphrates River, data obtained from death, air passenger, asylum areas in Germany. The last data set is belonging to covid-19 in the United Kingdom. It was applied to a total of 8 different data sets. In the study conducted by [39] for Kilayak FSM in 2021, they shared the results achieved in MAPE using the LSTM (long-short-term memory) networks for flow prediction and the model in which a GA (genetic algorithm) is integrated, and the linear regression method. When the shared results and the results produced by the three-layer architecture are compared, it is seen that the three-layer architecture is more successful. In the study conducted by [40] in 2021, analyzes were made using LSTM (long short-term memory), GRU (gated repetitive unit), CNN (convolutional neural network), and MCNN (multivariate convolutional neural network) models of covid-19 data from Brazil, Russia, and the United Kingdom obtained from the John Hopkins official site. When the MAPE values obtained for the United Kingdom from the models used in the study are compared with the MAPE values obtained by the three-layer architecture, it is seen that the three-layer architecture produces more successful results.

Three-layer architecture has shown higher-success compared to traditional architecture in studies using traditional methods, machine learning methods and finally the ANFIS method. For this reason, it is thought that it will achieve successful results in subjects such as bus stop arrival time, stream flow rate, air travel, death, and in many areas such as economic, social, and health. For future studies, researchers can improve the success rate achieved by the three-tier architecture by identifying and considering the conditions that cause fluctuations in the time series on a sectoral basis. In addition, parameters such as depth, lag and cluster of the three-layer architecture can be automated and made more useful.

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Conflict of Interest

The author(s) declare that there is no conflict of interest in this study. The study was written with the contributions of all authors.

Research and Publication Ethics Statement

The author(s) declare that they have complied with the scientific, ethical, and citation rules of the International Journal of Pure and Applied Sciences throughout all stages of the study.

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