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AI-OPTIMIZED FUZZY CONVOLUTIONAL PREDICTION FOR FINANCIAL TIME SERIES[1]

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Abstract: A deep convolutional prediction approach for financial time series is introduced in which fuzzy-cluster memberships and lagged observations are provided as inputs to a GA-tuned 1D convolutional network. Fuzzy C-Means clustering is fitted on the training segment to obtain memberships, whose nonlinear transforms are concatenated with scaled autoregressive lags to form a single feature block processed by the network. Hyperparameters—including lag order, number of clusters, fuzzifier, convolutional kernel size, filter counts, and mini-batch size—are selected through a genetic algorithm that minimizes validation RMSE. The proposed *AI-Optimized Fuzzy Convolutional Prediction* approach, incorporating fuzzy memberships and autoregressive lags, is evaluated on TAIEX datasets comprising 16 series. Across these datasets, lower error rates than state-of-the-art baselines are obtained, and close agreement between predictions and realized values is indicated by regression diagnostics and visual graphics. An intercept-free regression of observations on predictions yielded slopes and determination coefficients consistently near one, and scatter/residual plots exhibited limited dispersion and no salient error structure. The results suggest that integrating fuzzy membership–based feature construction with GA-tuned convolutional modelling yields accurate predictions on financial time series.

Keywords: Financial Time Series, Convolutional Prediction, Fuzzy C-Means Clustering, GA Hyperparameter Tuning, 1D Convolutional Neural Network

JEL Kodu: C22, C53, G17, C45.

FİNANSAL ZAMAN SERİLERİ İÇİN YAPAY ZEKA İLE OPTİMİZE EDİLMİŞ BULANIK EVRİŞİMSEL TAHMİN

Özet: Finansal zaman serileri için, bulanık küme üyelikleri ve gecikmeli gözlemlerin genetik algoritma ile ayarlanan tek boyutlu (1D) bir evrişimsel ağa girdi olarak verildiği derin evrişimsel bir öngörü yaklaşımı sunulmaktadır. Eğitim bölümüne Bulanık C-Ortalamalar uygulanarak üyelikler elde edilmekte; bu üyeliklerin doğrusal olmayan dönüşümleri, ölçeklenmiş otoregresif gecikmelerle birleştirilerek ağ tarafından işlenen tek bir özellik bloğu oluşturulmaktadır. Gecikme derecesi, küme sayısı, bulanıklık indeksi, evrişim çekirdeği boyutu, filtre sayıları ve mini-yığın boyutu dâhil hiperparametreler, doğrulama setleri üzerinden hata kareler ortalamasını en aza indiren bir genetik algoritma ile seçilmektedir. Bulanık üyelikler ve otoregresif gecikmelerle oluşturulan *Yapay Zekâ ile Optimize Edilen Bulanık Evrişimsel Tahmin* yaklaşımı, 16 farklı Tayvan Borsası zaman serisi ne uygulanmıştır. Bu veri setleri için, güncel yöntemlere kıyasla daha düşük hata oranları elde edilmiştir. Gözlemler üzerine, sabit terim içermeyen bir doğrusal regresyon kurulduğunda, eğim ve belirleme katsayılarının tutarlı biçimde bire yakın olduğu; saçılım ve artık grafiklerinde sınırlı yayılım ve belirgin bir hata yapısının bulunmadığı gözlenmiştir. Bulgular, önerilen tahmin modelinin oldukça başarılı tahminler sağladığını ortaya koymaktadır.

Anahtar Kelimeler: Finansal Zaman Serileri, Evrişimsel Tahmin, Bulanık C-Ortalamalar Kümeleme, GA Hiperparametre Ayarlama, 1B-Evrişimsel Sinir Ağı

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Introduction

Time-series prediction plays a key role in planning and risk control. In finance, short- and medium-horizon predictions are used to guide trading, hedging, and portfolio rebalancing. Decisions by individual investors and advisory institutions are shaped by these predictions, which inform entry and exit timing, position sizing, and capital allocation. Inaccurate signals may raise costs and risk, whereas accurate ones support liquidity management and compliance with limits. The task is complicated by non-stationarity, regime shifts, and nonlinear effects that are common in asset prices and volumes. For these reasons, methods that learn from data while accommodating changing patterns are actively sought for financial time series.

Traditional statistical approaches, such as exponential smoothing (ETS) and the Autoregressive Integrated Moving Average (ARIMA) family, have long been used as primary tools for time series prediction. These methods generally rely on modelling linear structures, assuming white noise residuals, and stationarity conditions; therefore, they are strongly dependent on model specification and residual analysis processes (Box, Jenkins, and Reinsel 2013). Due to the regime shifts, volatility clustering, and nonlinear responses frequently observed in financial time series, these assumptions often become challenging, and significant losses in prediction performance can occur when model fit deteriorates (Hyndman and Athanasopoulos 2018). Recent comparative studies have shown that, particularly in economic and financial data, linear ARIMA/ETS models are limited in capturing complex patterns and large data volumes compared to machine learning (ML) and deep learning-based (DL) methods, and they produce higher error rates (Kontopoulou et al. 2023; Sun and Deng 2025).

Machine learning and deep learning-based methods are widely used in time series prediction due to their ability to capture nonlinear relationships and automatically extract patterns from large volumes of data. However, most of these models treat time series observations as precise/sharp and fully definite numerical values, and the uncertainty and linguistic ambiguity inherent in the data are not directly represented (Fatima and Rahimi 2024). Noise, measurement errors, incomplete information, and unpredictability due to human behavior, particularly seen in financial series, can challenge the model under such sharp representations.

Fuzzy set theory offers a natural framework for such situations by allowing the model to represent the partial affiliation of concepts through membership degrees (Zadeh 1965). The fuzzy time series approach, developed by Song and Chissom (1993a), is designed for the prediction of dynamic processes where observations are expressed in linguistic terms and fuzzy sets, and aims to relax the assumptions of classical methods.

Subsequent studies emphasize that fuzzy time series-based models can directly handle uncertainty and approximate information without requiring additional assumptions, thus providing a more suitable representation for most economic and financial data structures (Alpaslan et al. 2012). Various comparative studies indicated that such fuzzy approaches can achieve lower error measures than both classical ETS/ARIMA models and certain artificial neural network applications and produce more realistic predictions, especially in series where uncertainty is significant(Cheng et al. 2008; Nor Syazwina Binti Mohd Hanafiah et al. 2022; Wang 2011).

Fuzzy time series approaches were first introduced in the models of Song and Chissom (1993a, 1993b, 1994), where relationships were defined through matrix operations. These models were subsequently enriched with methods based on fuzzy relationship tables developed by Chen (1996, 2002). This line was later advanced by Aladag et al. (2009) and Egrioglu et al. (2009), who employed artificial neural networks to learn relationships. In addition to these methods, prediction models based on fuzzy regression functions, which handle fuzzy relationships functionally without requiring explicit rule inference, have also been successfully implemented, unlike adaptive-network-based fuzzy inference system (ANFIS) (Jang 1993a), which, like other fuzzy time series models, is widely used for time series prediction in the literature and relies on a rule-based relationship identification mechanism. These models are essentially based on the fuzzy regression functions proposed by Türkşen (2008) for regression problems and utilize this structure in the prediction process.

Aladag et al. (2016) proposed a type-1 fuzzy time series function approach where lagged variables are selected using binary PSO and tested the method on both well-known classical time series and Istanbul Stock Exchange data. Dalar et al. (2017) applied a type-1 fuzzy function approach to predict time series data on Australian beer consumption and Turkish electricity consumption, demonstrating its applicability to real data from various domains. Tak et al. (2018a) developed a recurrent type-1 fuzzy function approach based on particle swarm optimization and examined the method's prediction performance on different data sets. Bas et al. (2019a) presented a Type-1 Fuzzy Function Approach Based on Ridge Regression, where the linear functions established for each fuzzy set are estimated using ridge regression instead of ordinary least squares, aiming to reduce the effect of multicollinearity. As another study addressing the multicollinearity problem, (Tak and İnan 2022) proposed the fuzzy regression functions approach with elastic net regularization and performed a comprehensive analysis on twelve practical time series datasets for performance evaluation.

