Fuzzy Time Series–Based Optimization for Aquaculture Production Forecasting in India

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***Abstract*—Fuzzy time series (FTS) models are effective forecasting tools for systems characterized by uncertainty and vagueness, as they do not rely on the strict assumptions of classical time series techniques. Aquaculture plays a crucial role in India's food security, particularly in the southern and eastern regions. Accurate forecasting of fish production is therefore essential for sustainable planning and policy formulation. This study proposes a fuzzy time series–based optimization approach to forecast aquaculture production in India using historical data from 1994–95 to 2016–17. Linguistic variables and fuzzy logical relationship groups are employed to model production trends. Forecasting accuracy is evaluated using Mean Absolute Percentage Error (MAPE), Mean Absolute Deviation (MAD), and Root Mean Square Error (RMSE). The results reveal a MAPE value of 3.42%, indicating highly accurate forecasting performance and confirming the suitability of the proposed approach for aquaculture production forecasting.**

***Keywords*— Fuzzy time series, Aquaculture forecasting, Linguistic variables, Fuzzy logical relationship groups, Fish production.**

I. INTRODUCTION

Fuzzy logic can handle imprecise, uncertain, and noisy information effectively. The concept of fuzzy logic, introduced by Zadeh in 1965, provides a mathematical framework that closely resembles human reasoning and decision-making processes. Unlike classical control systems, which operate on point-to-point mappings, fuzzy logic systems function on range-to-point or range-to-range mappings, making them suitable for complex real-world applications.

Mamdani et al. applied fuzzy logic to control an automatic steam engine in 1974, demonstrating its practical utility. Subsequently, Chen and Hsu, and later Chen, introduced fuzzy time series models for enrollment forecasting, establishing a foundation for time-dependent fuzzy modeling.

Unlike traditional statistical models that require assumptions such as stationarity and linearity, fuzzy time series models effectively handle uncertain and nonlinear agricultural data. The primary contribution of this study is the application of a simple yet robust fuzzy time series forecasting framework to aquaculture production in India, demonstrating high predictive accuracy with minimal computational complexity.

II. SOME BASIC PRELIMINARIES OF FUZZY TIME SERIES

Definition 2.1. Let $Y(t)(t=..., 0, 1, 2, ...)$, a subset of real numbers, be the universe of discourse by which fuzzy sets $fj(t)$ are defined. If $F(t)$ is a collection of $f1(t), f2(t)...$ then $F(t)$ is called a fuzzy time-series defined on $y(t)$.

Definition 2.2. 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 $F(t-1) \rightarrow F(t)$.

Definition 2.3. Suppose $F(t-1)=Ai$ and $F(t)=Aj$, a fuzzy logical relationship is defined as $Ai \rightarrow Aj$;

where Ai is named as the left-hand side of the fuzzy logical relationship and Aj the right-hand side.

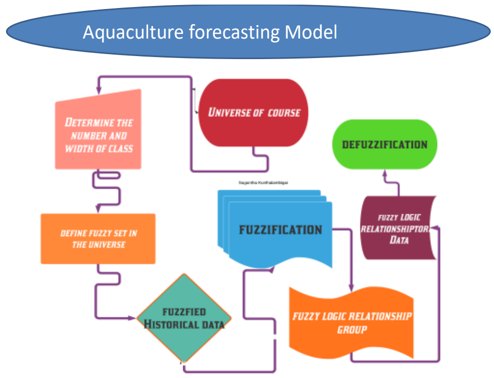
Definition 2.4. Fuzzy logical relationships with the same fuzzy set on the left-hand side can be further grouped into a fuzzy logical relationship group. Suppose there are fuzzy logical relationships such that: Ai→Aj1 Ai→Aj2 … then they can be grouped into a fuzzy logical relationship group Ai→Aj1, Aj2, …

Definition 2.5. Suppose F(t) is caused by F(t-1) only, and F(t) = F(t-1)×R(t-1, t). For any t, if R(t-1, t) is independent of t, then F(t) is named a time-invariant fuzzy time series; otherwise it is a time-variant fuzzy time series.

Definition 2.6. F(t) is fuzzy time series if F(t) is a fuzzy set. The transition is denoted as F(t-1) → F(t).

