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Development of a novel hybrid model (PDES–ANFIS) for time series applications

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Abstract

Most time series with a clear overall trend in their data and graphs require a model that effectively addresses the overall trend. If the time series also includes various fluctuations and random variations, nonlinear models are the ideal approach. To improve the prediction error and make it very small, a new model was applied to the time series of annual cancer cases in Iraq for the period from 1976 to 2023. This series contains a general trend covering more than 85% of the data, in addition to various random fluctuations and variations. The proposed hybrid model consists of two parts: the first part addresses the strong overall trend in a linear manner by partitioning the series into an optimal number of parts according to the optimal division that gives the lowest value for RMSE and MAPE, and applying a double exponential smoothing method to all parts to address the upward trend. The second part detects nonlinear patterns in the residuals of the first model using an adaptive network-based fuzzy inference system (ANFIS). The proposed hybrid model, Partitioned Double Exponential Smoothing (PDES-ANFIS), has proven to be more efficient compared to the unpartitioned hybrid model and single models by using the root mean square error (RMSE).

Keywords: Cancer, ANFIS, Double exponential smoothing, Hybrid models, PDES-ANFIS, Iraq

1. Introduction

Hybrid models have shown clear improvement and greater flexibility when dealing with different changes in data and have recorded a clear superiority over traditional individual models. They have become widely spread and have widespread application areas due to their ability to capture complex patterns and trends. Application areas have emerged in public health, epidemics, economics, finance, weather, climate, and more. Hybrid models offer several advantages, one is their ability to uncover hidden patterns in data. Another advantage is their tendency to enhance the accuracy of predictions. Additionally, by combining different modeling techniques, researchers can reduce the risk of choosing an unsuitable model, which also makes the model selection process more manageable [1]. Researchers usually distinguish hybrid models according to how their components are connected. The three main patterns are: models arranged in a series, models working side by side called a parallel-series setup, and those that mix both approaches, forming what's called a parallel–series setup.

Researchers have combined different types of models to create various hybrid models, such as linear and nonlinear hybrid models, linear and linear, or nonlinear and nonlinear. The most widely used hybrid models are linear and nonlinear. Over the course of more than two decades, various hybrid models have emerged, and researchers have been creatively developing and improving them to achieve the best prediction accuracy.

Zhang [2] was the first to propose a prediction model that combines a linear and a nonlinear model between neural networks and Box-Jenkins models. This was followed by the emergence of many different hybrid models, especially those that handle nonlinear regression using support vector machines (SVMs) and combine them with ARIMA [3]. The proposed model gave promising results. Researchers [4] used neural networks with ARIMA and confirmed that nonlinear models give better performance. Aladag et al. [5] proved that using recurrent neural networks with ARIMA gives better predictive performance and accuracy. Che and Wang [6] proposed a hybrid model that combines support vector regression and ARIMA (SVRARIMA) and demonstrated its superiority. Research by [7] used a hybrid methodology that combines multilayer perceptron (MLP) neural networks and Holt's exponential smoothing methods for interval-valued time series.

Aladag et al. [8] proposed a hybrid model of ARFIMA and feedforward neural networks (FNN) and demonstrated that the hybrid model performed better. The paper by [9] developed a hybrid model consisting of double exponential smoothing (DES) with SVM, which proved effective. The paper in [10] used an ARIMA model with artificial neural networks (ANNs); the hybrid model gives more accurate predictions. The authors in [11] proposed separating the linear and nonlinear components of the series using a Discrete Wavelet Transform (DWT). The authors in [12] demonstrated that ARIMA with an Adaptive-Neuro-Fuzzy-Inference-System) ANFIS significantly reduces the mean squared error (MSE). The authors in [13] used a series approach to combine back propagation (BP), ANFIS, and diff-SARIMA (back propagation), with optimal weight coefficients. The method proved to outperform the single models used.

Hybrid prediction with the discrete wavelet transform (DWT) and artificial neural network (ANN) yielded better results [14]. The paper in [15] combined wavelets, SARIMA, and the GJR-GARCH model. The paper in [16] applied a technique using ARIMA and ARIMA-SVR after wavelet analysis and demonstrated that the proposed model is effective for prediction. The authors of [17] confirmed that autoregressive AR-ANFIS provides accurate predictions. The paper in [18] applied a hybrid model by combining backpropagation with the simulated annealing (SA) algorithm, and their proposed method was effective for prediction.

