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A BOOMING AND INNOVATIVE REGRESSION BASED FUZZY TIME SERIES FOR FORECAST OF CROPS

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Abstract:
Time-Series models have been totally managed for predictions in variegated and unique areas in scholastic enlistments, forecasting, rice creation and so forth., where in is by and large excogitated or thought up dependent on its past, regularly a perception that is absolutely dependent on its past statistically driven perception. The pondering of fuzzy time series was uncovered at first by Music and Chissom. This paper could be the absolute outcome of inspiration from research work wherein we portray a relapse based fuzzytime series strategy, which handles second thought, obscurity, veracity, and falseness parts of the fuzzy contexture and outfits an improved and an increasingly veracious outcome in correlation with techniques that are accepted and obvious. Accordingly, Fuzzy Logical connections of differing and known degrees have been executed to effectuate the fuzzy classification. Moreover, A Regression Evaluation Model has been implemented to play out the de-fuzzy classification technique. To explain the obligation of estimating, we've utilized the chronicled information of rice yield of University of Technology and Agriculture, India.

INTRODUCTION:

The gauging technique is very befitting in the occasions where incertitude connected to the not so distant future is concrete. The forecast of results later on is accomplished through this procedure. Appropriate charts and information are pondered and questioned to make ideal with respect to predictions. The work of time series anticipating has got into picture for two reasons overwhelmingly. In the first place, time series arrangement information shapes a dominant segment territory of the information existing maintaining a business, monetary, and money related zones. Next, positively simple to evaluate and effortless to assess,significant number of improvements are obtainable for valuation of time series metrics. A fuzzy arrangement is a course of things with a continuum of evaluations of enrollment. Such a fixed arrangement is viewed as an ordinary enrollment (component) work which allots to each question a nature of participation running somewhere in the range of zero and one. The thoughts of incorporation, association, convergence, supplement, connection, convexity, and so forth.Are drawn out to such pieces, and different properties the ideas with regards to fuzzy pieces are built up. In particular, a partition hypothesis for curved fuzzy sets or units is demonstrated without requiring that the pieces being disjoint.

RELATED WORK:

Fuzzy measurement estimation could be a vigilant interpretation of implicit and inaccuracy in the data. Besides fuzzy measurement will fix situations that don't give the investigation and examination of floats or the visual picture of in measurement. Elusive examination work been adroit on anticipation perplexity exploitation of this idea. Fuzzy measurement observations and definitions were introduced by Zadeh further more evaluated by Song and Chrisom and Chrisom besides. They conjointly portray the thoughts and ideas of variation and invariant measurement [2-4]. In Fuzzification crossroads, against use of the segment of the universe of talk, higher sorted out appearances have been in Egrioglu et al. appearances have been commit to present day times Egrioglu et al forward. [5, 6] stead fasted equivalent term stretches planted on|6] fasted equivalent length spans Disjointedly to decide the dynamic length of the search span, Park et al. [7], Egrioglu et al. [9] presented molecule swarm optimization strategy. As indicated by the approach, all participations were dependant on FCM strategy in lieu of the investigation of Yu and Huang [8]. Figured fuzzy intelligent relations are utilized for investigation of time arrangement instead of consistent relations and for examination of time arrangement than rather irregular and non-arbitrary capacities seeing that with respect to common time and non-arbitrary capacities while in the whole instance of normal time arrangement investigation by B. Garg et al [10]. The repeat amount of the fuzzy relationship in the period of defuzzification is taken into consideration. A fuzzy time arrangement strategy predicated on loads relies on the quantity of approach predicated on loads relies on the genuine number of repeats of fuzzy relations, Egrioglu et al [12]. Priority matrix is evaluated by utilizing consistently increasing monotonic and is structured by utilizing routinely exactness among the most imperative components when adapting to figure utilizing time series models. Precision relies on relative load of past perceptions used to foresee gauge esteem. Way to deal with total of past perceptions can be of huge factor with time arrangement examination where persistence of following perception is dependent just on past data. Past basis on fuzzy time arrangement for recommending future rewarded fuzzy relationship is likewise significant and probably won't need appropriately reflected requirement for every specific individual fuzzy relationship in estimating that discharged incorrectness in results. In this paper, we propose an ordered weighted averaging (OWA) for fuzzy time arrangement and further style of all the throwing model images of viability of the proposed thought, fair of utilizing fuzzy time arrangement can be to adapt to anticipation inside the fuzzy environmental factors climate regular habitat, ambiguity and imprecision. OWA is helpful to create loads of past fuzzy perceptions; consequently disposing of the requirement for huge quantities of recorded perceptions important to conjecture esteem. OWA weights are dependent on utilizing consistently regularly increasing monotonic (RIM) quantifiers dependent on fuzzy set up significance utilizing priority matrix.

