ADAPTATION OF A HYBRID FUZZY TIME SERIES TECHNIQUE FOR FORECASTING MINNA-BIDA HIGHWAY ACCIDENT DATA

[1]Alhassan Mohammed B., [2]Maina W. A. Tarfa [3]F. O. Anafi, [4]Cosmos A. Anle, [5]Shehu Mohammed Yusuf

[1,2,4]Nigerian Institute of Transport Technology (NITT), Zaria
[3,5]Department of Geography, Ahmadu Bello University, Zaria, Nigeria.
balarabealhassan@nitt.gov.ng

Abstract:

This paper improved the forecasting performance of Fuzzy Time Series (FTS) by incorporating Cat Swarm Optimization Clustering (CSO-C) and Particle Swarm Optimization (PSO) with FTS. In the three stages of FTS, clustering technique (CSO-C) was applied at the first stage (fuzzification) to objectively partition universe of discourse and eliminate the need for defining universe of discourse. At the second stage (determination of fuzzy relation), disambiguated fuzzy relations were obtained using Fuzzy Set Group (FSG). PSO was implemented at the last stage (defuzzification) to optimize by tuning weights assigned to fuzzy sets in a rule. Auto Regressive Integrated Moving Average (ARIMA) and Seasonal Auto Regressive Integrated Moving Average (SARIMA) are the most common methods used locally to forecast accident data. However, they are not applicable to every season even though they also yield a good result. Hybrid fuzzy time series method is applicable regardless of season. Minna-Bida highway data forecast gave a RMSE of 2.494 and MAPE of 0.386% while Yusuf et al (2015) gave RMSE of 2.894 and MAPE of 0.456%. It implies that; this method outperformed other conventional and non-conventional methods existing in literature using Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) as performance metrics.

Keywords: Forecasting, Fuzzy Time Series, Cat Swarm Optimization based Clustering, Particle Swarm Optimization, Road Traffic Accident.

1. Introduction

In business, estimation or calculation of what is imminent cannot be avoided (Singh, 2016). This is a concept that facilitates decision, planning and development in science, technology and engineering (Songh & Chissom, 1993). The rate at which information and technology is currently growing cannot be overemphasized. Hence, extensive use of data becomes unavoidable. Time series data is the most applicable form of data in use by researchers and technical analysts today.
As a problem-solving method and a tool for analysis, the edge Fuzzy Time Series (FTS) has over its equals is in terms of the ability to handle both numeric and linguistic time series data. Forecasting is an exercise in development that has application in every aspect of our lives; ranging from economy to technology including every aspect in between. In the context of economy, a more accurate forecasting result can help to improve a countries GDP and GNP, currency strength, job market, industrial expansion, inflation rate, interest rates and balance of payments.

The influence of technology has made forecast to produce new technical developments that could change how organizations operate. An example, in computing; is how the advent of transistors put conventional vacuum tubes totally out of business.

Contrary to traditional methods, Fuzzy time series forecasting is the application of linguistic mathematical reasoning to model and predict the future value of a variable from a time series historically presented or available in either numeric or imprecise form. FTS is a reliable method that deals with uncertainties in observations recorded over successive period. Not only that but also, restrictive assumptions and too much back ground knowledge of the forecast variable under consideration is not required.

Fuzzy time series forecasting was first introduced by Song and Chissom in 1993. FTS comprise of three stages namely; fuzzification, determination of fuzzy relationships (fuzzy inference) and defuzzification. In the fuzzification stage crisp observations are converted into linguistic values by identifying variations in the crisp data. In this first stage, determination of interval length is very important in partitioning the universe of discourse. In this work interval lengths were objectively obtained using Cat Swarm Optimization based Clustering (CSO-C),

define memberships that best explains the unknown structure of the observations; with these steps taken, there is no need to define of deriving future crisp forecasts from fuzzy forecasting rules. Then, fuzzy set group was introduced to eliminate recurrent fuzzy relationships. Finally, particle swarm optimization was utilized to assign weights to elements of forecasting rules and obtain defuzzified forecasts.

universe of discourse, in fuzzy time series forecasting. Defuzzification is the final stage in fuzzy time series forecasting. This is the process

The rest of the paper is presented as follows: a brief discussion of Cat Swarm Optimization based Clustering (CSO-C) and Particle Swarm Optimization (PSO) were explained in section 2. Section 3 discusses Fuzzy Time Series (FTS). Section 4 discusses the results obtained from the application of the proposed forecasting model to two data sets. Finally, the conclusion was presented in Section 6.

1.1. Particle Swarm Optimization

It was first introduced in 1995 by Kennedy and Eberhart (Kennedy and Eberhart 1995). PSO is a population-based evolutional algorithm that mimics the behaviour of birds flocking or fish grouping in search for the location of food (Eleruja et al., 2012). Particle Swarm Optimization (PSO) is in the class of evolutionary computation (EC) and it is related to genetic algorithm and evolutionary programming, (Kennedy & Eberhart, 1999). The only thing it needs is traditional mathematical operators and in terms of speed and memory requirement it is computationally economical, (Amjad et al., 2012). Empirically, it has been proven to be effective with different kinds of problems not only in the forecasting domain.

Problem optimization in PSO is achieved by having a population of candidate solution, in this process

dubbed particles are moved around within a search space in accordance with simple mathematical formula over the particles position. The particles are also guided towards the best-known position in the search space and are updated as better positions are found by other particles (Amjad et al., 2012).