Vaghasia [19] proposed ARIMA with Fuzzy Discrete Wavelet Transform by developing fuzzy rules for data classification. The authors in [20] proposed a hybrid prediction model using a clustering algorithm after analyzing the influencing factors to reach the optimal input combination. Jaseena and Kovoor [21] proposed models that combine the features of wavelet transform (WT), long memory, and support vector regression (SVR); the proposed model was more efficient. The authors of [22] presented a hybrid forecasting model consisting of fuzzy time series and Markov chains combined with ensemble techniques (C-Meen). The proposed model contributed to generating optimal period lengths, resulting in efficient performance. In [23], the model used was ARMA-GJR-GARCH. They demonstrated that the model yielded promising results. The authors of [24] proposed a hybrid model, the first part of which relies on discrete wavelet analysis, which analyzes data according to their frequency, and the other part relies on a methodology for training the prophecy to predict components. This model, named DWT-Prophet, has proven to outperform several single models.

The paper in [25] demonstrated that ARIMA/ANN outperformed single-model models when predicting the number of cancer patients in Yemen. The paper in [26] demonstrated the superiority of a model consisting of Bidirectional Long Short-Term Memory (Bi-LSTM) and Exponential Smoothing (ES) hybrid model. The paper in [27] used a hybrid model that combines Box-Jenkins models and wavelet analysis to forecast Euro–Dinar Exchange. The paper in [28] used various hybrid combinations consisting of ARIMA, state space for exponential smoothing, and others. The hybrid models demonstrated superior performance. The paper in [29] demonstrated the superiority of the hybrid Neural Prophet (NP-LSTM) model, built on a parallel-series architecture, over single-model models. The paper in [30] demonstrated the superiority of Seasonal Autoregressive Integrated Moving Average and Nonlinear Autoregressive Neural Network (SARIMA-NARNN) over single model models.

In [31], they built a two-part composite model, combining exponential smoothing and backpropagation neural networks (ES-BP) that outperformed uncombined models. Abd and Almohana used two hybrid models: Autoregressive Distributed Lag (ARDL) with LSTM and Gated Recurrent Unit (GRU). The ARDL-LSTM model proved to be superior [32]. In [33], they proposed a hybrid model using Maximal Overlap Discrete Wavelet Transform (MODWT) with ARIMA, which proved to be superior. In [34], they used a hybrid model consisting of the eigenvalue decomposition of the Hankel matrix (EVDHM) and the ARIMA model. The hybrid model proved to be highly efficient compared to the ARIMA model. In [35], researchers adopted a hybrid approach with ANFIS and Particle Swarm Optimization (PSO) and ANFIS with Gray Wolf Optimizer (GWO) algorithms, and compared several hybrid models, where ARIMA-ANFIS-PSO was the best. Shejul et al. [36] proposed a method that combines exponential smoothing (ES) and convolutional neural networks (CNN) with LSTM and demonstrated superior performance.

From the above, we note that there is no single ideal model or unique algorithm that is suitable for all types of time series. This is because each time series has a characteristic or feature that may not be present in other time series. Each time series has a variable specific to it, and therefore, the methods and means for predicting future values have varied. The model presented here may not be suitable for other time series unless they have similar characteristics. The research is intended to develop a hybrid model for time series forecasting that merges a linear framework to reflect the underlying long-term progression of the data, with a nonlinear component for handling short-term irregularities and dynamic fluctuations. It is proposed that such a combined modeling strategy will yield more accurate forecasts than relying solely on individual linear or nonlinear models. To achieve this, an Exponential Smoothing (ES) model is employed with an alternative proposal for implementation in the series to capture the trend component, while the residuals resulting from this model are further analyzed using a nonlinear method, such as INFIS. The outputs from both stages are then merged to produce the final forecast. The accuracy and reliability of the hybrid model are assessed using standard performance metrics, including RMSE.

2. The proposed hybrid model (Partitioned Double Exponential Smoothing (PDES - ANFIS)

If the time series contains a clear and increasing trend in the data, the proposed method for modeling it is to use a hybrid model based on series hybrid modeling. The residuals of the first model are used as inputs to the second model; the final model is a series hybrid model.