PROPOSED METHOD:

This method recommends a route for rice produce anticipation by exploiting real produce for the explanation that Universe of builds of discourse and Intervals based for the most part isolating. We've obtained outfitted another system for visualization the value, which might be clearly disclosed inside the lines to return. Which might be disclosed inside the lines to return plainly. The forecast method rehearses the succeeding steps:

Stage-1: First, depict the Universe of Discourse U and Partition U into equal sized intervals.

We would determine the Universe of discourse designs, for example the spans at stretches that estimations of rice assembling would be found. for setting out the Universe of discourse, absolute minimum worth of production Dmin and all value of production Dmax of a given time frame. Here, in sync with the given information, 3219 is the minimum worth and 4554 is that the maximum worth. so the Universe of discourse U = [Dmin-D1, Dmax+D2] where D1 and D2 unit two positive numbers. The university of discourse would be [3219, 4554]. Below is the year wise historical data

TABLE I PRODUCTION

Year	Production(Kg/hectare)
1981	3552
1982	4177
1983	3372
1984	3455
1985	3702
1986	3670
1987	3865
1988	3592
1989	3222
1990	3750
1991	3851
1992	3231
1993	4170
1994	4554
1995	3872
1996	4439
1997	4266
1998	3219
1999	4305
2000	3928

Stage-2: Now, Depict fuzzy sets Fi as follows:

In our work we have examined four unique intervals to cover a varied assortments. We isolated the Universe of Discourse into 5,7,9 and 11 equal intervals shown in Tables 2, 4, 6 and 8 separately. We further progressively separated the intervals in relation to the recurrence of the data values of the respective segment. We use this methodology as frequency based partitioning, shown in Tables 3, 5, 7 and 9 for all intervals.

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a) 5 equal intervals

TABLE II FREQUENCY DISTRIBUTION (5 INTERVAL)

FUZZY SETS	UPPER	LOWER	FREQUENCY
F1	3200	3480	5
F2	3480	3760	5
F3	3760	4040	4
F4	4040	4320	4
F5	4320	4600	2

Fuzzy sets are divided in Frequency based partition

TABLE III FREQUENCY BASED PARTITION (5 INTERVAL)

FUZZY SETS	UPPER	LOWER	NEW FUZZY SETS
F1	3200	3256	F1
	3256	3312	F2
	3312	3368	F3
	3368	3424	F4
	3424	3480	F5
F2	3480	3536	F6
	3536	3592	F7
	3592	3648	F8
	3648	3704	F9
	3704	3760	F10
F3	3760	3830	F11
	3830	3900	F12
	3900	3970	F13
	3970	4040	F14
F4	4040	4110	F15
	4110	4180	F16
	4180	4250	F17
	4250	4320	F18
F5	4320	4460	F19
	4460	4600	F20

Similarly, 7, 9 and 11 Intervals are also calculated

b) 7 equal intervals

TABLE IV FREQUENCY DISTRIBUTION (7 INTERVAL)

FUZZY SETS	UPPER	LOWER	FREQUENCY
F1	3200	3400	4
F2	3400	3600	3
F3	3600	3800	3
F4	3800	4000	4
F5	4000	4200	2
F6	4200	4400	2
F7	4400	4600	2

