International Journal of Statistics and Applied Mathematics 2025; 10(5): 01-06

International Journal of Statistics and Applied Mathematics

ISSN: 2456-1452
Maths 2025; 10(5): 01-06

https://www.mathsjournal.com
Received: 04-02-2025
Accepted: 06-03-2025

Chinmayee Patra
1) College of Agriculture, Odisha University of Agriculture and Technology, Bhubaneswar, Odisha, India
2) Department of Agricultural Statistics, Palli Sikhsha Bhavan, Sriniketan, West Bengal, India

Digvijay Singh Dhakre
Department of Agricultural Statistics, Palli Siksha Bhavana, Sriniketan, West Bengal, India

Debasis Bhattacharya
Department of Agricultural Statistics, Palli Siksha Bhavana, Sriniketan, West Bengal, India

Kader Ali Sarkar
Department of Agricultural Statistics, Palli Siksha Bhavana, Sriniketan, West Bengal, India

Corresponding Author:
Chinmayee Patra
1) College of Agriculture, Odisha University of Agriculture and Technology, Bhubaneswar, Odisha, India
2) Department of Agricultural Statistics, Palli Sikhsha Bhavan, Sriniketan, West Bengal, India

Enhancing wheat price forecasting with fuzzy time series: A case study from Birbhum District of West Bengal

Chinmayee Patra, Digvijay Singh Dhakre, Debasis Bhattacharya and Kader Ali Sarkar

DOI: https://www.doi.org/10.22271/maths.2025.v10.i5a.2025

Abstract
Ensuring a stable and efficient market requires an in-depth analysis of commodity prices. Such analysis plays a crucial role in shaping strategic decisions and management policies by leveraging predictive and diagnostic tools to assess both current trends and future economic conditions of Birbhum district of West Bengal. This research focuses on applying fuzzy time series forecasting methods to predict wheat prices. A new methodology is introduced, utilizing fuzzy logic principles to improve prediction accuracy. To validate this approach, monthly wheat price data from January 2017 to December 2023 is analyzed. The study adopts the Chen method, where growth rate variations are used to define fuzzy sets within the universe of discourse. This technique, adapted from Chen's model, employs the monthly price data as a foundation for forecasting future price levels. Findings indicate that this approach achieves greater precision, with a Mean Absolute Percentage Error (MAPE) of 7.66% and lower RMSE, outperforming other time series models. Furthermore, this study suggests refinements to the model to enhance forecasting reliability and enable more accurate one-step-ahead predictions. The findings of this research can support policymakers in developing data-driven pricing strategies, ensuring market stability, and optimizing supply chain decisions for wheat production.

Keywords: MAPE, Chen method, wheat, fuzzy time series, fuzzy logic

1. Introduction

Wheat is one of the key crops in West Bengal, influencing both the livelihood of farmers and the daily diets of millions. However, wheat prices often fluctuate due to factors like seasonal changes, production levels, government policies, and transportation costs. These unpredictable price shifts impact not just farmers but also traders and consumers. Being able to predict wheat prices accurately can help farmers decide when to sell, assist traders in making informed business choices, and enable policymakers to implement better market strategies. This study focuses on analyzing past price trends and using forecasting techniques to anticipate future prices. By doing so, we aim to provide insights that can help stabilize the market and support the agricultural community in West Bengal.

Forecasting is an essential tool for making informed decisions in various fields like finance, weather prediction, agriculture, and energy management. However, real-world data is often unpredictable and uncertain, making it difficult for traditional forecasting methods to provide accurate results. Classical time series models, such as ARIMA and exponential smoothing, rely on strict assumptions about data trends and patterns. When dealing with complex and uncertain data, these traditional models may not always perform well. To tackle these challenges, Fuzzy Time Series (FTS) forecasting offers a more flexible approach by incorporating fuzzy set theory. Unlike conventional models, FTS methods can handle uncertainty and imprecise data, making them particularly useful for predicting trends in volatile environments. One of the most widely used models in this field is Chen's fuzzy time series model, introduced by Shyi-Ming Chen in 1996.

This model simplifies the forecasting process by defining fuzzy relationships and performing arithmetic operations, avoiding the need for complex mathematical calculations. As a result, it is easy to implement, computationally efficient, and suitable for real-world applications.