While these studies offer a flexible and functional framework for defining fuzzy relationships, their essentially linear mapping between inputs and outputs can be viewed as a significant limitation. However, many of the interrelationships observed in time series contain complex and sometimes chaotic nonlinear patterns. Therefore, numerous studies in the literature have used artificial neural networks of different structures to capture fuzzy and nonlinear relationships between inputs and outputs. For example, Yu and Huarng (2008a), Aladag et al. (2009; 2010), and Egrioglu (2014) have proposed artificial neural network-based models for identifying fuzzy relationships. Cagcag Yolcu and Alpaslan (2018) obtained predictions for the TAIEX index using a hybrid model combining a single multiplicative neuron artificial neural network and a fuzzy time series approach. Kocak et al. (2020) developed an ARMA-type fuzzy time series model based on a Pi–Sigma artificial neural network. In a more recent study, Aktoprak and Cagcag Yolcu (2025) proposed an alternative approach in which multiple feedforward artificial neural networks are used in a functional structure. Moreover, Polater et al. (2026) introduced a Picture Fuzzy C-Means–based ensemble forecasting approach that combines lagged inputs, picture-fuzzy degrees, and degree-based nonlinear transformations within a two-stage aggregation structure for financial time series.

These studies can be said to have gained significant capabilities in capturing nonlinear patterns by defining fuzzy relationships through artificial neural networks. However, the network architectures used in most of these approaches are relatively shallow in terms of the number of layers and their representational power, and tend to be limited when modeling deeper and hierarchical relationships between inputs and outputs. It is not always possible to fully represent the intertwined, multi-scale, and regime-shifting dynamics frequently encountered in financial time series with structures consisting of only a few layers. Therefore, deep neural networks with more layers and feature extraction steps are thought to have the potential to produce more realistic and relatively low-error predictions, both in extracting meaningful patterns from inputs enriched with fuzzy membership representations and in revealing nonlinear, deep patterns in time series. Such a combination could provide additional gains in prediction performance by combining the uncertainty-based strengths of the fuzzy time series framework with the representational power of deep learning.

Accordingly, in this study, a fuzzy time series prediction model was developed that utilizes inputs, lagged time series, memberships obtained by fuzzifying them using the fuzzy C-means clustering algorithm, and some nonlinear transformations of these memberships (as in fuzzy regression function approaches). A deep fuzzy time series prediction strategy was developed using a convolutional artificial neural network to capture deeper-fuzzy and hierarchical relationships between inputs and outputs. The hyperparameters of the components of this prediction strategy (such as FCM, autoregressive structure, and CNN) were determined using GA, an artificial intelligence technique. Therefore, the proposed GA-Tuned CNN with fuzzy memberships and autoregressive lags is named AI-Optimized Fuzzy Convolutional Prediction (AI-opt-FConvP).

The second section of the study is devoted to the details of the proposed methodology and the presentation of its algorithm. The third section compiles the details and results of the financial time series analysis, while the fourth and final section presents the discussion of the obtained results.

The Proposed Methodology

This study proposes an AI-optimized fuzzy convolutional prediction framework, denoted by AI-opt-FConvP, for univariate financial time-series prediction. The proposed framework integrates fuzzy clustering, membership-based feature enrichment, one-dimensional convolutional learning, and genetic-algorithm-based hyperparameter optimization within a unified architecture. The method is motivated by two considerations. First, financial time series often exhibit regime changes, noise, and gradual transitions between market conditions; therefore, Fuzzy C-Means (FCM) is employed to represent such uncertainty through soft memberships rather than hard assignments. Second, financial dynamics are typically nonlinear and lag-dependent; accordingly, a one-dimensional convolutional neural network (1D-CNN) is used to learn predictive patterns from a single feature block formed by lagged observations and transformed fuzzy memberships. The overall procedure consists of five main stages. First, the original series is partitioned chronologically into training, validation, and test segments, and a min-max transformation is estimated using only the training segment. Second, lagged inputs and fuzzy membership-based features are constructed from the scaled series. Third, these features are supplied to a 1D-CNN to produce prediction values in the scaled domain. Fourth, a genetic algorithm (GA) is used to optimize the main hyperparameters of the fuzzy and convolutional components using validation RMSE as the fitness criterion. Finally, the best configuration is retained and evaluated on the held-out test segment in the original data scale.

Data Splitting and Transformation

Let $\{y_t\}_{t=1}^{T}$ denote the observed univariate financial time series. The series is split chronologically into three consecutive segments: *training*, *validation*, and *test*. The last n_{test} observations are reserved for test evaluation, the preceding $n_{test} = n_{val}$ observations are used for validation, and all earlier observations constitute the training segment. This chronological partition preserves the temporal order of the data and ensures a genuinely out-of-sample evaluation design. After the partition is defined, min-max scaling is performed using only the training segment. Specifically, the minimum and maximum values obtained from the training data are used to transform the training, training-validation, and full-series segments into the $[0, 1]$ interval. In this way, all preprocessing parameters are estimated exclusively from the training segment, thereby preventing information leakage from the validation or test periods. The scaled series is then used to construct lagged inputs up to order M, where M is treated as a tuneable hyperparameter.

Fuzzy Membership-Based Feature Construction

To capture latent regime structure, FCM clustering is applied to the scaled training series. This yields cluster centres and corresponding membership degrees that quantify the extent to which each observation belongs to each fuzzy cluster. Unlike hard partitioning, this representation allows gradual transitions between market states to be encoded numerically.

The raw membership values are then enriched through nonlinear transformations. For each cluster membership u, the original membership, its squared value, its exponential transform, and its log-ratio transform are computed. These transformed terms allow the model to respond differently to weak, moderate, and strong cluster associations. The transformed membership features are then aligned with the lagged observations generated from the scaled series and concatenated horizontally to form a unified feature matrix.

Using the cluster centres estimated from the training segment, analogous membership-based feature matrices are constructed for the training-validation segment and for the full series. Because both the scaling parameters and the fuzzy structure are anchored to the training stage, the resulting feature construction remains consistent with a leakage-free forecasting protocol.

CNN-Based Predictive Architecture

The unified feature matrix is used as the sole input to a one-dimensional convolutional neural network. Each time point is represented by a feature vector containing lagged observations together with the raw and transformed fuzzy memberships. These vectors are reshaped appropriately and provided to the 1D-CNN, which is designed to extract local nonlinear patterns from the combined feature structure.

The network consists of a sequence input layer, followed by two one-dimensional convolutional layers with batch normalization and ReLU activation, a flatten layer, and a fully connected output layer with a single neuron for prediction. The kernel size and the number of filters are treated as tunable hyperparameters. The network is trained on the training feature block using the Adam optimizer, while the mini-batch size is also selected as part of the optimization process. The output of the network is a sequence of scaled prediction values, which is subsequently transformed back to the original data scale by inverse min-max scaling.

Genetic Algorithm for Hyperparameter Selection

The hyperparameters of the proposed model are selected by a genetic algorithm. Each chromosome represents a candidate configuration containing the *lag order*, *the number of fuzzy clusters*, *the fuzzifier parameter*, *the convolutional kernel size*, *the number of filters*, *the mini-batch size*, and *an internal seed* controlling stochastic components of model training. These variables jointly define both the fuzzy feature-generation stage and the CNN prediction stage.

For each chromosome, the corresponding feature matrices are constructed, the CNN is trained on the training segment, and validation predictions are obtained from the training-validation segment. The validation RMSE, computed in the original data scale, is then used as the fitness value. The population is iteratively updated through elitism, roulette-wheel selection, single-point crossover, and mutation. After the termination criterion is met, the chromosome with the lowest validation RMSE is retained as the best model configuration.

Final Prediction and Test Evaluation

Once the optimal hyperparameter configuration is identified, the corresponding model is retained and used to generate final validation and test predictions. These predictions are expressed in the original scale of the time series through inverse transformation. Model performance is then assessed on the test segment using standard error measures such as RMSE and MAPE. In this way, the final evaluation reflects the true out-of-sample predictive ability of the proposed framework.