2. Statement of the Problem

In Nigeria and the world at large, Road Traffic Crash (RTC) or Road Traffic Accident (RTA) is an issue of concern that accounts for over one million deaths in the world yearly. The World Health Organization (WHO) has classified road traffic accident as one of the top ten causes of death in the world, using International Statistical

Classification of Diseases (ICD) and Related Health Problems (Organization, 2013). The Global status report on road safety 2013 presents information on road safety from 182 countries, accounting for almost 99% of the world's population (Organization, 2013). The report indicates that worldwide, the total number of deaths due to road traffic remains unacceptably high at 1.24 million per year. However, only 28 countries, covering 7% of the world's population, have comprehensive road safety laws on five key risk factors: drinking and driving, speeding, failing to use motorcycle helmets, failing to use seat-belts, and child restraints (Organization, 2013). Cases of road traffic accident is increasing in recent years in Nigeria, due to nonchalant attitude of the government to road construction, and violation of traffic rules by motor users in the country. This shows that the causes of road traffic accident are multi-factorial, ranging from government factor (inability to construct motor able roads), drivers' factor (violating traffic rules; exceeding speed limit, using out-modelled cars, drinking or making mobile call while driving, etc.).

Road authorities, road designers and road safety practitioners need prediction tools; commonly known as accident prediction models (APMs) to improve road infrastructure safety management. It allows them to announce the potential safety issues, to identify safety improvements and to estimate the potential effect of these improvements in terms of crash reduction.

The accuracy of FTS forecasting result is affected by arbitrary decisions such as static interval lengths, parametric partitioning of universe of discourse at fuzzification level, and assigning weights to recurrent fuzzy rules. It has become necessary for an FTS forecasting technique that optimizes the partitions of universe of discourse into unequal interval length, deal with recurrent fuzzy rules and assigns optimal weights to elements of a forecasting rule. As a consequence, employing CSO-C algorithm in fuzzification, Fuzzy Set Groups (FSGs) to generate logical relationships and PSO algorithm in defuzzification will improve fuzzy time series forecasting accuracy.

Objectives

The objectives of the research are as follows:

i. To modify an FTS forecasting technique based on CSO-C and PSO.
ii. To apply the Improved FTS forecasting technique to forecast road traffic crash along Minna-Bida highway data set.
iii. To compare the results obtained using the improved hybrid forecasting technique with results obtained using the FCM based fuzzy time series technique and to validate using University of Maiduguri enrolment data, Minna-Bida highway accident data and monthly temperature data of Jigawa state.

3. Methods

Over decades, different methods have been used to improve FTS forecasting. The beauty in FTS forecasting is that regardless of the stage a researcher chooses to work upon, an appreciative reduction of error or increase in accuracy can be achieved in the FTS forecasting technique (Egrioglu *et al*, 2016). The complicated maximum minimum composition operation was replaced by a simplified arithmetic operation (Chen 1996), in order to achieve effective interval length, it is advisable to set the heuristic in a way that at least half the fluctuation in the time series will be reflected by the chosen lengths of intervals (Huarng 2001), population-based optimization algorithm; Cat Swarm Optimization Clustering (CSO-C) was utilized to avoid subjective judgments for determining the interval lengths while discrete weights assigned to fuzzy relation that occurred in the defuzzification process. Consequently, improved result was presented (Bas *et al.,* 2013), temporal information was utilized to partition the universe of discourse into intervals with unequal lengths through Gath-Geva clustering (Wang *et al.,* 2013), a hybrid FTS forecasting model with empirical mode decomposition to partition universe of discourse, three layer back propagation artificial neural network for the determination of fuzzy relation and particle swarm optimization to optimize the weights and threshold of bpANN (Huang and Wu, 2017), an adaptive FTS model for multivariate forecasting of Shanghai Stock Exchange; Cuckoo search was utilized to partition a training data set into unequal intervals. Then relationships were generated using Fuzzy Logic Relationship Group. The results showed an improvement in forecasting accuracy. However, computational complexities involved might make the model not work effectively for higher variable sets (FLRG) (Zhang *et al.,* 2017).

3.1 Cat Swarm Optimization based Clustering (CSO-C)

This algorithm was used to code the fuzzification module of the hybrid FTS forecasting model, so as to objectively determine interval length among other steps in the first stage. Cat Swarm Optimization for Clustering was first proposed by Santosa and Ningrum in 2009 (Bahrami *et al*., 2018). CSO-C is made up of two parts namely:

i) Clustering of data and
ii) Searching for the best cluster centre with the aid of CSO algorithm.

The following are inputs for clustering CSO:

i) Population of data to be used
ii) Number of clusters k
iii) Number of copies

The phases of CSO-C are described as follows:

Phase 1: Defining the initial cluster centre: In this phase, k point is chosen arbitrarily from the collected data in order to form the initial cluster centre.

Phase 2: Grouping data into clusters: Data is imputed into cluster with the closest cluster centre. Distance between data and cluster data can be obtained by (Bahrami *et al*., 2018):

$$d(x,y)=\|x-y\| = \sqrt{\sum_{i=1}^{n}(x_i-y_i)^2} \quad (1)$$

Phase 3: Calculating the Sum of Squared-Error (SSE): The fitness function of the algorithm can be obtained by:

$$SSE=\sum_{i=1}^{k}\sum_{x\in Di}(\|x-m_i\|^2) \quad (2)$$

Where:

$x = data,\ member\ of\ cluster\ D$

$m_i = cluster\ center\ i$

$k = number\ of\ cluster$

Phase 4: Clustering optimization with CSO: With regard to this algorithm, the cat is represented by a cluster centre, while the new cluster centre will be the solution set and is expected to come up with a smaller SSE value than before. A few adjustments are necessary in order to gain efficiency in the application of CSO to CSO-C. The adjustments are:

i. In order to allow every cat pass through the seeking and tracing mode; it becomes necessary to remove the Mixture Ratio (MR). Consequently, the time needed to find the best cluster centre will be reduced.
ii. If the value of CDC were always assumed to be 100% in the seeking mode, it will allow a change for every dimension of cat copy.