Over the years, Chen's model has been applied in various fields, including stock market predictions, weather forecasting, energy demand estimation, and agricultural price forecasting. Researchers have also introduced several improvements to enhance its accuracy and adaptability. Given its ability to manage uncertain data effectively, Chen's fuzzy time series model remains a valuable tool for forecasting in unpredictable environments.

This study aims to explore the use of Chen's model in fuzzy time series forecasting, highlighting its methodology, benefits, and real-world applications. By analyzing real-world datasets, we hope to demonstrate how this model can improve prediction accuracy and provide better insights for decision-making. In a world where uncertainty is a constant challenge, fuzzy-based forecasting methods like Chen's model can offer a practical and reliable solution.

2. Material Methods

Monthly price data of Wheat in Birbhum district of West Bengal was collected from Agmarknet from January 2018 to December 2023. The monthly price is used for forecasting.

2.1 Concept of Fuzzy Time Series

Let Y(t) (t=…,0,1,2,3,…), a subset of real numbers, be the universe of discourse by which fuzzy sets $f_j(t)$ are defined. If F(t) is a collection of $f_1(t), f_2(t), \dots$ is called fuzzy time series defined on y(t).

If there is a fuzzy relationship R (t-1, t), such that $F(t) = F(t-1) \times R(t-1, t)$, where $\times$ is an operator, then F(t) is said to be caused by F(t-1). The relationship between F(t) and F(t-1) can be denoted by $F(t-1) \rightarrow F(t)$.

Suppose $F(t-1) = A_i$ and $F(t) = A_j$ a fuzzy logical relationship is defined as $A_i \rightarrow A_j$ where Ai is named as the left hand side of fuzzy logical relationship and A_j the right hand side.

Fuzzy logical relationship with the same fuzzy se on the left hand side can be further grouped into a fuzzy logical relationship group. Suppose there are fuzzy logical relationships such that $A_i \rightarrow A_{j1}, A_i \rightarrow A_{j2}$ ...then they can be grouped into a fuzzy logical relationship group $A_i \rightarrow A_{j1}, A_{j2}$.

2.2 Models for Fuzzy Time Series Forecasting

Different models have been developed to forecast the data using fuzzy techniques. In this study two models have been used to forecast the wheat price of Birbhum district of West Bengal. The models Chen model (1996) [4].

Chen Model (1996) [4]: Chen (1996) [4] improved the Song & Chissom model by introducing simplified fuzzy relationships and a weighted average defuzzification method, making FTS computationally efficient. This model eliminates the need for complex matrix calculations required in the original model. It enhances practical applications by making FTS more adaptable for real-world time series forecasting problems such as stock market prediction and weather forecasting.

Formula for Defuzzification

$$X_{t+1} = \frac{\sum_{i=1}^{n} Midpoint(A_i).W_i}{\sum_{i=1}^{n} W_i}$$

Where,

- Midpoint (A_i) is the center of fuzzy set A_i.
- W_i is the frequency weight of each fuzzy set in FLRs.

2.3 The procedure of forecasting with fuzzy time series

There are different steps for fuzzy time series forecasting. Each model follows same steps in forecasting and the forecasting steps are

Step 1: Define the Universe of Discourse (UOD)

The universe of discourse is the range within which the time series data falls. It is defined as:

$$U = [(Dmin - d_1), (Dmax + d_2)]$$

Where,

d_1, d_2 are any positive integer. but the value shouldbe less than Dmax & Dmin.

Step 2: Partition the Universe of Discourse into Fuzzy Sets

The universe of discourse *U* is divided into equal intervals, each corresponding to a fuzzy set A_i. The fuzzy sets are defined as: $A_1, A_2, A_3, \dots, A_n$

For selecting the numbers of intervals different methods are

Method	Suitable for data type	Formula
Equal-Length Partitioning	Simple datasets	$W = \frac{U_{max} - U_{Min}}{N}$
Doane's Rule	Skewed data	$W = 1 + log_2(N) + log_2(1 + g_1)$ g_1-skewness N-Number of observation
Freedman-Diaconis Rule	Large datasets, Highly variable data (outliers present)	$W = 2 \times \frac{Q_3 - Q_1}{N^{1/3}}$
Scott's Rule	Normally distributed data	$W = 3.5 \frac{\sigma}{N^{1/3}}$
K-Means Clustering	Complex datasets	Using Elbow method or silhouette score