A step-by-step algorithm for the operation of the proposed AI-opt-FConvP is given as follows:

Algorithm. AI-Optimized Fuzzy Convolutional Prediction

Input:

- Univariate financial time series

$$\{y_t\}_{t=1}^{T}, \quad y_t \in \mathbb{R} \tag{1}$$

- Test length $n_{test} \in \mathbb{N}$,
- Genetic Algorithm (GA) settings:
  - Population size $P = 50$
  - Elite ratio $r_{elite} = 0.20 \Rightarrow$ elite count $E = \lfloor r_{elite} P \rfloor$
  - Crossover fraction $r_{cross} = 0.80$
  - Mutation rate $r_{mut} = 0.01$
  - Maximum number of generations $G_{max} = 20$
  - Selection mechanism: $roulette - wheel$
  - Crossover: $single - point$
  - Mutation: $adaptive\ feasible$

Each individual (chromosome) in the GA is a vector,

$$\boldsymbol{x} = (x_1, x_2, \cdots x_7)^{\mathrm{T}} \in [0, 1]^7 \tag{2}$$

Output:

- Best chromosome $\boldsymbol{x}^*$
- Hyperparameter set decoded from $\boldsymbol{x}^*$
- Test predictions $\{\hat{y}_t^{test}\}$ in the original scale
- Error measures on test segments (e.g. RMSE, MAPE)

Step 1. *Time-series partitioning.*

Partition the index set $\{1,2,\cdots,T\}$ into **training**, **validation**, and **test** segments

$$\mathcal{T}_{test} = \{T - n_{test} + 1, \cdots, T\} \Rightarrow y_t^{test} = y_t, \quad t \in \mathcal{T}_{test} \tag{3}$$

$$\mathcal{T}_{val} = \{T - 2n_{test} + 1, \cdots, T - n_{test}\} \Rightarrow y_t^{val} = y_t, \quad t \in \mathcal{T}_{val} \tag{4}$$

$$\mathcal{T}_{train} = \{1,2, \cdots, T - 2n_{test}\} \Rightarrow y_t^{train} = y_t, \quad t \in \mathcal{T}_{train} \tag{5}$$

Step 2. *Min–max scaling (based on training only).*

- Compute the minimum and maximum of the training segment:

$$y_{min} = \min_t y_t^{train} \tag{6}$$

$$y_{max} = \max_t y_t^{train} \tag{7}$$

$$r = y_{max} - y_{min} > 0 \tag{8}$$

- Scale *training*, *training + validation*, and *entire* series using these parameters:

$$\tilde{y}_t^{train} = \frac{y_t^{train} - y_{min}}{r} \tag{9}$$

$$\tilde{y}_t^{train+val} = \frac{y_t^{train+val} - y_{min}}{r} \tag{10}$$

$$\tilde{y}_t^{entire} = \frac{y_t^{entire} - y_{min}}{r} \tag{11}$$

Step 3. *GA search space and hyperparameter decoding.*

For each chromosome $\boldsymbol{x} = (x_1, x_2, \cdots x_7)^{\mathrm{T}} \in [0,1]^7$, define the model hyperparameters as follows:

- *Lag order M* (number of autoregressive lags):

$$M = round(8x_1 + 2) \in \{2, 3, \cdots, 10\} \tag{12}$$

- *Number of fuzzy clusters K*:

$$K = round(7x_2 + 3) \in \{3, 4, \cdots, 10\} \tag{13}$$

- *Fuzzifier* m for Fuzzy C-Means:

$$m = 1.5 + 1.5x_3 \in [1.5, 3.0] \tag{14}$$

- *Convolution kernel size* k for 1D conv layers:

  Compute an index

$$i_k = round(2x_4 + 1) \in \{1, 2, 3\} \tag{15}$$

and select according to this index

$$i_k = 1 \Rightarrow k = 3;\ i_k = 2 \Rightarrow k = 4;\ i_k = 3 \Rightarrow k = 5; \quad k \in \{3, 4, 5\} \tag{16}$$

- *Number of filters in the first convolutional layer,* $\boldsymbol{f_1}$**:**

  Compute an index

$$i_f = round(3x_5 + 1) \in \{1, 2, 3, 4\} \tag{17}$$

and select according to this index

$$i_f = 1 \Rightarrow f_1 = 2; i_f = 2 \Rightarrow f_1 = 4; i_f = 3 \Rightarrow f_1 = 6; i_f = 4 \Rightarrow f_1 = 8; f_1 \in \{2, 4, 6, 8\} \tag{18}$$

The second convolutional layer uses:

$$f_2 = f_1 \tag{19}$$

- *Mini-batch size b* for CNN training:

Compute an index

$$i_b = round(3x_6 + 1) \in \{1,2,3,4\} \tag{20}$$

and select according to this index

$$i_b = 1 \Rightarrow b = 1; i_b = 2 \Rightarrow b = 2; i_b = 3 \Rightarrow b = 3; i_b = 4 \Rightarrow b = 4; b \in \{1,2,3,4\} \tag{21}$$

- *Internal seed* parameter:

Map x_7 to an integer

$$s = round(x_7 \cdot 10^8) \tag{22}$$

and use s to initialize random number generators in the implementation.

Step 4. *GA initialization.*

- Initialize a population of $P = 50$

$$\left\{\boldsymbol{x}_p^{(1)}\right\}_{p=1}^{P} \tag{23}$$

each drawn independently from the uniform distribution on $[0,1]^7$.

- Set generation counter $g = 1$

Step 5. *For each chromosome.*

(a) construct lagged observations up to order M;

(b) fit FCM on the scaled training segment;

(c) compute raw and transformed memberships;

(d) concatenate lagged values and fuzzy features to form the input matrices;

(e) reshape the feature matrices for 1D-CNN processing;

(f) train the CNN on the training segment;

(g) obtain validation predictions and compute validation RMSE in the original scale.

Step 6. *Use validation RMSE as the fitness value and update the GA population through elitism, roulette-wheel selection, crossover, and mutation.*

Step 7. *Repeat Steps 5–6 until the termination criterion is met.*

Step 8. *Select the chromosome with the minimum validation RMSE.*

Step 9. *Retain the best configuration, generate final validation and test predictions, transform them back to the original scale, and compute RMSE and MAPE on the test segment.*

As illustrated in Figure 1, the proposed AI-opt-FConvP framework transforms the raw time series into a unified feature representation composed of lagged observations, fuzzy memberships, and their nonlinear transformations, which is then processed through successive CNN layers to generate the final prediction.

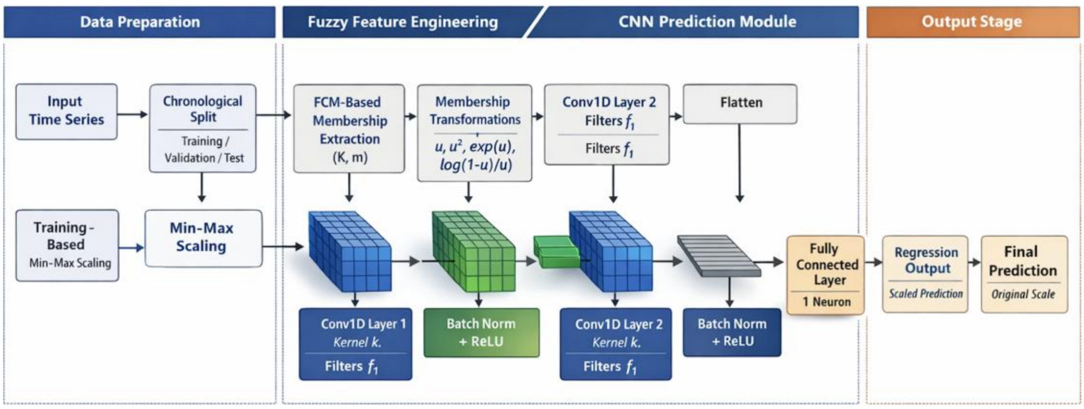


Figure 1. Schematic architecture of the proposed AI-opt-FConvP framework

Empirical Framework

Data Specification and Partition Strategy

In this study, the TAIEX (Taiwan Capitalization Weighted Stock Index, daily) series were employed. Two blocks were analyzed: five yearly series from 2000–2004 and eleven yearly series from 2008–2018. For each year, observations were partitioned chronologically: the earliest portion was used for training, the next block for validation, and the final block for testing (no shuffling). The split sizes are listed in Table 1.