Phase 4.1: Seeking mode: The function of seeking mode is to enable the possession of the ability to search for best points around the cluster centres that have possibilities of attaining optimal fitness value. This is the reason that necessitated the need to define three parameters as outlined below:

i) Seeking Memory Pool (SMP): this will represent the number of copy a cluster have.

ii) Seeking Range of the Selected Dimension (SRD): this declares the mutative ratio, with a value between [0, 1].

iii) Self-Position Considering (SPC): it is a Boolean random value (Amjad *et al.*, 2012).

The algorithm for seeking mode in CSO-C is given as follows (Santosa & Ningrum, 2009):

1. Evaluation of the parameter of seeking mode which include; SMP, SRD, SPC
2. For i = 1 to k (number of clusters centre), do
   Copy cluster centre (i) position as many as SMP.
   Determine j value
   Compute the shifting value (SRD*cluster centre (i))
3. For m = 1 to SMP, do
   Addition or subtraction of cluster centres with shifting value is performed randomly.
   The output will be (SMP x k) cluster centre candidates
4. Compute the distance, sub classify data into clusters, and compute SSE
5. Choose a candidate to be the new cluster centre roulette wheel selection

Phase 4.2: Updating SSE and cluster centre

Comparison is carried out between the value(s) of SSE obtained from seeking mode with the previous value of SSE; if seeking SSE value is less than earlier SSE value then the cluster centre resulting from seeking will become the new cluster centre. Conversely, if the value of seeking SSE is greater than or equal to the value of earlier SSE, we use the previous cluster centre.

Phase 4.3: Tracing Mode: The aim of the tracing mode is to shift point of concentration to a better position for obtaining optimal fitness value.

The Tracing Mode algorithm for CSO Clustering is as follows (Bahrami *et al.*, 2018):

1. For i = 1 to k, do
   Update velocity (i)
   Update position (i),
   get the new cluster centre (i)
2. Calculate the distance, grouping data into clusters, and calculate SSE

Phase 4.4: Repeat step 4.2 for tracing SSE and cluster centre: The value of SSE obtained from tracing mode is then compared with the previous value of SSE; if tracing SSE is less than earlier SSE then the cluster centre resulting from tracing will become the new cluster centre. Conversely, if the value of tracing SSE is greater than or equal to earlier SSE, use the previous cluster centre.

Phase 5: Repeat phase 4 until it reaches the stopping criteria.

Table 3.1: CSO-C Parameters and Specifications

Parameters	Specifications
SMP	5
CDC	100%
SRD	0.2
Const1	2
r1	[0,1]
Velmax	0.9
Number of clusters	7
Maximum number of iterations	100

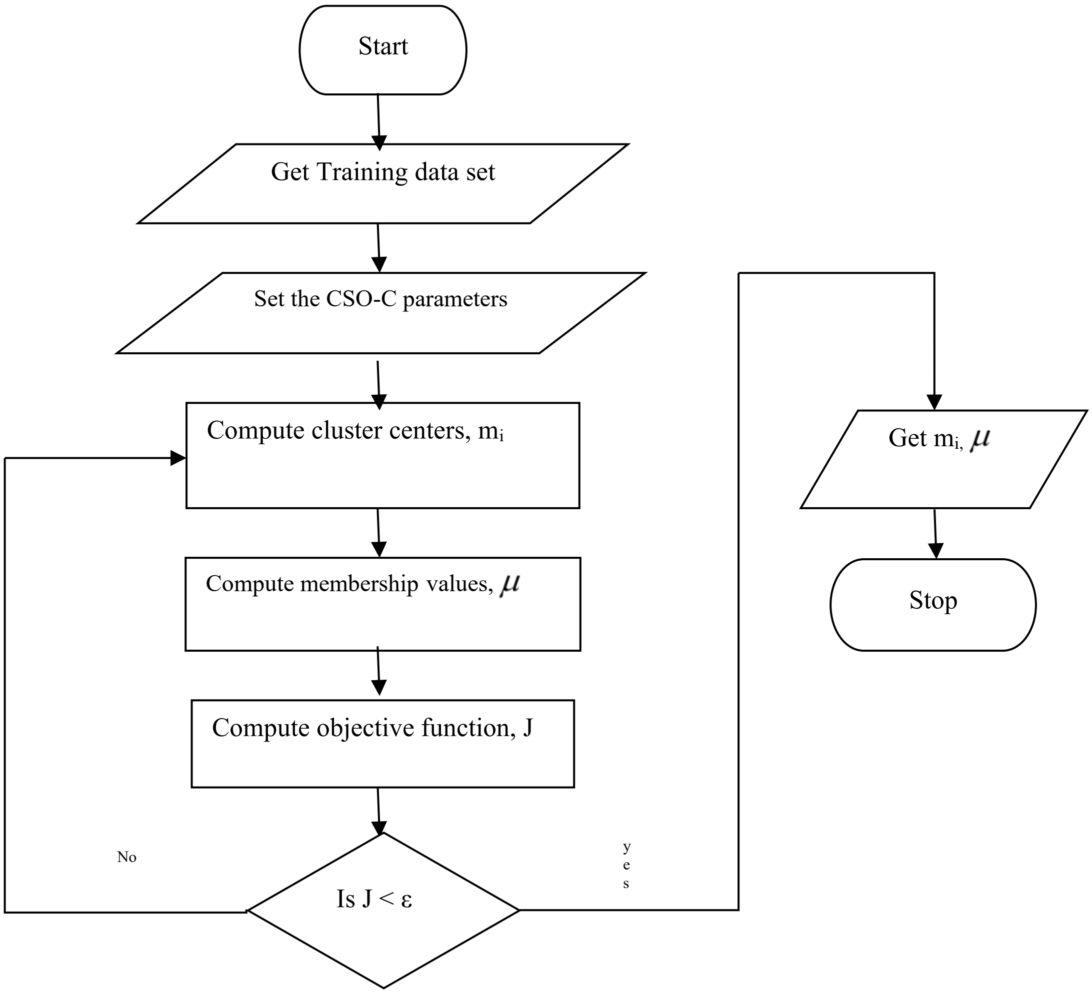

Fig 1. Flowchart of the CSO-C modification Module

3. Results and Discussions

The FTS forecasting modules were coded in MATLAB 2016a, on a laptop computer with Intel core i7-1065G7 CPU at 1.30GHz 1.50 GHz microprocessor, frequency speed rate (2.30 GHz) and Random-Access Memory (RAM) of 16.00 GB.