Fuzzy sets are divided Frequency based partition

TABLE V FREQUENCY BASED PARTITION (7 INTERVAL)

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FUZZY	UPPER	LOWER	NEW FUZZY SETS
F1	3200	3250	F1
	3250	3300	F2
	3300	3350	F3
	3350	3400	F4
F2	3400	3466.667	F5
	3466.667	3533.334	F6
	3533.334	3600.001	F7
F3	3600.001	3666.668	F8
	3666.668	3733.335	F9
	3733.335	3800.002	F10
F4	3800.002	3850.002	F11
	3850.002	3900.002	F12
	3900.002	3950.002	F13
	3950.002	4000.002	F14
F5	4000.002	4100.002	F15
	4100.002	4200.002	F16
F6	4200.002	4300.002	F17
	4300.002	4400.002	F18
F7	4400.002	4500.002	F19
	4500.002	4600.002	F20

c) 9 equal intervals

TABLE VI FREQUENCY DISTRIBUTION (9 INTERVAL)

FUZZY SETS	UPPER	LOWER	FREQUENCY
F1	3200	3355.325	3
F2	3355.325	3510.65	2
F3	3510.65	3665.975	2
F4	3665.975	3821.3	3
F5	3821.3	3976.625	4
F6	3976.625	4131.95	0
F7	4131.95	4287.275	3
F8	4287.275	4442.6	2
F9	4442.6	4600	1

Fuzzy sets are divided Frequency based partition

TABLE VII FREQUENCY BASED PARTITION (9 INTERVAL)

FUZZY SETS	UPPER	LOWER	NEW FUZZY SETS
F1	3200	3251.85	F1
	3251.85	3303.7	F2
	3303.7	3355.55	F3
F2	3355.55	3433.325	F4
	3433.325	3511.1	F5
F3	3511.1	3588.875	F6
	3588.875	3666.65	F7
F4	3666.65	3718.5	F8
	3718.5	3770.35	F9
	3770.35	3822.2	F10
F5	3822.2	3861.088	F11
	3861.088	3899.975	F12
	3899.975	3938.863	F13
	3938.863	3977.75	F14
F7	4133.3	4185.15	F15
	4185.15	4237	F16
	4237	4288.85	F17
F8	4288.85	4366.625	F18
	4366.625	4444.4	F19
F9	4444.4	4600	F20

Fuzzy sets are divided Frequency based partition

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TABLE VIII FREQUENCY BASED PARTITION (11 INTERVAL)

FUZZY SETS	UPPER	LOWER	NEW FUZZY SETS
F1	3200	3242.4233	F1
	3242.4233	3284.8467	F2
	3284.8467	3327.27	F3
F2	3327.27	3454.54	F4
F3	3454.54	3518.175	F5
	3518.175	3581.81	F6
F4	3581.81	3624.2333	F7
	3624.2333	3666.6567	F8
	3666.6567	3709.08	F9
F5	3709.08	3836.35	F10
F6	3836.35	3868.1675	F11
	3868.1675	3899.985	F12
	3899.985	3931.8025	F13
	3931.8025	3963.62	F14
F8	4090.89	4154.525	F15
	4154.525	4218.16	F16
F9	4218.16	4281.795	F17
	4281.795	4345.43	F18
F10	4345.43	4472.7	F19
F11	4472.7	4600	F20

Stage-3: Now, Fuzzify the data with Fuzzy Logic Relationships (FLR) mapping.