Table 1. A summary of the splitting strategy.

#	Series			# Observations	Size of Training	Size of Validation & Testing
1	TAIEX	2000	T00	271	177	47
2		2001	T01	244	158	43
3		2002	T02	248	162	43
4		2003	T03	249	163	43
5		2004	T04	250	160	45
6	TAIEX	2008	T08	249	163	43
7		2009	T09	247	159	44
8		2010	T10	250	160	45
9		2011	T11	247	159	44
10		2012	T12	246	162	42
11		2013	T13	244	158	43
12		2014	T14	248	162	43
13		2015	T15	244	156	44
14		2016	T16	242	154	44
15		2017	T17	243	157	43
16		2018	T18	245	161	42

Pre-processing methodology. *Min–max* scaling parameters were learned from the *training* partition and applied to *validation/test*, lagged predictors of order M were formed, FCM obtained fuzzy memberships on the *training* partition, and the unified feature stack $\left[U, U^2, exp(U),\ \log\frac{1-U}{U},\ lags\right]$ was constructed as the single CNN input.

Training protocol. A one-dimensional CNN was trained on the training partition using Adam (100 epochs, initial learning rate 5×10^{-3}); the *mini-batch size* was determined by GA. Validation predictions were generated by running the trained model on the concatenated *training* and *validation* features and extracting the last T points; test predictions were generated analogously from the *training*, *validation*, and *test* features. Inverse scaling was then applied.

Hyperparameter search. A genetic algorithm minimized the validation RMSE over the following ranges:

- $M \in \{2, 3, \cdots, 10\}$
- $K \in \{3, 4, \cdots, 10\}$
- $m \in [1.5, 3.0]$
- $kernel\ size \in \{3, 4, 5\}$
- $\#\ filters\ \in \{2, 4, 6, 8\}$
- $mini - batch\ size \in \{1, 2, 3, 4\}$

Baselines and Evaluation Protocol

Comparisons were carried out against established fuzzy time-series and hybrid predictors reported for TAIEX. For each year, identical train/validation/test boundaries were taken. Baseline metric values were taken from the respective sources to present findings, while the results of the proposed model were acquired using the procedure described above.

Error Criteria and Relative Benchmarks

Predictive accuracy on the **test** segment was summarized by RMSE and MAPE:

$$RMSE = \sqrt{mean((Actual_t - Predicted_t)^2)} \quad ; \ t \in \mathcal{T}_{test} \tag{31}$$

$$MAPE = mean\left(\left|\frac{Actual_t - Predicted_t}{Actual_t}\right| \times 100\%\right) \quad ; \ t \in \mathcal{T}_{test} \tag{32}$$

Relative performance with respect to the naïve predictor was assessed by the median relative absolute error (MdRAE). Where:

$$r_t = \frac{Target_t - Forecasted_t}{Target_t - Forecasted_t^*}\ , \quad t \in \mathcal{T}_{test} \tag{33}$$

$$MdRAE = median|r_t|\ , \quad t \in \mathcal{T}_{test} \tag{34}$$

Alignment between predictions and realizations was further checked by fitting the slope-only regression,

$$Y_t = \beta \hat{Y}_t + \varepsilon_t\ , \quad t \in \mathcal{T}_{test} \tag{35}$$

on the test segment; values of regression coefficient β and determination coefficient R^2 approaching 1 indicate close agreement.

Error Criteria and Relative Benchmarks

For each annual series, RMSE/MAPE/MdRAE and slope-only regression summary were reported on the test segment. Percentage reductions versus the best and second-best competitors were also provided to indicate improvements. Visual summaries included (*i*) observed versus predicted trajectories and (*ii*) per-time-step residual line plots, both displayed on the original scale after reconversion.

Results, Diagnostics, and Comparative Analysis for AI-opt-FConvP on TAIEX

TAIEX (2000–2004) Analysis

To assess the predictive capability of the proposed AI-Optimized Convolutional Prediction approach, the five year-specific TAIEX daily series from 2000 to 2004 were analysed. For every yearly series, the first eight months were assigned to training, the next two months were used for validation, and the last two months of the year were reserved for hold-out testing. Series-specific results, in terms of the RMSE metric values produced by the proposed AI-opt-FConvP, are reported, and by a consolidated comparison against the reference methods in Table 2.

Table 2. Competing methods for T00–T04 test sets: RMSE gains and MAPE errors of AI-opt-FConvP

Models		**Time Series / TAIEX Data Sets**					**Average**
		T00	**T01**	**T02**	**T03**	**T04**	
Song & Chissom (1993c)		293	116	76	77	82	129
S. M. Chen (1996b)		225	116	76	77	82	115
Huarng (2001) - *Average-based*		473	359	234	247	384	339
Huarng (2001) - *Distribution-based*		473	810	116	308	384	418
Huarng & Yu (2006)		133	124	82	62	85	97
Hsu et al. (2010)		152	130	84	56	116	108
Huarng et al. (2007)		154	124	93	66	72	102
Yu & Huarng (2008b)		131	130	80	58	67	93
Aladag et al. (2010b)		168	120	76	58	63	97
Chen & Chang (2010)		129	113	67	54	60	85
Egrioglu et al. (2010)		255	130	84	56	116	128
Chen & Chen (2011)		124	115	71	58	58	85
Chen et al. (2012)		120	114	67	52	52	81
Yolcu et al. (2013)		227	102	66	51	55	100
Chen & Chen (2015)		125	115	65	53	53	82
Cai et al. (2015)		132	113	60	52	50	81
Bas et al. (2015)		140	120	77	60	59	91
Cheng et al. (2016)		126	113	63	51	54	81
Chen et al. (2016)		180	134	81	77	55	105
Tak et al. (2018b)		128	106	65	52	54	81
Jang (1993b)		137	115	66	57	61	87
Egrioglu et al. (2015)		124	112	63	52	54	81
Sarica et al. (2018)		123	111	66	52	54	81
Bas et al. (2019b)		120	113	63	49	52	79
Cagcag Yolcu et al. (2020)		122	110	54	51	50	77
Kirisci & Cagcag Yolcu (2022)		105	110	60	51	50	75
LSTM		136	101	89	92	70	108
Tak (2022)		121	107	66	52	54	80
Tak & İnan (2022)		119	104	64	51	52	81
Aktoprak and Cagcag Yolcu (2025)		100	96	51	44	48	68
Polater et al. (2026)		100	103	61	47	48	65
AI-opt-FConvP		<u>**95**</u>	<u>**60**</u>	<u>**44**</u>	<u>**38**</u>	<u>**47**</u>	<u>**57**</u>
Progress (%) **Comparison with the**	**best of others**	05	38	14	14	02	12
	second best of others	10	41	19	19	06	17
MAPE values for AI-opt-FConvP ***(%)***		**1.28**	**1.03**	**0.76**	**0.46**	**0.66**	**0.84**

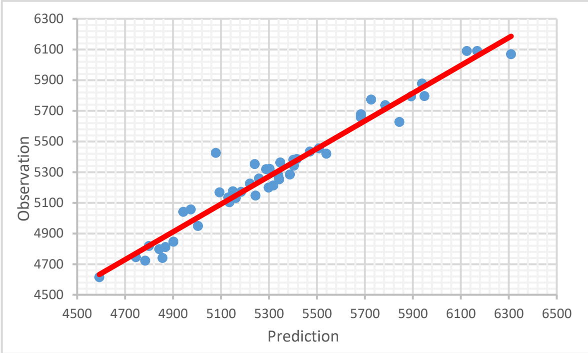
Table 2 summarizes the out-of-sample errors for the five TAIEX series (T00–T04). For each series, the lowest RMSE is attained by AI-opt-FConvP, and the average RMSE over all series equals 57. The best competing method across the panel (Polater et al., 2026) yields an average RMSE of 65; thus, an average reduction of approximately 12% is observed. Series-wise improvements over the best alternative amount to 05% (T00), 38% (T01), 14% (T02), 14% (T03), and 2% (T04), indicating consistent gains, with the largest margins on T01, T02 and T03. In addition, the mean absolute percentage errors reported for AI-opt-FConvP remain low—1.28% (T00), 1.03% (T01), 0.76% (T02), 0.46% (T03), and 0.66% (T04)—with a panel average of 0.84%. Taken together, these results demonstrate that the proposed approach achieves the best accuracy in each series, while maintaining MAPE values close to and below 1% in the majority of cases.