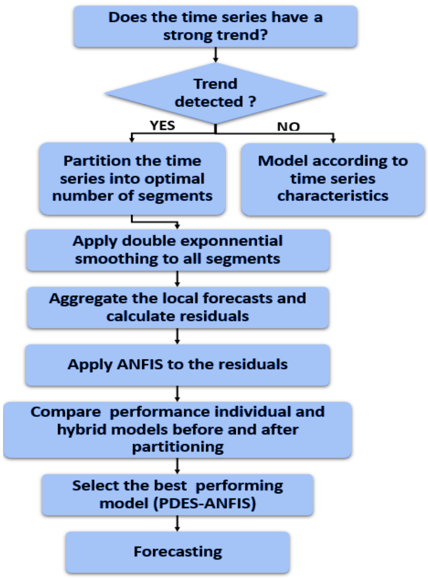

Figure 1. PDES-ANFIS forecasting framework

Implementing the PDES-ANFIS model involves the six steps:

1. Partitioning the series into the optimal number of groups.

2. Computing the exponential smoothing for each group to obtain the predictions within the series.

3. Computing the residuals by subtracting the actual values from the predicted values.

4. The ANFIS model is trained using the residuals, with the objective of uncovering data patterns that the exponential smoothing stage fails to represent.

5. Merging the final predictions by combining the predicted values from the exponential smoothing with the ANFIS predictions.

6. Final Prediction. The following diagram summarizes the steps of the proposed method.

3. Data description

Data were obtained from the Ministry of Health and Environment – Iraqi Cancer Board. The data represent a time series for people with cancer of all types in Iraq for the period from 1976 to 2023, which shows that the number of new cases of cancer increased with time. The series contains a sharp general trend. From 1976 to 2023, there was a noticeable rise in the incidence of new infection cases, increasing from 31.5 to 99.4 per 100,000 people [37]. This steady growth appears to reflect the influence of increasing population density throughout the years.

The time series shows a general upward trend (growth trend) over the long term, despite some fluctuations and declines in some years. It can be observed that the values tend to increase over time, indicating a general upward trend. This can be confirmed using trend analysis or applying a linear regression model to verify the strength and impact of the trend.

4. Double exponential smoothing (DES)

In this method, the series is divided into two components: trend and level, which are calculated as follows [38]:

$$L_t = \alpha y_t + (1 - \alpha)(L_{t-1} + T_{t-1}) \tag{1}$$

$$T_t = \gamma(L_t - L_{t-1}) + (1 - \gamma)T_{t-1} \tag{2}$$

After selecting appropriate values for α and γ, the level component L_t is computed to represent the smoothed value of the series at time t. Subsequently, adding the level and trend components at the same point in time provides a basis for estimating the next value in the series is (t + 1).

5. Adaptive-Neuro-Fuzzy-Inference-System (ANFIS)

The Adaptive Neuro-Fuzzy Inference System (ANFIS) is a hybrid intelligent framework that blends the reasoning capabilities of fuzzy logic with the adaptive learning power of neural networks [39]. This integration allows ANFIS to learn directly from data and generate fuzzy inference rules automatically, without requiring manual programming. Structurally, ANFIS resembles a layered neural network modelled after the Takagi–Sugeno fuzzy system [40]. Its architecture typically includes five or six sequential layers, each corresponding to a specific phase in the fuzzy inference process: transforming input values into fuzzy membership grades (fuzzification), applying fuzzy IF–THEN rules (rule layer), normalizing rule strengths, generating rule outputs (defuzzification), and aggregating the final output. Learning in ANFIS is achieved through a combination of backpropagation and least squares estimation, enabling effective adjustment of system parameters. What sets ANFIS apart is its ability to model complex nonlinear relationships with high precision while retaining interpretability. It has proven effective across various applications, such as control systems, dynamic modelling, and time series forecasting. Empirical evaluations show that ANFIS often surpasses traditional neural networks in both accuracy and transparency, making it a valuable tool for data-driven modelling tasks.

6. Results and discussion

The information about the time series in Table 1 under analysis exhibits a standard deviation of 10,878.1, which is considerably large relative to its average value of 14,289.3. This suggests that the data points are spread across a wide range rather than concentrated around the mean, indicating that the behavior of the series may not be consistent over time. Given this level of variation, dividing the series into smaller segments becomes a practical choice, since a single predictive model might fail to capture underlying shifts or abrupt changes in trend. In this context, applying a model like ANFIS to the residuals, after smoothing, allows for learning complex, nonlinear patterns that conventional linear methods may overlook.