Once, the recurrence based partitioning has been derived, each partition is depicted as F (I), where (I) indicates the interval in which the value lies. The value of I is directly proportional to the output. For instance, in the event that we happen to examine data at 7 intervals, each partition would be denoted as below:

F1: VERY POOR YIELD

F2: POOR YIELD

F3: NOT SO GREAT YIELD

F4: AVERAGE PRODUCE

F5: GOOD YIELD

F6: VERY GOOD YIELD

F7: REMARKABLE YIELD

Hence, increase in (I) is correlated with higher yield of Rice produce and providing this relation would help the intended audience to easily understand what each interval signifies

After this classification, Fuzzy Logic Relationships (FLR) is built between each set of values, explained below:

Refer table 4;

In 1981, Yield = 3552 (has a place with F2)

In 1982, Yield = 4177 (has a place with F5)

In 1983, Yield = 3372 (has a place with F1)

In 1984, Yield =? (Let F be the interval of the respective value)

First order Fuzzy Logic relationship would appear as:

F6 ← F5

F4 ← F6

Furthermore, These Logical associations help us to predict the value of a specific year using the fuzzified values of past years. Similarly, a second order Fuzzy Logic relationship would look as:

F4 ← F6, F5

Which means that F4 stretch can be thought utilizing the earlier intervals of F6 and F5.

FLR 2ND Degree:

TABLE IX (5 INTERVALS)

YEAR	YEILD	FUZZY	FUZZY SETS	FLR RELATION	AVG
1981	3552	3564	F7	-	-
1982	4177	4145	F16	-	-
1983	3372	3396	F4	F4<-F16,F7	3854.5
1984	3455	3452	F5	F5<-F4,F16	3770.5
1985	3702	3676	F9	F9<-F5,F4	3424
1986	3670	3676	F9	F9<-F9,F5	3564
1987	3865	3865	F12	F12<-F9,F9	3676
1988	3592	3564	F7	F7<-F12,F9	3770.5
1989	3222	3228	F1	F1<-F7,F12	3714.5
1990	3750	3732	F10	F10<-F1,F7	3396
1991	3851	3865	F12	F12<-F10,F1	3480
1992	3231	3228	F1	F1<-F12,F10	3798.5
1993	4170	4145	F16	F16<-F1,F12	3546.5
1994	4554	4530	F20	F20<-F16,F1	3686.5
1995	3872	3865	F12	F12<-F20,F16	4337.5
1996	4439	4390	F19	F19<-F12,F20	4197.5
1997	4266	4285	F18	F18<-F19,F12	4127.5
1998	3219	3228	F1	F1<-F18,F19	4337.5
1999	4305	4285	F18	F18<-F1,F18	3756.5
2000	3928	3935	F13	F13<-F18,F1	3756.5

Similarly this table can be made for 7th, 9th and 11th intervals

FLR 3RD DEGREE:

TABLE X (5 INTERVALS)

YEAR	YEILD	FUZZY	FLR	AVG
1981	3552	3564	-	-
1982	4177	4145	-	-
1983	3372	3396	-	-
1984	3455	3452	F5<-F4,F16,F7	3701.7
1985	3702	3676	F9<-F5,F4,F16	3664.3
1986	3670	3676	F9<-F9,F5,F4	3508
1987	3865	3865	F12<-F9,F9,F5	3601.3
1988	3592	3564	F7<-F12,F9,F9	3739
1989	3222	3228	F1<-F7,F12,F9	3701.7
1990	3750	3732	F10<-F1,F7,F12	3552.3
1991	3851	3865	F12<-F10,F1,F7	3508
1992	3231	3228	F1<-F12,F10,F1	3608.3
1993	4170	4145	F16<-F1,F12,F10	3608.3
1994	4554	4530	F20<-F16,F1,F12	3746
1995	3872	3865	F12<-F20,F16,F1	3967.7
1996	4439	4390	F19<-F12,F20,F16	4180
1997	4266	4285	F18<-F19,F12,F20	4261.7
1998	3219	3228	F1<-F18,F19,F12	4180
1999	4305	4285	F18<-F1,F18,F19	3967.7
2000	3928	3935	F13<-F18,F1,F18	3932.7

Stage-4: Now, take the average of the midpoints of the fuzzified intervals

For example, in the second order FLR,

F4 ← F6, F5

If A is the midpoint of Interval F6 and B is the midpoint of Interval F5, then:

$C = (A + B)/2$

Where C is the midpoint of the fuzzy Interval F4

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Similarly, for third order FLR,

F ← F4, F6, F5

If A is the midpoint of range F6, B is the midpoint F5 and C is the midpoint of F4, then:

D = (A+ B + C)/3,

Where, D is mean of the year of prediction (1984).This Now would be utilized as a variable to Linear Regression Model, for complete defuzzification. Utilizing the outcome, we can compute the predicted value. Therefore the general equation looks as

Mean Fuzzified Value = (Sum of n previous fuzzy values)/ n

Where, n means FLR degree (2 or 3 in our model). Using above equation table 10 are computed for 5, 7, 9 and 11 second and third order FLR intervals.