Table 3. SLR-Based Concordance Between AI-opt-FConvP Predictions and TAIEX Observations over the test sets (2000–2004) ($Y_t = \beta\hat{Y}_t + \varepsilon_t$)

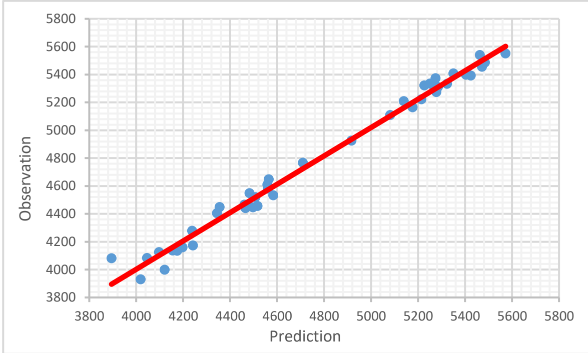
Time Series	Model Estimation	St. Error of $\hat{\beta}$	Sig. of β	R^2	Confidence Interval of β	
					Lower Bound	Upper Bound
T00	$Y_t = 0.993731\hat{Y}_t$	0.0024	< 0.0001	0.999723	0.988819	1. 004852
T01	$Y_t = 1.003464\hat{Y}_t$	0.0018	< 0.0001	0.999855	0.999698	1.007230
T02	$Y_t = 0.998222\hat{Y}_t$	0.0014	< 0.0001	0. 999879	0.995305	1.001140
T03	$Y_t = 1.000021\hat{Y}_t$	0.0010	< 0.0001	0.999958	0.998000	1.002042
T04	$Y_t = 1.002124\hat{Y}_t$	0.0011	< 0.0001	0.999949	0.999957	1.004290

A simple no-intercept regression $Y_t = \beta\hat{Y}_t + \varepsilon_t$ was fitted for each series (T00–T04) by treating the predictions as the regressor and the realized values as the response. The estimated slopes cluster tightly around 1 ($\hat{\beta} = 0.9937, 1.0035, 0.9982, 1.0000, 1.0021$) with very small standard errors ($\approx 0.0010 - 0.0024$), and all 95% confidence intervals contain 1. Significance levels are $p < 0.0001$ throughout, and the coefficients of determination are essentially unity ($R^2 \approx 0.9997 - 0.9999$). Taken together, these diagnostics indicate an almost one-to-one correspondence between predictions and observations, with no evidence of systematic scaling or bias across the five TAIEX series.

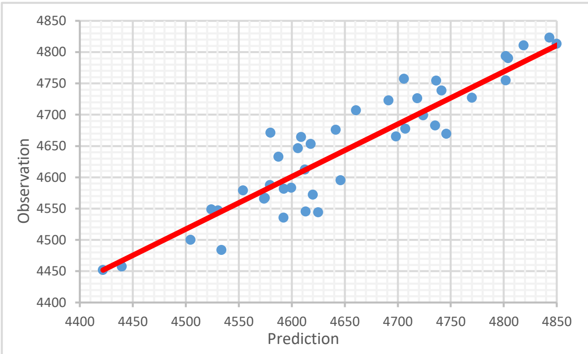
A visual assessment (see Figure 2) was carried out by plotting the AI-opt-FConvP predictions on the horizontal axis against the observed TAIEX values on the vertical axis, with a fitted least-squares line superimposed. Across series T00–T04, the point clouds concentrate tightly around the fitted line, with slopes visually close to unity and only modest vertical dispersion, indicating strong concordance between predictions and observations. The spread appears approximately symmetric and nearly constant over the prediction range, and no systematic curvature or banding is evident, suggesting an absence of scale-dependent error or directional bias. Slight widening at the extremes is minimal and consistent with sampling variability. Taken together, these graphics support the quantitative findings by showing that the AI-opt-FConvP outputs track market levels with limited deviation across the full evaluation window.



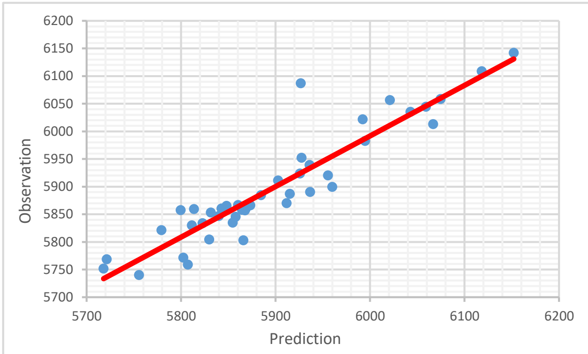
(a) T00



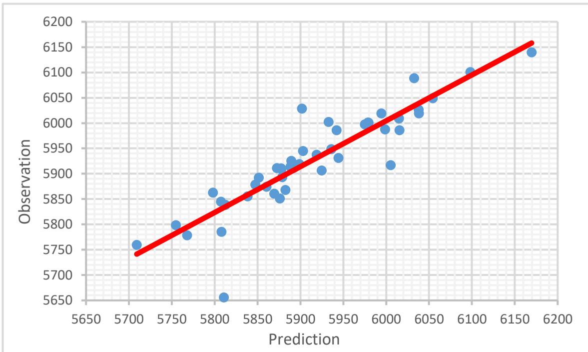
(b) T01



(c) T02



(d) T03



(e) T04

Figure 2. Observed vs. Predicted Scatter with Fitted Line for TAIEX T00–T04 (AI-opt-FConvP)

TAIEX (2008–2018) Analysis

To extend the assessment beyond the early-2000s window, eleven daily TAIEX series from 2008–2018 (T08–T18) were analyzed. For each series, the first eight months were used for training, observations from September to October were reserved for validation to select the AI-opt-FConvP hyperparameters via a genetic algorithm, and the final two months were held out for testing. Data were pre-processed using the min–max scaling described earlier; fuzzy memberships and their nonlinear transforms were concatenated with lagged observations to form a single CNN input. Test-set performances were summarized by RMSE and MAPE; MdRAE relative to the naïve $t-1$ benchmark was also reported. From Table 4, the RMSE criterion favours AI-opt-FConvP for every series in the 2008–2018 panel. Relative to the best competing method in each column, RMSE reductions span 4%–20%: the largest margin occurs for T14 (20%), while double-digit gains are seen for T09 (12%), T13 (12%), T10 (11%), and T11 (10%). More moderate, but still positive, differences are obtained for T08 (7%), T12 (7%), T15 (7%), T17 (5%), T16 (4%) and T18 (4%). When these column-wise improvements are averaged, an overall RMSE reduction of 9% against the best alternative is indicated. The advantage is more pronounced when the second-best competitor is taken as a reference. Column-wise improvements range from 9% to 44%, with the largest gains at T14 (44%) and T17 (44%), followed by T13 (39%), T16 (36%), T12 (29%), T15 (29%), T11 (28%), T09 (28%), and T10 (23%); smaller but positive margins are observed for T08 (16%) and T18 (9%). The average improvement over the second-best model reaches 30% across the eleven series.

The MAPE results in Table 5 corroborate these findings. Sub-percent errors are obtained for nearly all years, and the panel average of AI-opt-FConvP remains around the half-percent band. The "Progress (%)" rows indicate that enhancements over the strongest baseline are recorded in most years (with ties reflected as "NaN"), while the improvements over the second-best alternative are consistently large across the board. These patterns suggest that the lower RMSE is accompanied by uniformly small relative errors. Finally, Table 6 reports MdRAE values computed against the naïve benchmark. Values well below one are observed for the AI-opt-FConvP predictions throughout the panel, and the "Progress (%)" lines show advantages over the best and second-best baselines in the majority of years (and systematically against the latter). Taken together, the three tables indicate that AI-opt-FConvP delivers lower dispersion (RMSE), lower relative error (MAPE), and stronger performance against a naïve yardstick (MdRAE) across all eleven TAIEX series, with the largest margins concentrated in the mid-panel years and uniformly positive differentials elsewhere.

