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Time Series Prediction of Pregnant Women with COVID–19 in Mexico

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Abstract. This study focuses on the prediction of the daily number of pregnant women infected with SARS–CoV–2 in Mexico. In particular, we developed a Fuzzy Time Series Model (FTSM) from 910 historical observations. The accuracy of the proposed model was measured by the well–known Root Mean Square Error (RMSE) index. Specifically, our FTSM obtained a RMSE value of 34.45 units. This indicates that the forecasted values fit relatively well the real data. Thus, taking into account the empirical evidence, we conclude that the values forecasted by our FTSM are really close to the real values and could be helpful in medical decision–making.

Keywords: COVID–19, pregnant patients, fuzzy time series.

1 Introduction

Pregnant women constitute an important group of risk in the COVID–19 pandemic. This population group needs to take additional precautions due to the high risk of vertical transmission, that is, the transmission of SARS–CoV–2 from the mother to the offspring. Furthermore, the presence of diseases during pregnancy such as gestational diabetes mellitus or preeclampsia increase the risk of COVID–19 infection since the immune system might be weaken [8, 9].

To June 28, 2022, in Mexico there have been $50,303$ pregnant women infected with SARS–CoV–2 and 377 of these patients sadly passed away. In the literature, some works have been mainly focused on the maternal mortality [2, 6].

Due to the aforementioned issues, it is important to know in advance the estimated number of cases for the population group under study. The estimated number could be used by the Health Minister to make appropriate decisions to prevent, control and manage COVID–19 during pregnancy. In this paper we propose a Fuzzy Time Series Model (FTSM) to forecast the daily number of pregnant women with COVID-19 in Mexico.

The main motivation to use fuzzy logic is due to the successful applications in several domains reported in the literature [7, 5, 4]. The proposed FTSM uses the average–based method to partition the universe of discourse. We use the publicly available data from the Mexican Federal Government.

The data include the documented cases from the beginning of the pandemic to date. In order to assess our FTSM, we use the Root Mean Square Error (RMSE) index. The RMSE value for the proposed FTSM was 34.45 units. This value strongly suggest a high accuracy of the model.

The remainder of this paper is organized as follows. In Section 2 we utterly describe the proposed Fuzzy Time Series Model, including the data acquisition. Section 3 reports the empirical validation of the model. Finally, in Section 4 we present the conclusions of this research.

2 Forecasting Model

2.1 Time Series Computation

The Mexican Government maintains a website devoted to share information about the dynamics of the COVID–19 pandemic [6]. The information is updated on a daily basis and distributed in a CSV (comma–separated values) file. At the time of this research, the database contains over 16.7 millions of records.

In order to obtain the time series of interest, we computed the daily number of pregnant women infected with SARS–CoV–2 from January 1, 2020 to June 28, 2022. This computation gave us a time series consisting of 910 observations. Figure 1 shows the time series under study.

2.2 Universe of Discourse

In the context of fuzzy time series, the universe of discourse is the closed interval $U = [D_{\text{min}} - D_1,\ D_{\text{max}} + D_2]$, where D_{min} and D_{max} are the minimum and maximum values observed in the time series; and D_1 and D_2 are two positive numbers conveniently determined [3]. In this study, $D_{\text{min}} = 0$, $D_{\text{max}} = 660$, $D_1 = 0$ and $D_2 = 15$. Therefore, the universe of discourse considered for this study is $U = [0,\ 675]$.

2.3 Data Partitioning

The data partitioning consists in computing a collection of sub–intervals u_i (for $i = 1, 2, \ldots, n$) from the universe of discourse U. The sub–interval lengths can be of either equal or different size [1]. In this study we partition the universe of discourse with equally–sized sub–intervals. More precisely, we use the so–called average–based partition method [10]. This method is deterministic and operates in the following way.

The first step is to compute the average of the absolute differences between each pair of consecutive observations, that is:

$$\text{avg} = \left\lfloor \frac{|0-0| + |0-0| + \cdots + |251-77| + |224-251|}{909} \right\rfloor = \left\lfloor \frac{16,514}{909} \right\rfloor = 18.$$

Then, we have to divide the average by 2, i.e., $\text{half}_{\text{avg}} = \text{avg}/2 = 9$. As can be observed, the value of half_{avg} has one digit. In this case, the partition length ℓ must be the value of half_{avg}, that is, $\ell = 9$.