Average Forecasting Error deficit (AFER)

$$AFER = \left(\sum_n^{i-1}\left(\left|A_i - F_i\right| / A_i\right)\right) / n * 100\%$$

Mean Squared Error (MSE).

$$MSE = \left(\sum_n^{i-1}(A_i - F_i)^2\right) / n$$

Where

A_i implies the actual production value

F_i implies the predicted value of year i

Linear

Y =mX + c

Y - Predicted value for a year

X - Numerical Value of the year (1981, 1982, 1983, 1984… so on).

Using figure 1, we have calculate the values for as each year and then Mean Squared Error (MSE)

FLR 2ND DEGREE:

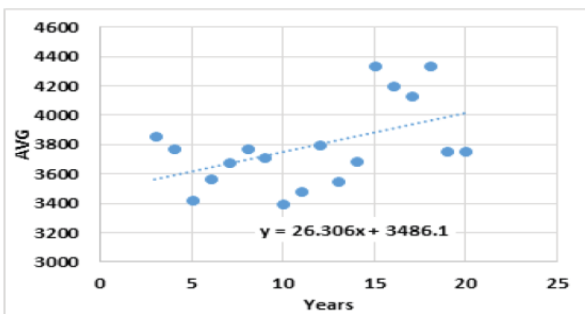

Fig. 1 (5 INTERVALS) refers. Table 10

RESULTS AND DISPUTE

The MSE and AFER as determined in 32 conditions have been broke down. We need to have toiled on second request fuzzy relationship and 0.33 request fuzzy logical relationship (FLR).Furthermore in each degree, we have also worked on 4 unique intervals, for example, fifth, seventh, ninth and eleventh stretches and among every stretch we have as of now have toiled on polynomial degree of order four.

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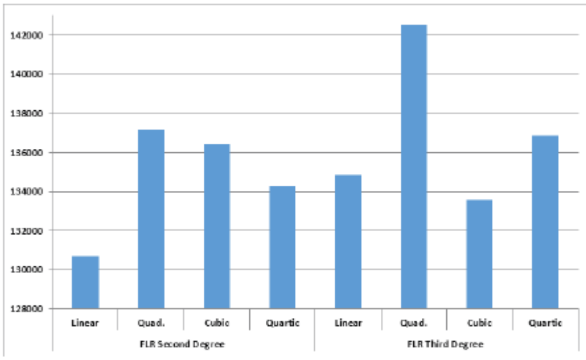


Fig. 2 Comparison among all degrees in 5 intervals.