Each fuzzy set is represented by a triangular or trapezoidal membership function

$$\mu_{A_i}(x) = \begin{Bmatrix} \frac{x-l_i}{m_i-l_i}, l_i \leq x < m_i \\ \frac{r_i-x}{r_i-m_i}, m_i \leq x \leq r_i \\ 0, \ otherwise \end{Bmatrix}$$

Where,

l_i is the left boundary of the fuzzy set A_i

m_i is the middle point.

r_i is the right boundary

Step 3: Fuzzification of Time Series Data

Each time-series value x_t is assigned a fuzzy set based on its membership function. If x_t falls into multiple fuzzy sets, it is assigned to the one with the highest membership value. For a given time-series data, $X = \{x_1, x_2, \dots, x_t\}$, fuzzification is done as:

$x_t \rightarrow A_k \ if \ \mu_{A_i}(x_t)$ is highest among all A_i.

Step 4: Identify Fuzzy Logical Relationships (FLRs)
Fuzzy Logical Relationships (FLRs) are determined based on consecutive time points. If: $x_t \rightarrow A_k$ and $x_{t+1} \rightarrow A_j$ then the FLR is $A_i \rightarrow A_j$ All such relationships are recorded as FLRs.

Step 5: Establish Fuzzy Logical Relationship Groups (FLRGs)
FLRs with the same left-hand side are grouped together to form FLRGs:

$$A_i \rightarrow \{A_j, A_K, \ldots, A_m\}$$

Where, $A_i \rightarrow \{A_j, A_K, A_m\}$ are the next possible states.

Step 6: Defuzzification-Forecasting Future Values
The predicted value $\hat{x}_{t+1}$ is obtained by defuzzification. Common defuzzification methods include:

Centroid Method $\hat{x}_{t+1} = \frac{\sum_{j=1}^{t} x_j \times \mu A_j(x)}{\sum_{j=1}^{t} \mu A_j(x)}$

Weighted mean method $\hat{x}_{t+1} = \frac{\sum_{j=1}^{t} w_j x_j}{\sum_{j=1}^{t} w_j}$

Where w_j is the weight assigned to fuzzy set A_j

Step 7: Performance Evaluation
To evaluate the accuracy of the model, common error metrics are used:

Mean Absolute Percentage Error (MAPE)

$$MAPE = \frac{100}{N} \sum_{t=1}^{N} \left| \frac{x_t - \hat{x}_t}{x_t} \right|$$

Root Mean Squared Error (RMSE)

$$RMSE = \sqrt{\frac{1}{N} \sum_{t-1}^{N} (x_t - \hat{x}_t)^2}$$

Where $\boldsymbol{x_t}$ is the actual value and $\boldsymbol{\hat{x}_t}$ is the predicted value.

3. Results and Discussion
Monthly price data of Wheat in Birbhum district was analyzed in R studio software for Chen model and Song & Chissom model. The detailed analysis was discussed below.

Step 1: D min and Dmax be the minimum and maximum value of historical data are 1492 (D min) and 3045(D max). The Universe of discourse was calculated by

If d_1 =100 & d_2 =50
$u = [(1492 - 100), (3045 + 50)]$

$u = [1392,3095]$

Step 2: According to the Doane's Rule and Freedman-Diaconis Rule, the universe of discourse "U" is partitioned into 9 intervals as the data is skewed and and it has high variance and outliers.

Table 1: Interval with their midpoints

Groups	Interval Range	Midpoints
u_1	1492.00-1664.55	1578.275
u_2	1664.55-1837.11	1750.83
u_3	1837.11-2009.66	1923.385
u_4	2009.66-2182.22	2095.94
u_5	2182.22-2354.77	2268.495
u_6	2354.77-2527.33	2441.05
u_7	2527.33-2699.88	2613.605
u_8	2699.88-2872.44	2786.16
u_9	2872.44-3045.00	2958.72

The number of intervals will be in accordance with the number of linguistic variables (fuzzy sets) [A_1, A2, A_3, A_4, A_5,A_6, A_7,A_8, A_9] to be considered.