The main objective of this study is to increase forecasting accuracy by using CSO-C in the fuzzification stage of FTS to objectively and unequally determine interval lengths. PSO was integrated into the defuzzification stage to optimize the process by tuning the “if-then” rules as discussed earlier.

Table 4.1 below shows the shows the set of values for the PSO parameters used (Yusuf *et al*., 2015).

Table 4.1: The PSO parameters used

Parameters	Specifications
Swarm Size	5
Maximum Number of Iterations	500
Target Fitness Value as MSE	1
Min and Max Particles Position	[0,1]
Limited to	[-0.01,0.01]
Min. and Max. Vel. Range	2
Learning Factors C_1 and C_2	1.4
Inertial Coefficient, w	100
Maximum number of iterations	

In the course of application, so as to verify the performance of the proposed hybrid forecasting model, it was applied to two different time series data sets: yearly deaths in car road accidents in Belgium data set and enrollments at the University of Alabama data set. The obtained results were compared with the results obtained from other fuzzy time series models in the literature using Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE) as performance metrics which are mathematically represented as shown:

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{T}\left(x_t - \hat{x}_t\right)^2} \qquad (5)$$

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\frac{\left|x_t - \hat{x}_t\right|}{x_t}\times 100 \qquad (6)$$

For each time series observations, the decided CSO-C parameters are as shown in table 3.1.

The definitions of the PSO parameters are also shown in table 4.1.

4.1 Forecasting Car Road Accident in Belgium

In a bid to verify efficiency of the developed model, the first implementation was carried out on a time series data set of the observation in the occurrence of car road accident in Belgium. Table 4.2 presents the cluster centers and their corresponding linguistic values obtained in ascending order. The generated fuzzy set groups and optimal weights assigned to the content of the forecasting rules, for the observation set is shown in table 4.4. In addition, a comparative presentation of enrollments forecasts and respective RMSE and MAPE values for both the proposed method and some other methods are given.

Table 4.2: Cluster Centers and Defined Fuzzy Sets for Yearly Deaths from Road Accidents in Belgium

Cluster	Center	Fuzzy Set
m1	1172.10	A_4
m2	1380.00	A_5
m3	1432.00	A_6
m4	1478.10	A_6
m5	1574.06	A_6
m6	1616.00	A_7
m7	1644.00	A_6

4.2 Forecasting Enrollments at University of Alabama

The implementation of the developed model was also carried out on University of Alabama student enrollment time series standard data set. Table 4.3 shows the cluster centers and their corresponding linguistic values as obtained in ascending order. Table 4.5 presents the generated fuzzy set groups and optimal weights assigned to the contents of the forecasting rules for the enrollment observation sets. A comparative presentation of enrollments forecasts and the RMSE and MAPE values for the proposed methods and some other methods is given.

Table 4.3: Cluster Centers and Defined Fuzzy Sets for Students Enrollment in University of Alabama.

Cluster	Center	Fuzzy Set
m1	49.20	A_1
m2	52.20	A_2
m3	60.10	A_2
m4	63.50	A_3
m5	65.50	A_3
m6	68.10	A_3
m7	73.20	A_4

Table 4.4: Fuzzy Set Groups and Optimal Weights for Accidents in Belgium.

Data points	Maps	Optimal weight(s)
1	#, # $\rightarrow A_4$	#,#
2	#, $A_5 \rightarrow A_5$	#,#
3	$A_5, A_6 \rightarrow A_6$	0.022442, 0.977558
4	$A_5, A_6, A_7 \rightarrow A_6$	0.23847,0.0023311, 0.81188
5	$A_7, A_7 \rightarrow A_6$	0.98302, 0
6	$A_7, A_7, A_6 \rightarrow A_7$	0.47619, 0.28692, 0.25285
7	$A_7, A_6, A_7 \rightarrow A_6$	0.45287, 0.08873, 0.43831
8	$A_6, A_7, A_6 \rightarrow A_4$	0.93558, 0, 0
9	$A_7, A_6, A_5 \rightarrow A_3$	0.081525,0.041537, 0.89499
10	$A_6, A_5, A_5 \rightarrow A_3$	0.47014, 0.19109, 0.25047
11	$A_5, A_5, A_4 \rightarrow A_2$	0.34784, 0.14902, 0.44225
12	$A_5, A_5, A_4, A_4 \rightarrow A_4$	0.983841, 0, 0, 0.016159
13	$A_5, A_5, A_4, A_4, A_5 \rightarrow A_2$	0.42501,0, 0.5797, 0,0
14	$A_4, A_5, A_4 \rightarrow A_3$	0.21641, 0.7953, 0
15	$A_5, A_4, A_5 \rightarrow A_4$	0, 0.076319, 0.96584
16	$A_4, A_5, A_5 \rightarrow A_5$	0.46637, 0.40469, 0.25499
17	$A_5, A_5, A_6 \rightarrow A_4$	0.54514, 0.24358, 0.21717
18	$A_5, A_6, A_5 \rightarrow A_2$	0.69881, 0, 0.26337
19	$A_6, A_5, A_4 \rightarrow A_2$	0 , 0
20	$A_6, A_5, A_4, A_4 \rightarrow A_3$	0.32258,0.42598,0.13994,0.082344
21	$A_6, A_5, A_4, A_4, A_5 \rightarrow A_1$	0.0073059,0, 0.034287, 0.86937
22	$A_5, A_3 \rightarrow A_1$	0.15219, 0.73786
23	$A_3, A_1 \rightarrow A_1$	0.72378, 0.23485
24	$A_1, A_2 \rightarrow A_1$	0.044945, 0.955055
25	$A_1, A_2, A_3 \rightarrow A_1$	0.33401, 0.68015, 0