Table 1. Descriptive statistics

N	Mean	Standard Deviation	Minimum	Maximum	Mode	Median
48	14289.3	10878.1	2872	43062	No mode	9,960.5

Trend analysis using a linear regression model yielded the following results. The trend coefficient (slope) = 720.58, indicating that the values increase at an average rate of 720.58 per year. The intercept = -1,427,000, which is the point where the model intercepts the y-axis. The R^2 value = 0.86, which means that 86% of the changes in the data can be explained by the overall trend. The P-value for the linear regression is < 0.05, indicating that the overall trend is statistically significant. Therefore, it is concluded that there is a strong upward trend in the time series, with values increasing significantly over time. However, there are some random fluctuations that may require additional analysis using more complex models, such as a hybrid linear and nonlinear time series model. In order to get the lowest values for the statistical comparison measures an exhaustive data-driven segmentation strategy was employed, where the time series was divided into varying numbers of segments (from 4 to 12), each fitted with Holt's exponential smoothing using $\alpha = 0.3$, $\gamma = 0.1$, The segmentation that gave the lowest values for RMSE and MAPE [41] was chosen, and the results are shown in Table 2.

Table 2. Data-driven segmentation with forecast error minimization

Segments	RMSE	MAPE (%)	The result
7	1297.76	8.03 %	The Best
4	1302.44	8.15 %	
6	1409.60	8.26 %	
5	1387.87	8.47 %	
8	1516.38	9.91 %	

It is clear from Table 2 that the best division is to divide the series into seven parts, each part contains seven observations except for the last or seventh group, which contains six observations. This is the optimal division that gave the lowest value for RMSE and MAPE, which means the lowest prediction error. Values that divide the series into more than eight sections were excluded because the model needs sufficient data to estimate the trend reliably. With a short series, the model may not be able to distinguish between noise and the true trend, leading to unstable estimates or non-convergence warnings. The time series was restructured into an input–output format (X, Y) in MATLAB so that historical observations served as predictors for the present value. The ANFIS model was then trained using a subset of the dataset, while the remaining portion was reserved for validation. The comparison between predicted and observed values was visualized through plots. Model characteristics were as follows: 32 nodes, 14 linear parameters, 21 nonlinear parameters, giving a total of 35 parameters. The dataset consisted of 43 training pairs and 5 checking pairs, with 7 fuzzy rules defined.

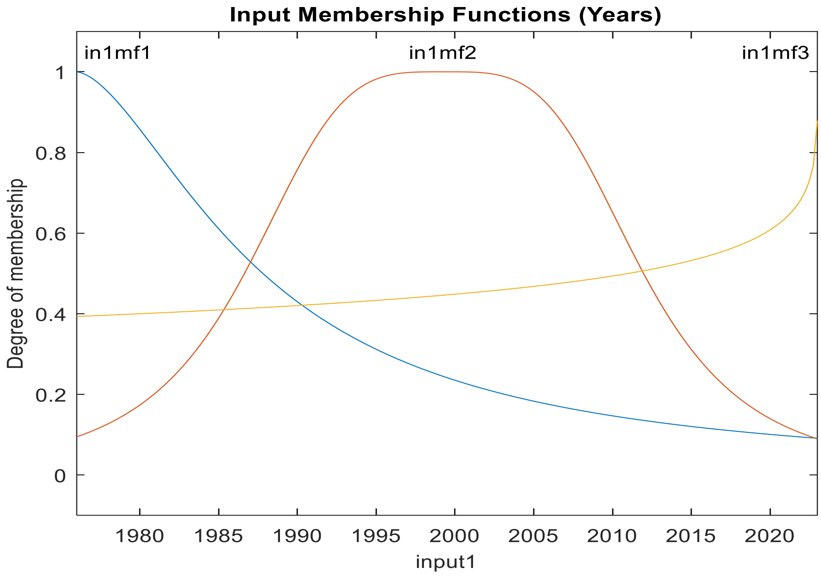

Figure 2. Degree of membership function for ANFIS for the system

Figure 2 shows that fuzzy membership functions determine how the range of years is "fuzzy," divided into fuzzy regions:

1. in1mf1: Represents the "old years" (1976–1990), has a high membership score at the beginning of the period, decreasing thereafter.
2. in1mf2: Represents the "middle period" (1990–2010), peaks midway through the period, declining on both sides.
3. in1mf3: Represents the "recent years" (after 2010), has a low membership score at the beginning, gradually increasing.