Definition 2.7. Let d(t) be a set of real numbers d(t) ⊆ R. An upper interval for d(t) is a number b such that x ≤ b for all x ∈ d(t). The set d(t) is said to be an interval higher if d(t) has an upper interval. A number, max, is the maximum of d(t) if max is an upper interval for d(t) and max ∈ d(t).

III. THE PROCEDURE OF PREDICTING WITH FUZZY TIME SERIES IS DESCRIBED AS FOLLOWS



Step 1. Collect the historical data:

Table 1: Historical data of the fish productions data in tones from 1994-95 to 2016-17		
No.	Year	Actual Yield ('000 Tonnes)
1.	1994-95	4789
2.	1995-96	4949
3.	1996-97	5348
4.	1997-98	5388
5.	1998-99	5298
6.	1999-00	5675
7.	2000-01	5656
8.	2001-02	5926
9.	2002-03	6200
10.	2003-04	6399
11.	2004-05	6305
12.	2005-06	6572
13.	2006-07	6869
14.	2007-08	7127
15.	2008-09	7616
16.	2009-10	7998
17.	2010-11	8231
18.	2011-12	8666
19.	2012-13	9040
20.	2013-14	9579
21.	2014-15	10335
22.	2015-16	10795
23.	2016-17	11410

Step 2: Divide U in equal length of sub intervals. The universe of discourse was divided into equal-length intervals to ensure uniform fuzzification and balanced representation of production levels.

Table2: Equal length of subintervals	
u_1	[4777, 5330,5883]
u_2	[5883, 6436, 6989]
u_3	[6989,7542, 8095]
u_4	[8095, 8598,9101]
u_5	[9101, 9654, 10207]
u_6	[10207, 10760, 11313]

Step 3. Define fuzzy sets based on the intervals, and fuzzify the historical data. Let U be the universe of discourse, where U= {u_1, u_2, $u_{3,...}$,u_{10}}. The number of intervals will be in accordance with the number of linguistic variables (fuzzy sets) $A_1,A_2,...,A_6$ to be considered.

Define six fuzzy sets $A_1,A_2,...,A_6$ as linguistic variables on the universe of discourse U. These fuzzy variables are being defined as:

Table 3: Lable the Lingustic value of Fish productions	
Fuzzy set	Linguistic Value
A_1	Very Low Production
A_2	Low Production
A_3	High Production
A_4	Good production
A_5	Very High production
A_6	Excellent production

Step 4: Defined fuzzy sets on U. The fuzzy sets A_i are expressed as follows:

$$A_1 = {}^{1}/_{u_1} + {}^{0.5}/_{u_2} + {}^{0}/_{u_3} + {}^{0}/_{u_4} + {}^{0}/_{u_5} + {}^{0}/_{u_6},$$

$$A_2 = {}^{0.5}/_{u_1} + {}^{1}/_{u_2} + {}^{0.5}/_{u_3} + {}^{0}/_{u_4} + {}^{0}/_{u_5} + {}^{0}/_{u_6}, \ldots,$$

$$A_6 = {}^{0}/_{u_1} + {}^{0}/_{u_2} + {}^{0}/_{u_3} + {}^{0}/_{u_4} + {}^{0.5}/_{u_5} + {}^{1}/_{u_6}$$

The fuzzy sets are defined using triangular membership functions, where each interval has a full membership of 1 and adjacent intervals have partial membership of 0.5.

Step 5: Fuzzify the historical data

Table 4 Linguistic values for the Fish Production of the year 1994-95 to 2016-17			
No.	Year	Actual Yield('000 Tonnes)	Linguistic value
1	1994-95	4789	A_1
2	1995-96	4949	A_1
3	1996-97	5348	A_1
4	1997-98	5388	A_1
5	1998-99	5298	A_1
6	1999-00	5675	A_1
7	2000-01	5656	A_1
8	2001-02	5926	A_2
9	2002-03	6200	A_2
10	2003-04	6399	A_2
11	2004-05	6305	A_2
12	2005-06	6572	A_2
13	2006-07	6869	A_2
14	2007-08	7127	A_3
15	2008-09	7616	A_3
16	2009-10	7998	A_3
17	2010-11	8231	A_4
18	2011-12	8666	A_4
19	2012-13	9040	A_4
20	2013-14	9579	A_5