26	$A_3, A_2 \rightarrow A_1$	0.99895, 0.025133
27	$A_3, A_2, A_3 \rightarrow A_2$	0, 0.13372, 0.92348
28	$A_3, A_4 \rightarrow A_1$	0.93486, 0
29	$A_4, A_1 \rightarrow A_1$	0.34751, 0.50543
30	$A_1, A_1 \rightarrow A_1$	0.023115, 0.82616

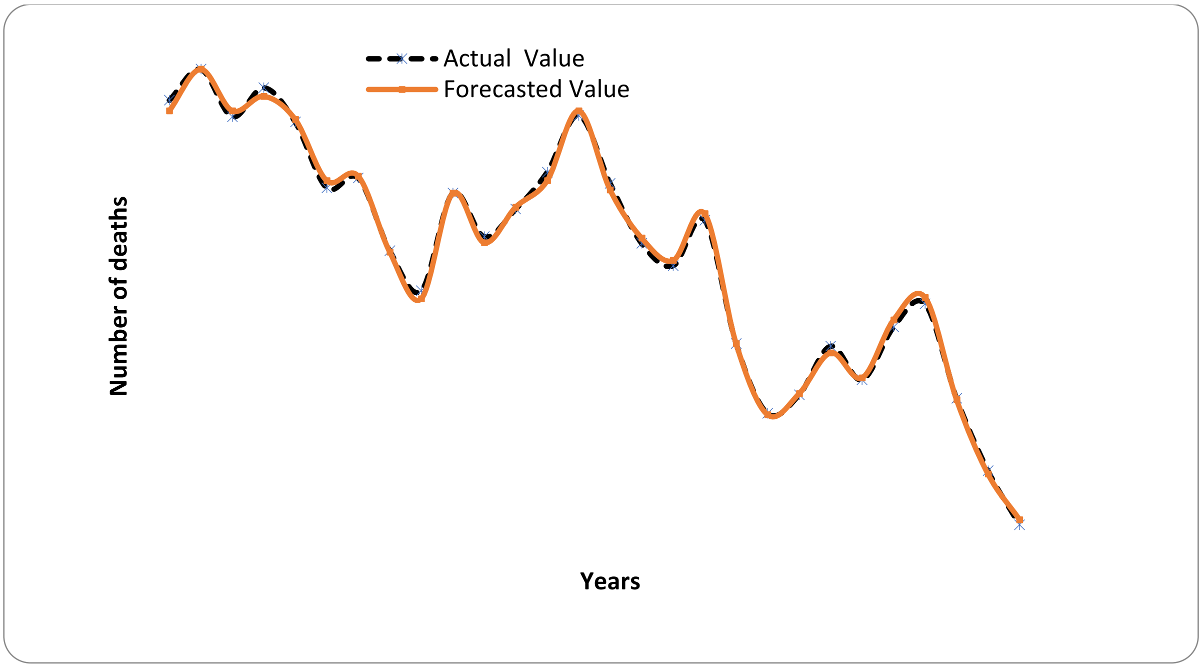

Figure 1: Graph of Forecasts of the Proposed Method and Actual Observations of Yearly Deaths from Accidents in Belgium

Table 4.5: Generated Fuzzy Set Groups and Optimal Weights for Enrollments

Data Points	Maps	Optimal Weight(S)
1	$\#, \# \rightarrow A_1$	#, #
2	$\#, A_1 \rightarrow A_2$	#, #
3	$A_1, A_1 \rightarrow A_2$	0 , 0.955055
4	$A_1, A_1, A_1 \rightarrow A_3$	0.85229, 0, 0.20749
5	$A_1, A_2 \rightarrow A_3$	0, 0.56155
6	$A_1, A_2, A_2 \rightarrow A_3$	0, 0.42887, 0.56148
7	$A_1, A_2, A_2, A_2 \rightarrow A_4$	0.9149, 0, 0, 0.18862
8	$A_2, A_3 \rightarrow A_4$	0.9743, 0.0257
9	$A_3, A_4 \rightarrow A_5$	0.052746, 0.947254
10	$A_3, A_4, A_6 \rightarrow A_5$	0, 0, 0.9743
11	$A_6, A_6 \rightarrow A_5$	0.21978, 0.74883
12	$A_6, A_5 \rightarrow A_3$	0.14587, 0.79113
13	$A_5, A_2 \rightarrow A_3$	0, 0.18867
14	$A_5, A_2, A_2 \rightarrow A_3$	0, 0.37964, 0.59998
15	$A_5, A_2, A_2, A_2 \rightarrow A_3$	0.80891, 0, 0
16	$A_2, A_2, A_2, A_2 \rightarrow A_4$	0, 0.033894, 0
17	$A_2, A_4 \rightarrow A_5$	0.95174, 0.13425
18	$A_2, A_4, A_6 \rightarrow A_6$	0.090562,0.28332,0.72234
19	$A_6, A_7 \rightarrow A_7$	0.090562,0.28332,0.72234

20	A_6, A_7, $A_7 \rightarrow A_7$	0.02116, 0, 0.97884
21	A_6, A_7, A_7, $A_7 \rightarrow A_7$	1,0, 0.085242, 0.042223
22	A_7, A_7, A_7, $A_7 \rightarrow A_7$	0, 0, 0.41191, 0.58313