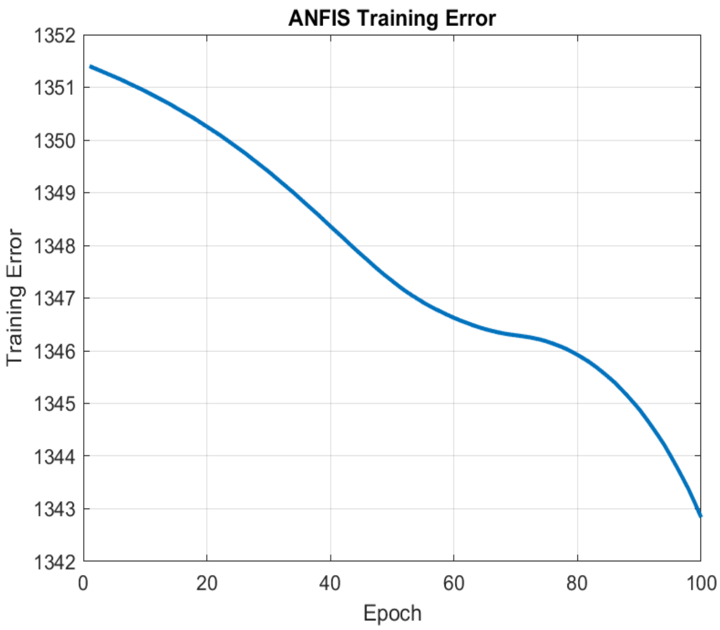

Figure 3. ANFIS training error

The curve in Figure 3 descends steadily without sharp fluctuations, indicating a stable training process. The error value starts at approximately 1351.4 and decreases to approximately 1342.8 by the end of training. The absence of error explosions or sudden declines indicates that the model did not suffer from overfitting during the training phase alone. The curve reflects a stable training process and gradual improvement in performance, indicating that ANFIS is learning patterns from the data well.

Table 3. Analysis of ANFIS performance in relation to the number of fuzzy inference rules using the RMSE metric

RULES	RMSE
3	1601.06
5	1433.97
7	1353.88
8	799.249
9	605.654

The table illustrates the effect of the number of fuzzy inference rules on the accuracy of the ANFIS model. The root mean square error (RMSE) measure was used to evaluate the model's performance across different experiments using a rule number ranging from 3 to 9. The results show that the higher the number of rules, the higher the predictive accuracy. Increasing the number of rules from 3 to 9 led to a gradual improvement in performance, with the RMSE decreasing from 1601.06 to 605.654. The improvement became more pronounced after exceeding 7 rules, with the RMSE decreasing by approximately 41% when moving from 7 to 8 rules. This indicates that the model was able to capture more accurate patterns in the data when using a more complex structure.

Figure 4 shows a performance comparison between the traditional double exponential smoothing (DES) model and the hybrid (DES + ANFIS) model for forecasting the time series from 1976 to 2023 without segmentation. It is clear that the DES model captures the overall upward trend of the series, but fails to accurately track sharp increases, especially in later years. In contrast, the hybrid model consistently matches the actual data more closely across all periods, particularly during phases of rapid growth. Evaluation metrics quantitatively confirmed this improvement. The DES model achieved a mean squared error (RMSE) of 858.01 and a mean average predicted error (MAPE) of 5.20%, while the hybrid DES-ANFIS model significantly reduced these errors to 607.38 and 3.79%, respectively. This represents an approximate 29% improvement in RMSE and 27% improvement in MAPE.

Figure 5 shows further improvement when the series is split into the optimal seven-partition model, where each part is smoothed separately before applying ANFIS to the combined residuals. This hybrid split model (PDES-ANFIS) achieves the best overall performance, with RMSE = 567.45 and MAPE = 3.35%, reflecting the advantage of simultaneously capturing local trends and nonlinear components.