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Table 4. RMSE comparison on the T08–T18 test sets: AI-opt-FConvP versus baselines, with "Progress (%)" against the best and second-best alternatives.

Models		**T08**	**T09**	**T10**	**T11**	**T12**	**T13**	**T14**	**T15**	**T16**	**T17**	**T18**	**Average**
Chen (1996b)		186	207	211	215	78	185	309	101	317	902	493	291
Huarng (2001)		105	78	104	118	59	50	88	91	81	63	186	93
Yu and Huarng (2008b)		129	70	67	123	58	50	69	78	81	64	104	81
Sadaei et al. (2016)[1]		109	121	75	128	60	51	79	95	80	79	88	88
Sadaei et al. (2016)[2]		109	69	52	113	59	49	66	80	82	64	75	74
(Dong and Ma 2021)[1]		102	106	63	124	82	66	46	103	82	62	102	85
(Dong and Ma 2021)[2]		92	57	45	90	44	34	46	59	53	37	71	57
AI-opt-FConvP		**86**	**50**	**40**	**81**	**41**	**30**	**37**	**55**	**51**	**35**	**68**	**52**
Progress (%)	**with the best of others**	***7***	***12***	***11***	***10***	***7***	***12***	***20***	***7***	***4***	***5***	***4***	***9***
	with the second best of others	***16***	***28***	***23***	***28***	***29***	***39***	***44***	***29***	***36***	***44***	***9***	***30***

Note: The results of the current counterparts' models are taken from (Dong and Ma 2021).

Table 5. MAPE comparison on the T08–T18 test sets: AI-opt-FConvP versus baselines, with “Progress (%)” against the best and second-best alternatives.

Models		**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**Average**
Chen (1996b)		3.49	2.41	1.90	2.61	0.86	1.77	3.31	0.97	3.20	8.45	4.73	3.06
Huarng (2001)		1.66	0.73	1.09	1.24	0.58	0.49	0.79	0.86	0.63	0.47	1.71	0.93
Yu and Huarng (2008b)		2.34	0.66	0.64	1.35	0.59	0.50	0.61	0.77	0.63	0.47	0.81	0.85
Sadaei et al. (2016)[1]		1.73	1.33	0.74	1.43	0.59	0.51	0.74	0.90	0.61	0.58	0.92	0.93
Sadaei et al. (2016)[2]		1.75	0.65	0.50	1.20	0.57	0.47	0.58	0.78	0.62	0.48	0.76	0.76
(Dong and Ma 2021)[1]		1.87	1.01	0.60	1.42	0.91	0.62	0.39	0.98	0.78	0.50	0.92	0.91
(Dong and Ma 2021)[2]		1.57	0.55	0.43	0.94	0.42	0.33	0.44	0.59	0.43	0.27	0.53	0.59
AI-opt-FConvP		**1.20**	**0.48**	**0.38**	**0.81**	**0.42**	**0.27**	**0.32**	**0.51**	**0.38**	**0.24**	**0.54**	**0.50**
Progress (%)	**with the best of others**	***24***	***13***	***12***	***14***	***0***	***18***	***18***	***14***	***12***	***11***	***NaN***	***15***
	with the second best of others	***28***	***26***	***24***	***33***	***26***	***43***	***27***	***34***	***38***	***49***	***29***	***34***

Note: The results of the current counterparts' models are taken from (Dong and Ma 2021).

Table 6. MdRAE comparison on the T08–T18 test sets: AI-opt-FConvP versus baselines, with "Progress (%)" against the best and second-best alternatives.

Models		**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**Average**
Chen (1996b)		2.3294	5.1835	4.0107	2.9861	1.4906	3.6261	7.4309	1.4596	6.8543	20.8460	7.9646	5.8347
Huarng (2001)		1.0254	0.9813	2.5643	0.9278	0.9387	1.0812	1.5661	1.4015	1.0697	1.1282	3.0914	1.4341
Yu and Huarng (2008b)		1.5375	0.9340	1.2959	1.1256	0.9341	1.1313	1.0279	0.9795	0.9720	1.0288	1.1297	1.0997
Sadaei et al. (2016)[1]		1.0000	2.6261	1.4819	1.4443	1.0000	1.0000	1.0000	1.0000	1.0000	1.3549	1.2929	1.3142
Sadaei et al. (2016)[2]		1.0499	0.8700	1.0397	0.9741	1.0261	1.0052	0.9875	0.9739	0.9991	1.1104	1.0042	1.0107
(Dong and Ma 2021)[1]		1.3628	1.2553	1.2433	1.4180	1.6564	0.9939	0.6507	1.2241	1.7314	0.9836	1.4136	1.2666
(Dong and Ma 2021)[2]		0.8938	0.7463	0.8529	0.8161	0.6368	0.7227	0.7275	0.7833	0.7738	0.5530	0.6912	0.7452
AI-opt-FConvP		**1.2195**	**0.7261**	**0.7454**	**0.6385**	**0.6180**	**0.4453**	**0.5188**	**0.6366**	**0.6296**	**0.3650**	0.8843	**0.6752**
Progress (%)	**with the best of others**	***NaN***	***3***	***13***	***22***	***3***	***38***	***20***	***19***	***19***	***34***	***NaN***	***9***
	with the second best of others	***NaN***	***17***	***28***	***31***	***34***	***55***	***29***	***35***	***35***	***63***	***12***	***33***

Note: The results of the current counterparts' models are taken from (Dong and Ma 2021).

Results, Diagnostics, and Comparative Analysis for AI-opt-FConvP on TAIEX

An end-to-end prediction framework, AI-opt-FConvP, was examined for daily financial time series. The approach fuses (i) fuzzy cluster memberships and their nonlinear transforms with (ii) lagged real-valued observations, and passes the joint feature block to a single 1-D CNN. Key architectural and pre-processing choices—model order, number of clusters, fuzzifier, filter size(s), number of filters, and mini-batch size—were tuned by a genetic algorithm using a validation window, while testing was performed on a hold-out segment.

Across the TAIEX 2000–2004 time series, the method achieved the lowest RMSE in all five series, yielding an average RMSE of 57. Relative to the best competing model per column, the average RMSE decrease reached 24% (and 26% against the second-best models). The accompanying MAPE values remained low (average 0.84%). For TAIEX 2008–2018, the panel-average RMSE was 52, with systematic gains over the best competitor in every year and an average reduction of 9% (rising to 30% versus the second-best models). Errors were small in relative terms as well: the average MAPE = 0.50%, with improvements over the best literature baseline in 9/11 years (average improvement ≈15% across those cases). The MdRAE summary indicated favourable behaviour (average ≈0.66), with gains over the best competitor in most years and consistent advantages over the second-best models (average improvement ≈34%).

Diagnostic checks supported these quantitative results. Simple no-intercept regressions of observations on predictions produced slope estimates near 1 with R^2 practically equal to 1 and confidence intervals that included unity for all five series in the first panel, indicating nearly correct scale and direction of change. Scatter plots of predictions versus observations showed tight clouds around the fitted lines without visible systematic deviations, suggesting that day-to-day fluctuations were tracked with limited dispersion.

The observed accuracy can be attributed to two design choices. First, memberships from fuzzy c-means and their transforms supply a compact description of state similarity, allowing the network to condition on soft regimes without an explicit rule base. Second, packaging all fuzzy features together with lagged signals into a single CNN reduces parameter fragmentation compared with per-cluster networks, which appears to help generalization under short financial training windows.

Future work may extend the study in four directions: (i) multivariate inputs and exogenous drivers; (ii) alternative clustering that adapts to anisotropic shapes (e.g., Gustafson–Kessel or possibilistic variants); (iii) probabilistic outputs via quantile or distributional losses for risk-aware applications; and (iv) adaptive or budgeted hyperparameter search (e.g., successive halving or Bayesian optimization) and regime-switching mechanisms that update memberships online.