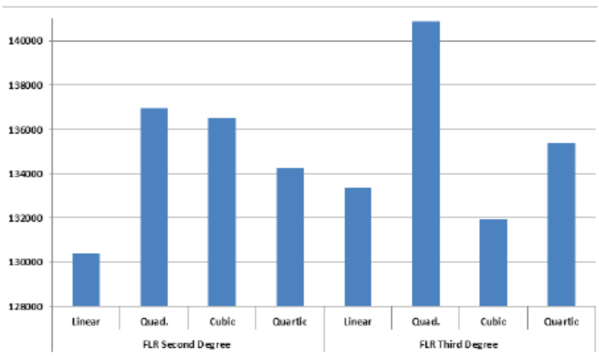


Fig. 3 Comparison among all degrees in 7 intervals

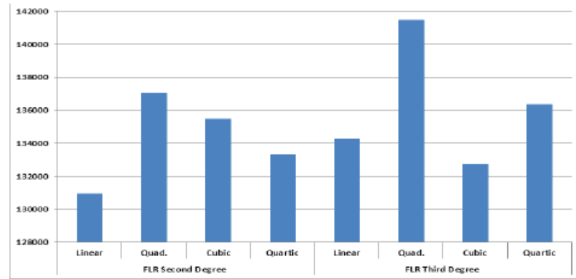
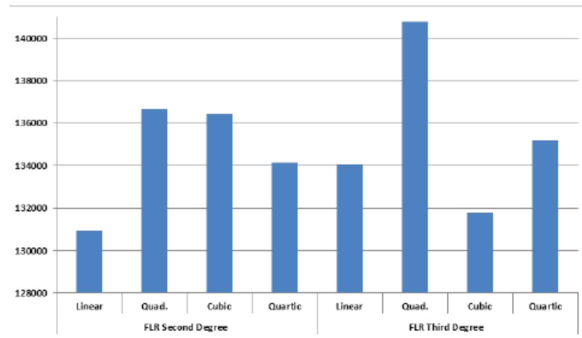


Fig. 4 Comparison among all degrees in 9 intervals.



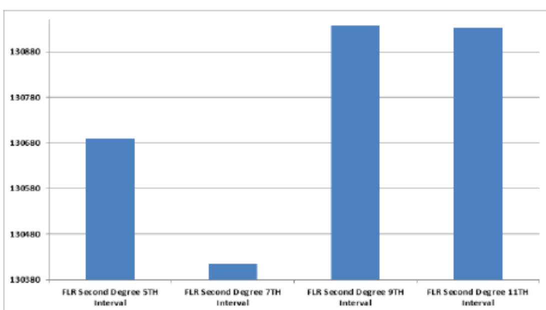


Fig. 6 Comparison among all intervals' best outcomes

To reduce the degree of error in our assessment and present everything through a comprehensible fashion we have compared all the values in a simple bar graph. As we can see in figure 2 demonstrates the correlation of Mean Squared Error (MSE) among all polynomial levels in second and third order fuzzy logical relationship (FLR) in the fifth span. From the figure it can be inferred that lowest MSE is achieved by linear second order FLR equation. Applying similar logic for each of the figures 2- 5 and comparing with figure 6, to decide the lowest MSE we found out that seventh interval of linear polynomial degree has the optimal result with MSE: 140619.2496

ROBUSTNESS

We have demonstrated the toughness of our calculation through haphazardly raising the creation estimations of some random year and we at that point determined the MSE using our algorithm. We elevated the produce of arbitrary years as 1992, 1994, 1996 and 1998 by 5.7% and the MSE has come out as 163521.69, which is fourteen percent higher to actual MSE. The variance between actual MSE and calculated MSE is negligible and this difference is due to the increased value of minimum and maximum values in the dataset by 5.7%, the entire universe

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of discourse has changed, on taking other produce values which are were not the maxima, the obtained MSE was almost constant. Likewise, on decreasing MSE by 5.7% in the equivalent 4 years, MSE was observed as 155619.56, which is just 11% inflated from actual MSE and is close to the actual MSE. In this manner we can infer that the proposed calculation is accurate and can be used to perform predictions in wide rang of datasets not only confined to rice production.

FUTURE SCOPE

We have recommended a procedure which utilizes Frequency based Partitioning. Then on, FLR is unquestionably used to fuzzify the data, subsequently to predictions, we have built up connections among the fuzzy intervals. Post regression analysis done by plotting the graphs between the Years (|used as 1,2,3,4... in this manner on), and the final predicted value from FLR. Thus, here regression analysis served as defuzzification method. Thus, values are predicted using proposed method. It has also been noticed that the proposed methodology would yield highly accurate MSE. Considering the long term scope of this work, this model is often extensible to multi-dimensional time series data. Another thought that we might want to work upon is to choose a different methodology to partition the Universe of Discourse. In future the new partitioning algorithm can be designed to produce more efficient predictions in comparison to the existing partition methods.

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