Figure 6 compares the performance of the PDES-ANFIS model with the standalone ANFIS model. The unhybridized ANFIS-based approach achieves the weakest results (RMSE = 1163.51, MAPE = 7.47%), confirming its limited ability to model long-term trend behavior without pre-smoothing. In contrast, the hybrid pre-splitting and post-splitting model achieves superior accuracy by combining structured linear smoothing with intelligent residual correction.

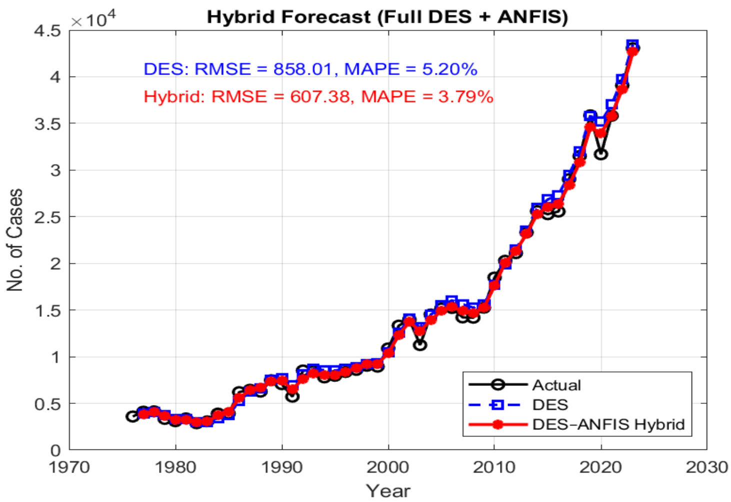

Figure 4. Hybrid model DES-ANFIS

Overall, the hybrid PDES-ANFIS model outperforms all alternatives, demonstrating its ability to balance the extraction of global trends and local nonlinearity. Thus, the hybrid DES-ANFIS model proves to be more robust and effective, making it the most reliable model for prediction.