In summary, the experiments indicated that AI-opt-FConvP captures nonlinear, fuzzy structure in financial series effectively and produces accurate short-horizon predictions. The combination of fuzzy similarity features and convolutional processing, guided by genetic hyperparameter tuning, yielded consistent improvements over strong baselines on two independent TAIEX panels, while leaving clear avenues for broadening scope and interpretive depth in subsequent studies.

Author Contributions

Furkan Keskin: Data curation, Investigation, Visualization, Writing-original draft, Writing-review & editing. ***Ozge Cagcag Yolcu:*** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Supervision, Validation, Visualization, Writing-original draft, Writing-review & editing. ***Sumeyye Polater:*** Data curation, Investigation, Visualization, Writing-original draft, Writing-review & editing.

All authors contributed equally to this study, and authorship credit, ownership rights, and responsibility for the content are shared equally among them.

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There is no need for ethics committee approval for the study.

Conflict of Interest

The authors have no conflicts of interest to declare relevant to this article's content.

Declaration of Generative AI and AI-assisted Technologies in the Writing Process

The data that support the findings of this study are available from the corresponding author upon reasonable request. The authors used ChatGPT for grammar and spelling checks during the preparation of this work. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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References

Aktoprak M.R. & Cagcag Yolcu O. (2025). A New Approach for Time Series Prediction: Fuzzy Regression Network Functions. *International Journal of Advances in Engineering and Pure Sciences*, 37(1), 36-52. doi:10.7240/jeps.1573839.

Aladag C.H., Basaran M.A., Egrioglu E., Yolcu U. & Uslu V.R. (2009). Forecasting in High Order Fuzzy Times Series by Using Neural Networks to Define Fuzzy Relations. *Expert Systems with Applications*, 36(3 PART 1). doi:10.1016/j.eswa.2008.04.001.

Aladag C.H., Yolcu U. & Egrioglu E. (2010a). A High Order Fuzzy Time Series Forecasting Model Based on Adaptive Expectation and Artificial Neural Networks. *Mathematics and Computers in Simulation*, 81(4). doi:10.1016/j.matcom.2010.09.011.

Aladag C.H., Yolcu U. & Egrioglu E. (2010b). A High Order Fuzzy Time Series Forecasting Model Based on Adaptive Expectation and Artificial Neural Networks. *Mathematics and Computers in Simulation*, 81(4). doi:10.1016/j.matcom.2010.09.011.

Aladag C.H., Yolcu U., Egrioglu E. & Turksen I.B. (2016). Type-1 Fuzzy Time Series Function Method Based on Binary Particle Swarm Optimisation. *International Journal of Data Analysis Techniques and Strategies*, 8(1), 2-13. https://dx.doi.org/10.154/IJDATS.2016.075970

Alpaslan F., Cagcag O., Aladag C.H., Yolcu U. & Egrioglu E. (2012). A Novel Seasonal Fuzzy Time Series Method. *Hacettepe Journal of Mathematics and Statistics*, 41(3).

Bas E., Egrioglu E., Aladag C.H. & Yolcu U. (2015). Fuzzy-Time-Series Network Used to Forecast Linear and Nonlinear Time Series. *Applied Intelligence*, 43(2). doi:10.1007/s10489-015-0647-0.

Bas E., Egrioglu E., Yolcu U. & Grosan C. (2019a). Type 1 Fuzzy Function Approach Based on Ridge Regression for Forecasting. *Granular Computing*, 4(4). doi:10.1007/s41066-018-0115-4.

Bas E., Egrioglu E., Yolcu U. & Grosan C. (2019b). Type 1 Fuzzy Function Approach Based on Ridge Regression for Forecasting. *Granular Computing*, 4(4). doi:10.1007/s41066-018-0115-4.

Box G.E.P., Jenkins G.M. & Reinsel G.C. (2013). *Time Series Analysis: Forecasting and Control: Fourth Edition*.

Cagcag Yolcu O. & Alpaslan F. (2018). Prediction of TAIEX Based on Hybrid Fuzzy Time Series Model with Single Optimization Process. *Applied Soft Computing Journal*, 66. doi:10.1016/j.asoc.2018.02.007.

Cagcag Yolcu O., Bas E., Egrioglu E. & Yolcu U. (2020). A New Intuitionistic Fuzzy Functions Approach Based on Hesitation Margin for Time-Series Prediction. *Soft Computing*, 24(11). doi:10.1007/s00500-019-04432-2.

Cai Q., Zhang D., Zheng W. & Leung S.C.H. (2015). A New Fuzzy Time Series Forecasting Model Combined with Ant Colony Optimization and Auto-Regression. *Knowledge-Based Systems*, 74. doi:10.1016/j.knosys.2014.11.003.

Chen S.M. (1996a). Forecasting Enrollments Based on Fuzzy Time Series. *Fuzzy Sets and Systems*, 81(3). doi:10.1016/0165-0114(95)00220-0.

Chen S.M. (1996b). Forecasting Enrollments Based on Fuzzy Time Series. *Fuzzy Sets and Systems*, 81(3). doi:10.1016/0165-0114(95)00220-0.

Chen S.M. (2002). Forecasting Enrollments Based on High-Order Fuzzy Time Series. *Cybernetics and Systems*, 33(1). doi:10.1080/019697202753306479.

Chen S.M. & Chang Y.C. (2010). Multi-Variable Fuzzy Forecasting Based on Fuzzy Clustering and Fuzzy Rule Interpolation Techniques. *Information Sciences*, 180(24). doi:10.1016/j.ins.2010.08.026.

Chen S.M. & Chen C.D. (2011). TAIEX Forecasting Based on Fuzzy Time Series and Fuzzy Variation Groups. *IEEE Transactions on Fuzzy Systems*, 19(1). doi:10.1109/TFUZZ.2010.2073712.

Chen S.M. & Chen S.W. (2015). Fuzzy Forecasting Based on Two-Factors Second-Order Fuzzy-Trend Logical Relationship Groups and the Probabilities of Trends of Fuzzy Logical Relationships. *IEEE Transactions on Cybernetics*, 45(3). doi:10.1109/TCYB.2014.2326888.

Chen S.M., Chu H.P. & Sheu T.W. (2012). TAIEX Forecasting Using Fuzzy Time Series and Automatically Generated Weights of Multiple Factors. *IEEE Transactions on Systems, Man, and Cybernetics Part A:Systems and Humans*, 42(6). doi:10.1109/TSMCA.2012.2190399.

Chen Y.S., Cheng C.H., Chiu C.L. & Huang S.T. (2016). A Study of ANFIS-Based Multi-Factor Time Series Models for Forecasting Stock Index. *Applied Intelligence*, 45(2). doi:10.1007/s10489-016-0760-8.

Cheng C., Chen T., Teoh H. & Chiang C. (2008). Fuzzy Time-Series Based on Adaptive Expectation Model for TAIEX Forecasting. *Expert Systems with Applications*, 34(2), 1126-1132. doi:10.1016/j.eswa.2006.12.021.

Cheng S.H., Chen S.M. & Jian W.S. (2016). Fuzzy Time Series Forecasting Based on Fuzzy Logical Relationships and Similarity Measures. *Information Sciences*, 327. doi:10.1016/j.ins.2015.08.024.

Dalar A.Z., Egrioglu E., Yolcu U. & Aladag C.H. (2017). Fuzzy Functions Approach for Time Series Forecasting. In A.Z. Dalar, E. Egrioglu, U. Yolcu & C.H. Aladag (Eds.), *Advances in Time Series Forecasting Volume: 2* (pp. 144-155).

Dong Q. & Ma X. (2021). Enhanced Fuzzy Time Series Forecasting Model Based on Hesitant Differential Fuzzy Sets and Error Learning. *Expert Systems with Applications*, 166. doi:10.1016/j.eswa.2020.114056.

Egrioglu E. (2014). PSO-Based High Order Time Invariant Fuzzy Time Series Method: Application to Stock Exchange Data. *Economic Modelling*, 38. doi:10.1016/j.econmod.2014.02.017.

Egrioglu E., Aladag C.H., Yolcu U. & Bas E. (2015). A New Adaptive Network Based Fuzzy Inference System for Time Series Forecasting. *Aloy Journal of Soft Computing and Applications*, 2(1).