Table 2: Label linguistic value of price

Fuzzified	Linguistic Value
A_1	Very very very low
A2	Very very low
A_3	Very low
A_4	Low
A_5	Moderate
A_6	High
A_7	Very high
A_8	Very very high
A_9	Very very very high

Step 3: The price data was fuzzified and each data assign to the linguistic value as per the intervals. The price data along with the fuzzified values are given in Table 3.

Table 3: Linguistic value of price

Month	Price (Rs. Per Quintal)	Fuzzified	Month	Price (Rs. Per Quintal)	Fuzzified
Jan-18	1674	A2	Jan-21	1936	A3
Feb-18	1679	A2	Feb-21	1934	A3
Mar-18	1600	A1	Mar-21	1887	A3
Apr-18	1592	A1	Apr-21	1899	A3
May-18	1618	A1	May-21	1934	A3
Jun-18	1657	A1	Jun-21	1893	A3
Jul-18	1686	A2	Jul-21	1770	A2
Aug-18	1743	A2	Aug-21	1751	A2
Sep-18	1745	A2	Sep-21	1866	A3
Oct-18	1823	A2	Oct-21	1874	A3
Nov-18	1926	A3	Nov-21	1962	A3
Dec-18	1967	A3	Dec-21	2001	A3
Jan-19	1983	A3	Jan-22	1986	A3
Feb-19	1993	A3	Feb-22	2034	A4
Mar-19	2045	A4	Mar-22	2131	A4
Apr-19	1955	A3	Apr-22	2132	A4
May-19	1825	A2	May-22	2108	A4
Jun-19	1833	A2	Jun-22	2165	A4
Jul-19	1840	A3	Jul-22	2313	A5
Aug-19	1865	A3	Aug-22	2686	A7
Sep-19	1894	A3	Sep-22	2833	A8
Oct-19	1917	A3	Oct-22	2903	A9
Nov-19	1905	A3	Nov-22	2993	A9
Dec-19	1919	A3	Dec-22	2925	A9
Jan-20	1944	A3	Jan-23	2970	A9
Feb-20	2056	A4	Feb-23	2995	A9
Mar-20	2098	A4	Mar-23	2886	A9
Apr-20	1967	A3	Apr-23	2700	A8
May-20	1876	A3	May-23	2627	A7
Jun-20	1921	A3	Jun-23	2795	A8
Jul-20	1933	A3	Jul-23	2770	A8
Aug-20	1934	A3	Aug-23	2850	A8
Sep-20	1941	A3	Sep-23	2787	A8
Oct-20	1944	A3	Oct-23	2905	A9
Nov-20	1943	A3	Nov-23	2753	A8
Dec-20	1956	A3	Dec-23	2570	A7

Step 4: After the fuzzyfication the fuzzy logical relationship established for each data point, table 4 shows the price value along with their fuzzy logical relation