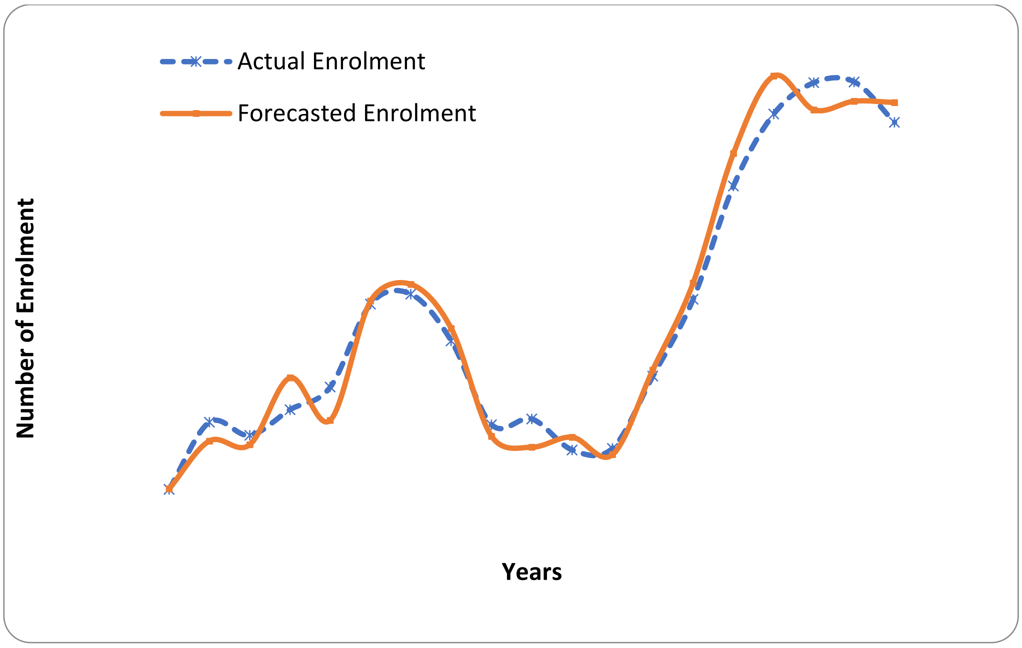

Figure 2: Graph of Forecasts of the Proposed Method and Actual Observations of Students Enrollment

Table 4.6: Cluster Centers and Defined Fuzzy Sets for Yearly Deaths from Road Accidents Mx-Bida Highway

Cluster	Center	Fuzzy Set
m1	1172.10	A_4
m2	1380.00	A_5
m3	1432.00	A_6
m4	1478.10	A_6
m5	1574.06	A_6
m6	1616.00	A_7
m7	1644.00	A_6

Table 4.7 Fuzzy Set Group and Respective Optimal Weights for RTA Minna-Bida Highway

Data Points	Maps	Optimal Weight(S)
1	#,# $\rightarrow A_1$	#, #
2	#, $A_1 \rightarrow A_1$	#, #
3	A_3, $A_3 \rightarrow A_4$	0.96888, 0.070553
4	A_3, A_3, $A_4 \rightarrow A_3$	0.02464, 0.22839, 0.00271
5	A_3, A_4, $A_3 \rightarrow A_4$	0.22839, 0.1745, 0.61559
6	A_4, A_3,$A_4 \rightarrow A_2$	0.96888, 0.31326, 0.61191

7	$A_4, A_2 \rightarrow A_3$	0.061413, 0.97133
8	$A_2, A_3 \rightarrow A_3$	0.013474, 0.98158
9	$A_2, A_3, A_3 \rightarrow A_4$	0.18357, 0.58789, 0.26039
10	$A_2, A_3, A_3, A_4 \rightarrow A_4$	0.230846, 0.042254, 0.070553
11	$A_3, A_4, A_4 \rightarrow A_3$	0.09823, 0.00237, 0.10643
12	$A_4, A_4, A_3 \rightarrow A_3$	0.09832, 0.36008, 0.61727
13	$A_4, A_3, A_3 \rightarrow A_3$	0.224562, 0.004632, 0.0084507
14	$A_3, A_3, A_3 \rightarrow A_2$	0.02245, 0.31325, 0.97183
15	$A_3, A_2 \rightarrow A_1$	0.49387, 0.44118
16	$A_2, A_1 \rightarrow A_1$	0.02321, 0.61559
17	$A_1, A_1 \rightarrow A_4$	0.11145, 0.042264
18	$A_1, A_4 \rightarrow A_6$	0.03267, 0.00256
19	$A_4, A_6 \rightarrow A_7$	0.01897, 0.027108
20	$A_6, A_7 \rightarrow A_4$	0.57553, 0.39372

Table 0.8 Improved Model Forecasts for Minna-Bida Highway RTA Data

Year	Minna-Bida HW(Actual value)	Minna-Bida HW (Forecast value)
2000	76	77
2001	94	79
2002	67	62
2003	66	61
2004	66	65
2005	42	40
2006	42	41
2007	39	44
2008	52	53
2009	50	48
2010	52	50
2011	61	59
2012	61	62
2013	62	62
2014	64	66
2015	58	57
2016	45	48
2017	43	44
2018	45	46
2019	42	41