Egrioglu E., Aladag C.H., Yolcu U., Uslu V.R. & Basaran M.A. (2009). A New Approach Based on Artificial Neural Networks for High Order Multivariate Fuzzy Time Series. *Expert Systems with Applications*, 36(7). doi:10.1016/j.eswa.2009.02.057.

Egrioglu E., Aladag C.H., Yolcu U., Uslu V.R. & Basaran M.A. (2010). Finding an Optimal Interval Length in High Order Fuzzy Time Series. *Expert Systems with Applications*, 37(7). doi:10.1016/j.eswa.2009.12.006.

Fatima S.S.W. & Rahimi A. (2024). A Review of Time-Series Forecasting Algorithms for Industrial Manufacturing Systems. *Machines*, 12(6), 380. doi:10.3390/machines12060380.

Hsu L.Y., Horng S.J., Kao T.W., Chen Y.H., Run R.S., Chen R.J., Lai J.L. & Kuo I.H. (2010). Temperature Prediction and TAIFEX Forecasting Based on Fuzzy Relationships and MTPSO Techniques. *Expert Systems with Applications*, 37(4). doi:10.1016/j.eswa.2009.09.015.

Huarng K.H., Yu T.H.K. & Hsu Y.W. (2007). A Multivariate Heuristic Model for Fuzzy Time-Series Forecasting. *IEEE Transactions on Systems, Man, and Cybernetics, Part B: Cybernetics*, 37(4). doi:10.1109/TSMCB.2006.890303.

Huarng K. (2001). Effective Lengths of Intervals to Improve Forecasting in Fuzzy Time Series. *Fuzzy Sets and Systems*, 123(3). doi:10.1016/S0165-0114(00)00057-9.

Huarng K. & Yu T.H.K. (2006). The Application of Neural Networks to Forecast Fuzzy Time Series. *Physica A: Statistical Mechanics and Its Applications*, 363(2). doi:10.1016/j.physa.2005.08.014.

Hyndman R.J. & Athanasopoulos G. (2018). 3 . 4 Evaluating Forecast Accuracy Training and Test Sets. *Forecasting: Principles and Practice* (Online-Version, Kontinuierlich Aktualisiert).

Jang J.S.R. (1993a). ANFIS: Adaptive-Network-Based Fuzzy Inference System. *IEEE Transactions on Systems, Man and Cybernetics*, 23(3). doi:10.1109/21.256541.

Jang J.S.R. (1993b). ANFIS: Adaptive-Network-Based Fuzzy Inference System. *IEEE Transactions on Systems, Man and Cybernetics*, 23(3). doi:10.1109/21.256541.

Kirisci M. & Cagcag Yolcu O. (2022). A New CNN-Based Model for Financial Time Series: TAIEX and FTSE Stocks Forecasting. *Neural Processing Letters*, 54(4). doi:10.1007/s11063-022-10767-z.

Kocak C., Dalar A.Z., Cagcag Yolcu O., Bas E. & Egrioglu E. (2020). A New Fuzzy Time Series Method Based on an ARMA-Type Recurrent Pi-Sigma Artificial Neural Network. *Soft Computing*, 24(11). doi:10.1007/s00500-019-04506-1.

Kontopoulou V.I., Panagopoulos A.D., Kakkos I. & Matsopoulos G.K. (2023). A Review of ARIMA vs. Machine Learning Approaches for Time Series Forecasting in Data Driven Networks. *Future Internet*, 15(8).

Nor Syazwina Binti Mohd Hanafiah, Nor Hayati Binti Shafii, Nur Fatihah Binti Fauzi, Diana Sirmayunie Mohd Nasir & Nor Azriani Mohamad Nor (2022). Comparison of Fuzzy Time Series and ARIMA Model for Predicting Stock Prices. *Journal of Computing Research and Innovation*, 7(2). doi:10.24191/jcrinn.v7i2.332.

Polater S., Yolcu U., Keskin F. & Cagcag Yolcu O. (2026). Picture Fuzzy C-Means–Based Ensemble of Forecasting Functions for Financial Time Series Forecasting. *International Journal of Advances in Engineering and Pure Sciences*, 38(1), 199-209. doi:10.7240/jeps.1818060.

Sadaei H.J., Enayatifar R., Lee M.H. & Mahmud M. (2016). A Hybrid Model Based on Differential Fuzzy Logic Relationships and Imperialist Competitive Algorithm for Stock Market Forecasting. *Applied Soft Computing Journal*, 40. doi:10.1016/j.asoc.2015.11.026.

Sarıca B., Eğrioğlu E. & Aşıkgil B. (2018). A New Hybrid Method for Time Series Forecasting: AR–ANFIS. *Neural Computing and Applications*, 29(3). doi:10.1007/s00521-016-2475-5.

Song Q. & Chissom B.S. (1993a). Forecasting Enrollments with Fuzzy Time Series - Part I. *Fuzzy Sets and Systems*, 54(1). doi:10.1016/0165-0114(93)90355-L.

Song Q. & Chissom B.S. (1993b). Fuzzy Time Series and Its Models. *Fuzzy Sets and Systems*, 54(3). doi:10.1016/0165-0114(93)90372-O.

Song Q. & Chissom B.S. (1993c). Fuzzy Time Series and Its Models. *Fuzzy Sets and Systems*, 54(3). doi:10.1016/0165-0114(93)90372-O.

Song Q. & Chissom B.S. (1994). Forecasting Enrollments with Fuzzy Time Series - Part II. *Fuzzy Sets and Systems*, 62(1). doi:10.1016/0165-0114(94)90067-1.

Sun G. & Deng S. (2025). Financial Time Series Forecasting: A Comparison Between Traditional Methods and AI-Driven Techniques. *Journal of Computer, Signal, and System Research*, 2(2), 86-93. doi:10.71222/339b9812.

Tak N. (2022). A Novel ARMA Type Possibilistic Fuzzy Forecasting Functions Based on Grey-Wolf Optimizer (ARMA-PFFs). *Computational Economics*, 59(4). doi:10.1007/s10614-021-10132-7.

Tak N., Evren A.A., Tez M. & Egrioglu E. (2018a). Recurrent Type-1 Fuzzy Functions Approach for Time Series Forecasting. *Applied Intelligence*, 48(1). doi:10.1007/s10489-017-0962-8.

Tak N., Evren A.A., Tez M. & Egrioglu E. (2018b). Recurrent Type-1 Fuzzy Functions Approach for Time Series Forecasting. *Applied Intelligence*, 48(1). doi:10.1007/s10489-017-0962-8.

Tak N. & İnan D. (2022). Type-1 Fuzzy Forecasting Functions with Elastic Net Regularization. *Expert Systems with Applications*, 199. doi:10.1016/j.eswa.2022.116916.

Türkşen I.B. (2008). Fuzzy Functions with LSE. *Applied Soft Computing Journal*, 8(3). doi:10.1016/j.asoc.2007.12.004.

Wang C.C. (2011). A Comparison Study between Fuzzy Time Series Model and ARIMA Model for Forecasting Taiwan Export. *Expert Systems with Applications*, 38(8). doi:10.1016/j.eswa.2011.01.015.

Yolcu U., Aladag C.H., Egrioglu E. & Uslu V.R. (2013). Time-Series Forecasting with a Novel Fuzzy Time-Series Approach: An Example for Istanbul Stock Market. *Journal of Statistical Computation and Simulation*, 83(4). doi:10.1080/00949655.2011.630000.

Yu T.H.K. & Huarng K.H. (2008a). A Bivariate Fuzzy Time Series Model to Forecast the TAIEX. *Expert Systems with Applications*, 34(4). doi:10.1016/j.eswa.2007.05.016.

Yu T.H.K. & Huarng K.H. (2008b). A Bivariate Fuzzy Time Series Model to Forecast the TAIEX. *Expert Systems with Applications*, 34(4). doi:10.1016/j.eswa.2007.05.016.

Zadeh L.A. (1965). Fuzzy Sets. *Information and Control*, 8(3). doi:10.1016/S0019-9958(65)90241-X.