Table 4: The first order fuzzy logical relationship on price data

Month	Price (Rs. per Quintal)	Fuzzified	FLR	Month	Price (Rs. per Quintal)	Fuzzified	FLR
Jan-18	1674	A2	A2 -> A2	Jan-21	1936	A3	A3 -> A3
Feb-18	1679	A2	A2 -> A1	Feb-21	1934	A3	A3 -> A3
Mar-18	1600	A1	A1 -> A1	Mar-21	1887	A3	A3 -> A3
Apr-18	1592	A1	A1 -> A1	Apr-21	1899	A3	A3 -> A3
May-18	1618	A1	A1 -> A1	May-21	1934	A3	A3 -> A3
Jun-18	1657	A1	A1 -> A2	Jun-21	1893	A3	A3 -> A2
Jul-18	1686	A2	A2 -> A2	Jul-21	1770	A2	A2 -> A2
Aug-18	1743	A2	A2 -> A2	Aug-21	1751	A2	A2 -> A3
Sep-18	1745	A2	A2 -> A2	Sep-21	1866	A3	A3 -> A3
Oct-18	1823	A2	A2 -> A3	Oct-21	1874	A3	A3 -> A3
Nov-18	1926	A3	A3 -> A3	Nov-21	1962	A3	A3 -> A3
Dec-18	1967	A3	A3 -> A3	Dec-21	2001	A3	A3 -> A3
Jan-19	1983	A3	A3 -> A3	Jan-22	1986	A3	A3 -> A4
Feb-19	1993	A3	A3 -> A4	Feb-22	2034	A4	A4 -> A4
Mar-19	2045	A4	A4 -> A3	Mar-22	2131	A4	A4 -> A4
Apr-19	1955	A3	A3 -> A2	Apr-22	2132	A4	A4 -> A4
May-19	1825	A2	A2 -> A2	May-22	2108	A4	A4 -> A4
Jun-19	1833	A2	A2 -> A3	Jun-22	2165	A4	A4 -> A5
Jul-19	1840	A3	A3 -> A3	Jul-22	2313	A5	A5 -> A7
Aug-19	1865	A3	A3 -> A3	Aug-22	2686	A7	A7 -> A8
Sep-19	1894	A3	A3 -> A3	Sep-22	2833	A8	A8 -> A9
Oct-19	1917	A3	A3 -> A3	Oct-22	2903	A9	A9 -> A9
Nov-19	1905	A3	A3 -> A3	Nov-22	2993	A9	A9 -> A9
Dec-19	1919	A3	A3 -> A3	Dec-22	2925	A9	A9 -> A9
Jan-20	1944	A3	A3 -> A4	Jan-23	2970	A9	A9 -> A9
Feb-20	2056	A4	A4 -> A4	Feb-23	2995	A9	A9 -> A9
Mar-20	2098	A4	A4 -> A3	Mar-23	2886	A9	A9 -> A8
Apr-20	1967	A3	A3 -> A3	Apr-23	2700	A8	A8 -> A7
May-20	1876	A3	A3 -> A3	May-23	2627	A7	A7 -> A8
Jun-20	1921	A3	A3 -> A3	Jun-23	2795	A8	A8 -> A8
Jul-20	1933	A3	A3 -> A3	Jul-23	2770	A8	A8 -> A8
Aug-20	1934	A3	A3 -> A3	Aug-23	2850	A8	A8 -> A8
Sep-20	1941	A3	A3 -> A3	Sep-23	2787	A8	A8 -> A9
Oct-20	1944	A3	A3 -> A3	Oct-23	2905	A9	A9 -> A8
Nov-20	1943	A3	A3 -> A3	Nov-23	2753	A8	A8 -> A7
Dec-20	1956	A3	A3 -> A3	Dec-23	2570	A7	<NA>

Step 5: Fuzzy logical relationship as in step 4 having the same the left-hand side and derive fuzzy logical relationship group (FLRG).

$$
\begin{gathered}
A_1 \rightarrow A_1, A_2 \\
A_2 \rightarrow A_2, A_1, A_3 \\
A_3 \rightarrow A_3, A_4, A_2 \\
A_4 \rightarrow A_3, A_4, A_5 \\
A_5 \rightarrow A_7 \\
A_6 \rightarrow 0\ character \\
A_7 \rightarrow A_8 \\
A_8 \rightarrow A_9, A_7, A_8 \\
A_9 \rightarrow A_9, A_8
\end{gathered}
$$

Step 6: The forecasted values are defuzzified to the actual value by weighted method in Chen model, the forecasted values are given in Table 4.

Table 5: Defuzzifing price with actual price

Month	Price (Rs. per Quintal)	Forecast price (Rs. per Quintal)	Month	Price (Rs. per Quintal)	Forecast price (Rs. per Quintal)
Jan-18	1674	NA	Jan-21	1936	1923.389
Feb-18	1679	1750.833	Feb-21	1934	1923.389
Mar-18	1600	1750.833	Mar-21	1887	1923.389
Apr-18	1592	1578.278	Apr-21	1899	1923.389
May-18	1618	1578.278	May-21	1934	1923.389
Jun-18	1657	1578.278	Jun-21	1893	1923.389
Jul-18	1686	1578.278	Jul-21	1770	1923.389