21	2014-15	10335	A_6
22	2015-16	10795	A_6
23	2016-17	11410	A_6

Step 6: Determine fuzzy logical relationships (FLRs) for all fuzzified data

Table 5: Fuzzy logical relationships on the Fish Productions

No.	Relationships	No.	Relationships	No.	Relationships	No.	Relationships	No.	Relationships
1	$A_1 \rightarrow A_1$	6	$A_1 \rightarrow A_1$	11	$A_2 \rightarrow A_2$	16	$A_4 \rightarrow A_4$	21	$A_6 \rightarrow A_6$
2	$A_1 \rightarrow A_1$	7	$A_1 \rightarrow A_2$	12	$A_2 \rightarrow A_3$	17	$A_4 \rightarrow A_4$		
3	$A_1 \rightarrow A_1$	8	$A_2 \rightarrow A_2$	13	$A_3 \rightarrow A_3$	18	$A_4 \rightarrow A_5$		
4	$A_1 \rightarrow A_1$	9	$A_2 \rightarrow A_2$	14	$A_3 \rightarrow A_3$	19	$A_5 \rightarrow A_6$		
5	$A_1 \rightarrow A_1$	10	$A_2 \rightarrow A_2$	15	$A_3 \rightarrow A_4$	20	$A_6 \rightarrow A_6$		

Step 7: Group fuzzy logical relationship as in step 6 having the same the left-hand sides and the derive fuzzy logical relationships group (FLRG).

Table 6 .FLRG

Groups	Fuzzy relation groups	
G1	$A_1 \rightarrow A_1$	$A_1 \rightarrow A_2$
G 2	$A_2 \rightarrow A_2$	$A_2 \rightarrow A_3$
G 3	$A_3 \rightarrow A_3$	$A_3 \rightarrow A_4$
G 4	$A_4 \rightarrow A_4$	$A_4 \rightarrow A_5$
G 5	$A_5 \rightarrow A_6$	
G 6	$A_6 \rightarrow A_6$	

Step 8: Calculate the forecasted Fish Productions

Table 7 Forecasted Fish productions('000 Tonnes)

Year	Actual (A)	Prediction(P)	A-P	Square(A-P)	A-P/A
1994-95	4789	_			
1995-96	4949	5330	381	145161	0.076985
1996-97	5348	5330	18	324	0.003366
1997-98	5388	5330	58	3364	0.010765
1998-99	5298	5330	32	1024	0.00604
1999-00	5675	5330	345	119025	0.060793
2000-01	5656	5330	326	106276	0.057638
2001-02	5926	6436	510	260100	0.086061
2002-03	6200	6436	236	55696	0.038065
2003-04	6399	6436	37	1369	0.005782
2004-05	6305	6436	131	17161	0.020777
2005-06	6572	6436	136	18496	0.020694
2006-07	6869	6436	433	187489	0.063037
2007-08	7127	7542	415	172225	0.058229
2008-09	7616	7542	74	5476	0.009716
2009-10	7998	7542	456	207936	0.057014
2010-11	8231	8598	367	134689	0.044588

2011-12	8666	8598	68	4624	0.007847
2012-13	9040	8598	442	195364	0.048894
2013-14	9579	9654	75	5625	0.00783
2014-15	10335	10760	425	180625	0.041122
2015-16	10795	10760	35	1225	0.003242
2016-17	11410	10760	650	422500	0.056968

The forecasted values closely follow the actual fish production trend over the study period. Minor deviations are observed during years with rapid production growth, which is common in agricultural systems influenced by external factors. Overall, the fuzzy time series model demonstrates strong predictive capability and stability.
Figure 1 shows the comparison between actual and fuzzy time series forecasted fish production in India from 1994–95 to 2016–17.