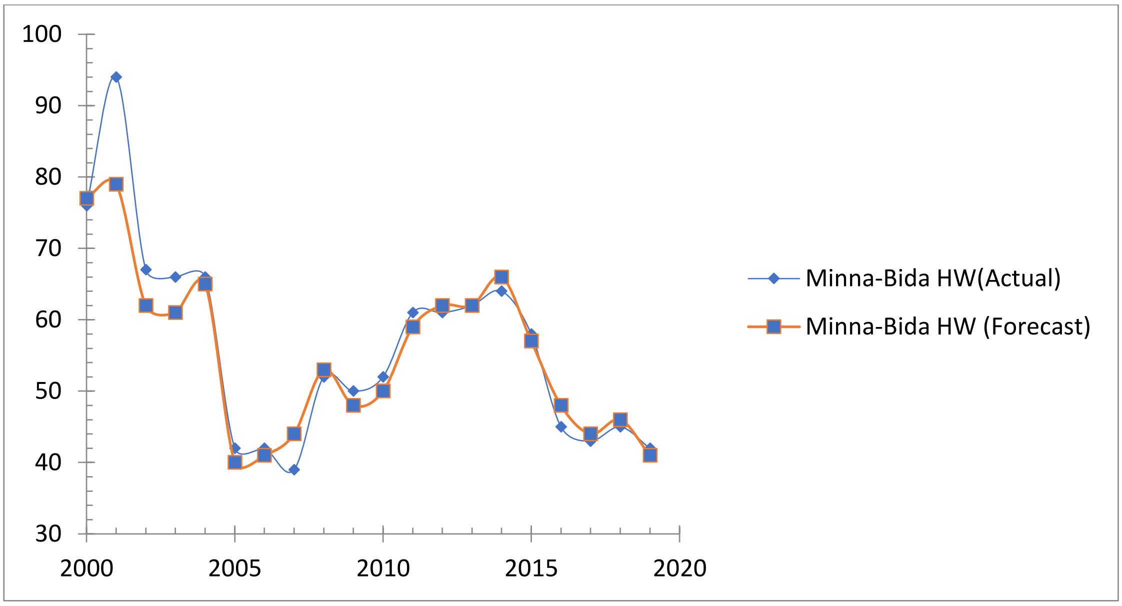

Figure 3: Graph of Forecasts of the Proposed Method and Actual Observations of Mx-Bida Highway Accident Data

Table 4.9: A Comparative Presentation of Yearly Deaths from Car Road Accidents Forecasts

Year	Actual	Egrioglu *et al* 2010	Jilani *et al* 2007	Uslu *et al* 2014	Yusuf *et al* 2015	Proposed Model
1974	1574		1497			
1975	1460		1497	1506		
1976	1536		1497	1453		1542
1977	1597	1500	1497	1598	1597	1588
1978	1644	1500	1497	1584	1643	1650
1979	1572	1500	1497	1584	1573	1560
1980	1616	1500	1497	1506	1633	1607
1981	1564	1500	1497	1584	1566	1572
1982	1464	1500	1497	1506	1464	1463
1983	1479	1500	1497	1453	1479	1487
1984	1369	1500	1497	1375	1369	1371
1985	1308	1400	1396	1383	1308	1315
1986	1456	1300	1296	1454	1457	1447
1987	1390	1500	1497	1453	1389	1390
1988	1432	1400	1396	1383	1432	1434
1989	1488	1400	1396	1509	1489	1484
1990	1574	1500	1497	1598	1574	1580
1991	1471	1500	1497	1506	1470	1462
1992	1380	1500	1497	1375	1380	1382
1993	1346	1400	1396	1383	1346	1338
1994	1415	1300	1296	1383	1414	1417

1995	1228	1400	1396	1231	1228	1229
1996	1122	1100	1095	1135	1065	1123
1997	1150	1200	1196	1180	1113	1148
1998	1224	1200	1196	1245	1223	1223
1999	1173	1200	1196	1135	1112	1177
2000	1253	1300	1296	1245	1212	1252
2001	1288	1300	1296	1284	1287	1288
2002	11445	1100	1095	1143	1146	1152
2003	1035	1000	995	970	1036	1041
2004	953	1000	995	970	954	945
	RMSE	85.35	83.12	41.61	19.2	5.931
	MAPE	5.25%	5.06%	2.29%	0.67%	0.34%

Adopted and modified from the work of (Yusuf *et al.,* 2015)

Table 4.10: Comparative Presentation of Enrollments Forecasts.

Year	Actual Enrollment	S&C 1993	Chen 1996	Huarng 2001	Huarng *et al* 2006	Uslu *et al* 2014	Yusuf *et al* 2015	Proposed Model
1971	13055							
1972	13563	14000	14000	14000	14242	13650		
1973	13867	14000	14000	14000	14242	13650	13873.3	13874
1974	14696	14000	14000	14000	14242	14836	14685	14701
1975	15460	15500	15500	15500	15474.3	15332	15465.6	15453
1976	15311	16000	16000	15500	15474.3	15447	15312.1	15307
1977	15603	16000	16000	16000	15474.3	15447	15600.7	15611
1978	15861	16000	16000	16000	15474.3	15447	15860	15860
1979	16807	16000	16000	16000	16146.5	16746	16813.5	16809
1980	16919	16813	16813	17500	16988.3	17075	16913.7	16921
1981	16388	16813	16813	16000	16988.3	16380	16389.9	16393
1982	15433	16789	16789	16000	16146.5	15457	15435.3	15430

1983	15497	16000	16000	16000	15474.3	15457	15508	15493
1984	15145	16000	16000	15500	15474.3	15457	15136.7	15150
1985	15163	16000	16000	16000	15474.3	15332	15174.3	15152
1986	15984	16000	16000	16000	15474.3	16027	15988.5	15985
1987	16859	16000	16000	16000	16146.5	16746	16860.9	16858
1988	18150	16813	16833	17500	16988.3	18211	18146.5	18162
1989	18970	19000	19000	19000	19144	19059	18979.3	18961
1990	19328	19000	19000	19000	19144	19059	19330.7	19340
1991	19337	19000	19000	19500	19144	19059	19348.4	19349
1992	18876		19000	19000	19144	19059	18887.4	18882
	RMSE	650	638	476	478	178	7.02	6.669
	MAPE	3.22%	3.11%	2.45%	2.20%	0.90%	0.04%	0.03%

Adopted and modified from the work of (Yusuf *et al.,* 2015)

Table 4.11: Comparative Presentation of Mx-Bida HW Accidents Forecasts.