Aug-18	1743	1750.833	Aug-21	1751	1750.833
Sep-18	1745	1750.833	Sep-21	1866	1750.833
Oct-18	1823	1750.833	Oct-21	1874	1923.389
Nov-18	1926	1750.833	Nov-21	1962	1923.389
Dec-18	1967	1923.389	Dec-21	2001	1923.389
Jan-19	1983	1923.389	Jan-22	1986	1923.389
Feb-19	1993	1923.389	Feb-22	2034	1923.389
Mar-19	2045	1923.389	Mar-22	2131	2095.944
Apr-19	1955	2095.944	Apr-22	2132	2095.944
May-19	1825	1923.389	May-22	2108	2095.944
Jun-19	1833	1750.833	Jun-22	2165	2095.944
Jul-19	1840	1750.833	Jul-22	2313	2095.944
Aug-19	1865	1923.389	Aug-22	2686	2268.5
Sep-19	1894	1923.389	Sep-22	2833	2613.611
Oct-19	1917	1923.389	Oct-22	2903	2786.167
Nov-19	1905	1923.389	Nov-22	2993	2958.722
Dec-19	1919	1923.389	Dec-22	2925	2958.722
Jan-20	1944	1923.389	Jan-23	2970	2958.722
Feb-20	2056	1923.389	Feb-23	2995	2958.722
Mar-20	2098	2095.944	Mar-23	2886	2958.722
Apr-20	1967	2095.944	Apr-23	2700	2958.722
May-20	1876	1923.389	May-23	2627	2786.167
Jun-20	1921	1923.389	Jun-23	2795	2613.611
Jul-20	1933	1923.389	Jul-23	2770	2786.167
Aug-20	1934	1923.389	Aug-23	2850	2786.167
Sep-20	1941	1923.389	Sep-23	2787	2786.167
Oct-20	1944	1923.389	Oct-23	2905	2786.167
Nov-20	1943	1923.389	Nov-23	2753	2958.722
Dec-20	1956	1923.389	Dec-23	2570	2786.167

Forecasting Performance measure: Chen model was selected on the basis of RMSE, MAE & MAPE value.

Table 6: Performance measures of Chen Model

Performance measure	Chen Model
Mean Absolute Error (MAE)	74.01
Root Mean Squared Error (RMSE)	105.83
Mean Absolute Percentage Error (MAPE)	3.39%

All the performance measures are lower in case of Chen model, so Chen model is used for further forecasting. Mean absolute percentage error (MAPE), value and applying Lewis's Scale (Lewis, 1982) the Chen model gives good forecast as the lowest MAPE value is 3.39%. However, depending of the data set, as to whether there is a significant trend or seasonal component, the MAPE may under or overestimate the accuracy of the model. The MAE value is 74.01 which indicate the overall forecasting error. The RMSE value is 105.83 indicating the accuracy of the forecast.

4. Forecasting with Chen model

Chen model is used for forecasting the future values upto 12 months ahead by using price data of wheat in birbhum district of West Bengal. The results are given in Table 7.

Table 7: Forecasted value for next 12 months

Month	Jan-24	Feb-24	Mar-24	Apr-24	May-24	Jun-24	Jul-24	Aug-24	Sep-24	Oct-24	Nov-24	Dec-24
Forecast Price	2784.857	2788.482	2782.951	2787.766	2792.76	2782.859	2783.807	2788.28	2786.081	2778.352	2793.085	2785.084

The graph shows that the predicted price of wheat is almost similar to actual price of wheat, as the MAPE value is 2.59% it result that the forecast is accqurate. The forecased value obtained by the method show its suitability in fuzzy time series forecasting of Wheat crop in Birbhum district of West-Bengal.