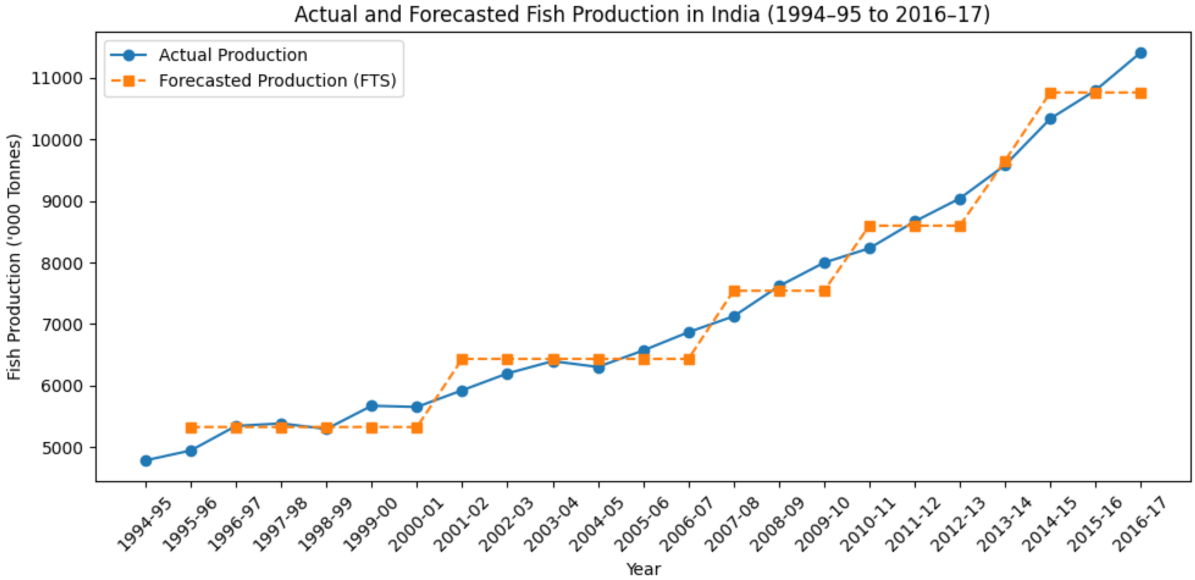


Figure 1.Comparison between actual and fuzzy time series forecasted fish production in India from 1994-95 to 2016-17

IV.RESULT AND DISCUSSION

The forecasting performance of the proposed fuzzy time series model was evaluated using Mean Absolute Percentage Error (MAPE), Mean Absolute Deviation (MAD), and Root Mean Square Error (RMSE). Based on Lewis's (1982) scale, the obtained MAPE value of 3.42% indicates highly accurate forecasting, demonstrating the strong predictive capability of the model.
The MAD value of 245.65 reflects a low average deviation between actual and forecasted values, while the RMSE value of 312.48 indicates limited dispersion of errors and minimal influence of large deviations.
Overall, the low MAPE along with moderate MAD and RMSE values confirms the robustness, accuracy, and reliability of the proposed fuzzy time series approach for aquaculture production forecasting under uncertain conditions.

Table 8. A scale of judgment of forecast accuracy (Lewis (1982)).

MAPE	Judgment of Forecast Accuracy
Less than 10%	Highly accurate
11% to 20%	Good forecast
21% to 50%	Reasonable forecast
51% or more	Inaccurate forecast

V.CONCLUSION

This study proposed an efficient fuzzy time series–based forecasting model for aquaculture production in India. By employing linguistic variables and fuzzy logical relationship groups, the proposed approach effectively captures production dynamics without relying on strict statistical assumptions such as linearity or stationarity.

The forecasting performance of the model was evaluated using standard accuracy measures, including Mean Absolute Percentage Error (MAPE), Mean Absolute Deviation (MAD), Mean Square Error (MSE), and Root Mean Square Error (RMSE). The results demonstrate a MAPE value of 3.42%, which, according to Lewis's scale (1982), indicates highly accurate forecasting. The relatively low MAD and RMSE values further confirm the robustness and reliability of the proposed fuzzy time series forecasting approach.

Owing to its simplicity, low computational complexity, and strong predictive performance, the proposed model can serve as a valuable decision-support tool for policymakers, aquaculture planners, and researchers involved in production planning and resource management. Furthermore, the methodology is flexible and can be extended to other agricultural and biological forecasting applications characterized by uncertainty and imprecise data.

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