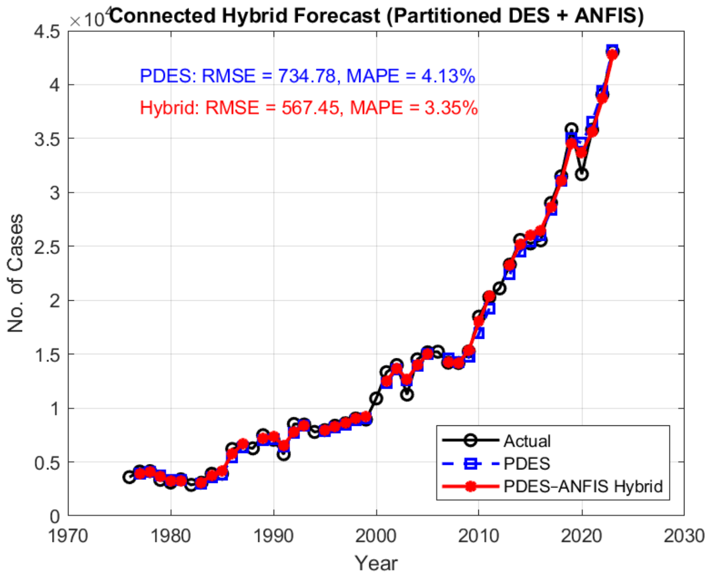

Figure 5. Hybrid model PDES-ANFIS

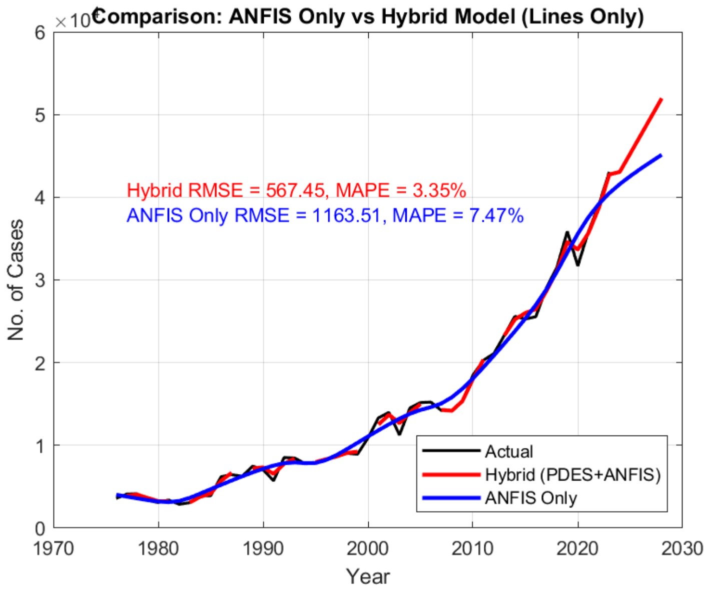

Figure 6. Hybrid model PDES-ANFIS and ANFIS

Table 4. Statistical comparison values

Model	RMSE	MAPE
DES	858.01	5.20%
PDES	734.78	4.13%
ANFIS	1163.51	7.47%
Hybrid (DES- -ANFIS)	607.38	3.79%
Hybrid (PDES- ANFIS)	567.45	3.35%

Table 4 presents a statistical comparison of the prediction accuracy of five forecasting models using both RMSE and MAPE. The results indicate that the DES model provided moderate forecasting performance, with RMSE = 850.01 and MAPE = 5.20%. Upon dividing the series into seven segments and applying the piecewise double exponential smoothing (PDES) approach, accuracy improved notably, with RMSE and MAPE reduced to

734.78 and 4.13%, respectively. This underscores the benefit of capturing localized trends within the time series. On the other hand, the standalone ANFIS model yielded the weakest results, recording RMSE = 1163.51 and MAPE = 7.47%, suggesting that while ANFIS handles nonlinear relationships well, it struggles to represent the series' underlying trend structure alone. The hybrid models that integrated ANFIS with either DES or PDES outperformed the individual approaches. Specifically, modeling the residuals via ANFIS significantly enhanced accuracy; the DES–ANFIS hybrid achieved RMSE = 607.38 and MAPE = 3.79%. Notably, the proposed PDES–ANFIS hybrid recorded the best results, with RMSE = 567.45 and MAPE = 3.35%, demonstrating its effectiveness in blending localized smoothing with intelligent residual correction—making it the most accurate and reliable model for predicting the number of annual cancer cases in Iraq.

Table 5. Forecasts for 2024–2028

Year	PDES_ Component	ANFIS_ Component	Hybrid_ Forecast
2024	43169	-109.23	43060
2025	45069	213.46	45282
2026	46968	539.02	47507
2027	48868	865.65	49733
2028	50767	1192.7	51960

Table 5 presents the hybrid forecast results (PDES - ANFIS) for the years 2024 to 2028. The predicted values demonstrate a consistent upward trend, which aligns well with the recent historical behavior of the time series. The PDES component provides the primary direction of growth, increasing almost linearly over the years, while the ANFIS component contributes dynamic corrections that capture nonlinear and residual patterns. Notably, in 2024, ANFIS applies a negative correction to counter a potential overestimation by PDES, whereas in the following years, the corrections become increasingly positive—indicating a possible acceleration in the trend. By 2028, the hybrid forecast reaches its highest value (51,960), reflecting the compounding effect of both local smoothing and intelligent residual learning. This confirms the model's capability to adapt to underlying patterns and project the series trajectory with improved accuracy.

7. Conclusions

The time series analysis revealed that the annual cancer incidence series in Iraq is non-stationary and contains a general trend with a trend coefficient exceeding 720. This means that the annual incidence rate of cancer patients in Iraq increases by an average of 721 cases per year. The general trend is a basic element in the time series, and 85% of the changes in the time series are a general trend, which is a statistically significant element. Random changes and various fluctuations are other basic influences.

The hybrid forecasting framework that integrates (PDES) with (ANFIS) exhibited notable accuracy in modeling the time series. The model effectively captured the data's nonlinear dynamics and projected future values for the 2024–2028 period with a consistent upward trajectory. These findings underscore the robustness of combining smoothing-based linear techniques with data-driven fuzzy inference systems for enhanced time series forecasting. The analysis of the ANFIS system also revealed that increasing the number of rules results in a significant reduction in the prediction error.

Declaration of competing interests

The authors confirm the absence of any financial or non-financial conflicts of interest related to this article.

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Author contribution

Lamyaa Mohammed Ali Hameed: Conceptualization of the study, methodology design, data collection, analysis, and interpretation of results. She also contributed to the writing and revision of the manuscript.

Suhail Najim Abbood: Contributed to the literature review, data analysis, and interpretation of findings. He played a significant role in drafting sections of the manuscript and ensuring the clarity and coherence of the text.

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