Year	Minna-Bida HW (Actual value)	Minna-Bida HW (Yusuf *et al* FV)	Minna-Bida HW (Forecast value)
2000	76	72	77
2001	94	79	79
2002	67	60	62
2003	66	60	61
2004	66	67	65
2005	42	39	40
2006	42	42	41
2007	39	40	44
2008	52	53	53
2009	50	47	48
2010	52	53	50
2011	61	55	59
2012	61	58	62
2013	62	62	62
2014	64	68	66
2015	58	57	57

2016	45	48	48
2017	43	44	44
2018	45	46	46
2019	42	41	41

A close visual inspection of table 4.11 will show that Yusuf *et al's* model in comparison with the actual forecast value in year 2011forecasted 55 while actual value was 61. Similarly, at 2012 Yusuf *et al* model got 58 while actual forecast value was 61 and in 2014 when Yusuf *et al* model forecasted 68 the actual forecast value was 64. It should be noted that these are the points of aberration revealed in figure 4 below.

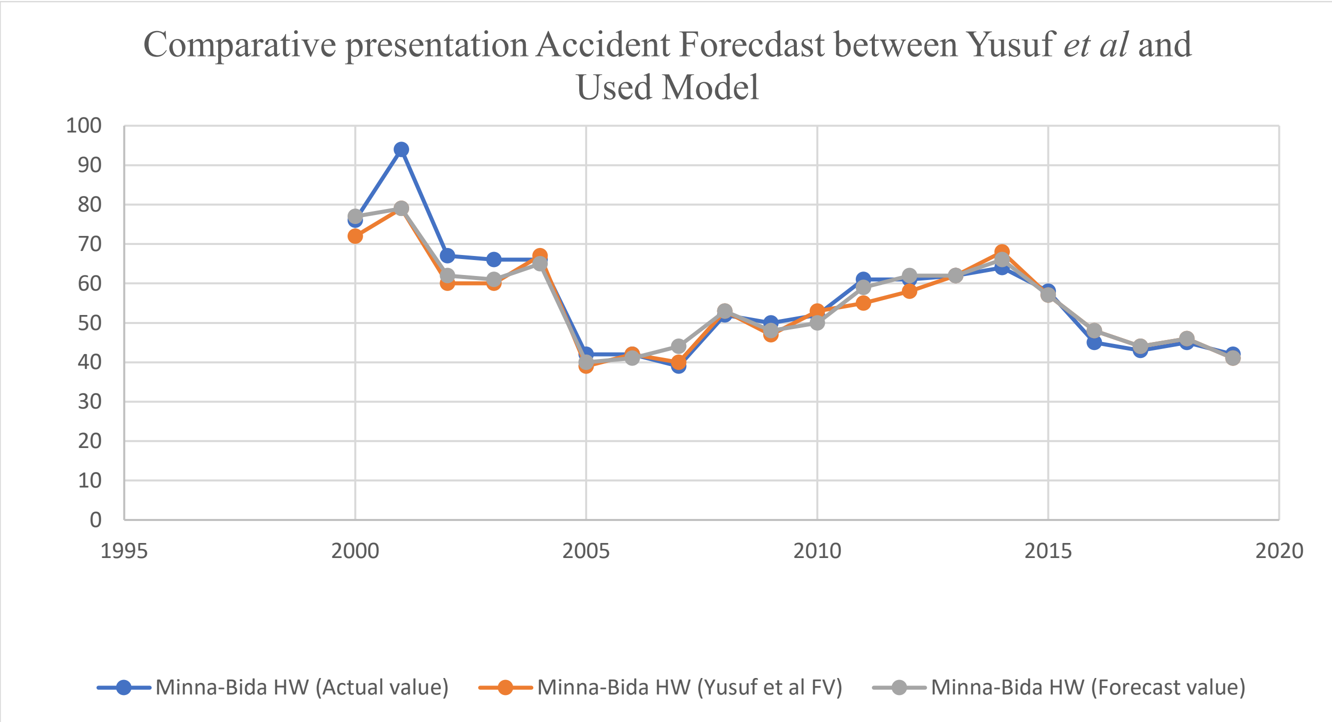

Figure 4: Graph of Forecasts of the Proposed Method and Yusuf *et al* in Comparison with Actual Observations of Mx-Bida Highway Accident Data

Figure 4 above is a graphical representation of actual forecast value, used model forecast value in comparison with Yusuf *et al* model forecast value. A close observation will show how both models follow actual pattern. However, Yusuf *et al* model pattern experienced a slight aberration from 2011 to 2014 which gradually picked up actual pattern from 2015 to 2019.

The datasets used in this work to train the modified model include: the Belgium road-traffic accident dataset, the University of Alabama enrollment dataset, the Jigawa temperature dataset, the University of Maiduguri enrollment dataset, the Taiwan future exchange (TAIFEX) dataset in order to forecast the Minna – Bida highway dataset. It is important to note that all of these datasets share a common characteristic; they are conceptually univariate in format.

6. Conclusion

Researchers' observation has revealed that, objective partitioning of universe of discourse and the use of optimization technique to improve both fuzzification and defuzzification stages of the FTS forecasting process brings about accuracy in obtained results. This study presented an improved hybrid FTS forecasting technique used to handle any form of univariate dataset. Cat Swarm Optimization based Clustering (CSO-C) algorithm was utilized to objectively partition the universe of discourse and learn membership in datasets, while Particle Swarm Optimization algorithm was utilized in assigning optimal weights to elements of a fuzzy rule at the defuzzification stage. Experimentally, the results obtained demonstrate that the proposed forecasting. In applying this technique on Minna-Bida highway data, an RMSE of 2.494 and MAPE of 0.386% was obtained. Relatively, the points on the plots followed a steady trend with the actual values for enrolment and temperature forecast respectively.

In a future development of forecasting model, it is necessary to consider other soft computing techniques that will be incorporated with FTS in order to form hybrid FTS techniques capable of handling errors caused by recurrence number of fuzzy relations and make objective choice of interval lengths.

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