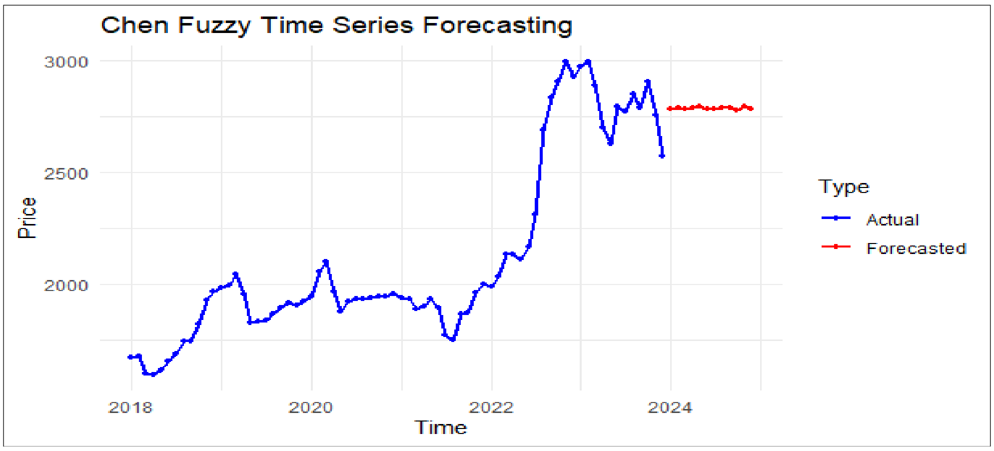

Fig 1: Chen fuzzy time series forecasting with predicted values

5. Conclusion

The comparative analysis of the Chen Model for fuzzy time series forecasting of wheat price demonstrated that the Chen Model performs better in terms of accuracy. The lower values of Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE) indicate that the Chen Model provides a more reliable and precise forecast. Applying Lewis's Scale (1982), the Chen Model is classified as a good forecasting method, with a MAPE value of 3.39%, significantly lower the 6.28%. Future studies can enhance the Chen Model by integrating hybrid approaches such as combining FTS with machine learning techniques (e.g., ANN, LSTM, or ARIMA-FTS models) for better performance. The improved FTS models can be applied in agriculture, stock market forecasting, climate modeling and economic planning, ensuring better decision-making.

6. Reference

1. Zadeh LA. Fuzzy sets. Information and Control. 1965;8(3):338-353.
2. Song Q, Chissom BS. Fuzzy time series and its models. Fuzzy Sets and Systems. 1993;54(3):269-277.
3. Song Q, Chissom BS. Forecasting enrollments with fuzzy time series, Part I. Fuzzy Sets and Systems. 1994;54(1):1-9.
4. Chen SM. Forecasting enrollments based on fuzzy time series. Fuzzy Sets and Systems. 1996;81(3):311-319.
5. Huarng K. Heuristic models of fuzzy time series for forecasting. Fuzzy Sets and Systems. 2001;123(3):369-386.
6. Kuo RJ, Chen CH. A decision support system for stock market forecasting using fuzzy neural networks. Expert Systems with Applications. 2004;26(4):409-420.
7. Chen SM, Hsu CC. A new method to forecast enrollments using fuzzy time series. International Journal of Applied Science and Engineering. 2004;2(3):234-246.
8. Lee LW, Wang LH, Chen SM. Temperature prediction and TAIFEX forecasting based on fuzzy logical relationships and genetic algorithms. Expert Systems with Applications. 2007;33(3):539-550.
9. Yu HC, Huarng K. A heuristic model for fuzzy time-series forecasting. Applied Soft Computing. 2008;8(1):372-379.
10. Jilani TA, Burney SMA, Ardil C. Fuzzy metric approach for fuzzy time series forecasting based on frequency density-based partitioning. International Journal of Computational Intelligence. 2008;4(1):37-43.
11. Egrioglu E, Aladag CH, Yolcu U. A high order fuzzy time series approach based on artificial neural networks. Expert Systems with Applications. 2009;36(4):7358-7365.
12. Aladag CH, Yolcu U, Egrioglu E. A new hybrid approach to fuzzy time series forecasting based on artificial neural networks. Applied Soft Computing. 2010;10(1):647-652.
13. Tsaur RC. Forecasting analysis using fuzzy time series and cellular automata. Expert Systems with Applications. 2012;39(7):6367-6378.
14. Li H, Fei J, Zhang Y. A hybrid fuzzy time series forecasting model based on multi-objective optimization. Mathematical and Computer Modelling. 2012;56(5-6):1236-1248.
15. Singh P, Borah B. Higher order fuzzy time series forecasting. Applied Mathematical Modelling. 2014;38(3):1338-1350.
16. Coban VM, Egrioglu E. A new forecasting model based on intuitionistic fuzzy time series. Soft Computing. 2018;22:5401-5412.
17. Saba T, Rehman A. A fuzzy time series model for forecasting temperature changes. Sustainable Computing: Informatics and Systems. 2020;28:100421.
18. Nuryani Y, Purnamasari I. Time series forecasting of agricultural commodity prices using fuzzy logical relationships. Agricultural Economics Research Review. 2021;34(1):45-57.