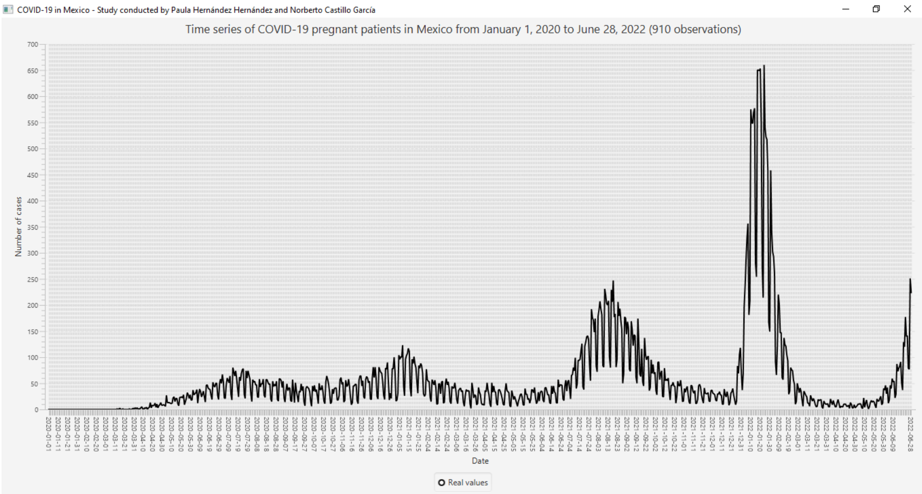

Fig. 1. Time series of pregnant women with COVID–19 in Mexico from January 1, 2020 to June 28, 2022.

The next step is to determine the number of sub–intervals n considering the bounds of the universe of discourse $U_{\text{min}} = 0$ and $U_{\text{max}} = 675$ as well as the lengths of the intervals $\ell = 9$ as follows:

$$n = \left\lfloor \frac{U_{\text{max}} - U_{\text{min}}}{\ell} \right\rfloor = \left\lfloor \frac{675}{9} \right\rfloor = 75.$$

This means that our FTSM will have $n = 75$ sub–intervals. The domain of each sub–interval is given by:

$$u_i = [U_{\text{min}} + (i-1) \times \ell,\ U_{\text{min}} + i \times \ell] \quad \forall i = 1, \ldots, n.$$

All the sub–intervals are shown in Table 1. Notice that the length of each sub–interval $u_1, \ldots, u_{75}$ has the same size ($\ell = 9$ units) and they cover the entire universe of discourse $U = [0,\ 675]$.

2.4 Fuzzification

The fuzzification consists in determining the fuzzy sets and their corresponding membership functions for the fuzzification model defined on the universe of discourse U. In this study, we adopt the approach proposed in [3], which exclusively uses triangular membership functions. Formally, triangular membership functions $T : U \to [0, 1]$ assign an element of the universe of discourse $x \in U$ to a real number between

Table 1. Sub–intervals of our Fuzzy Time Series Model.

$u_1 = [0,\ 9]$	$u_{20} = [171,\ 180]$	$u_{39} = [342,\ 351]$	$u_{58} = [513,\ 522]$
$u_2 = [9,\ 18]$	$u_{21} = [180,\ 189]$	$u_{40} = [351,\ 360]$	$u_{59} = [522,\ 531]$
$u_3 = [18,\ 27]$	$u_{22} = [189,\ 198]$	$u_{41} = [360,\ 369]$	$u_{60} = [531,\ 540]$
$u_4 = [27,\ 36]$	$u_{23} = [198,\ 207]$	$u_{42} = [369,\ 378]$	$u_{61} = [540,\ 549]$
$u_5 = [36,\ 45]$	$u_{24} = [207,\ 216]$	$u_{43} = [378,\ 387]$	$u_{62} = [549,\ 558]$
$u_6 = [45,\ 54]$	$u_{25} = [216,\ 225]$	$u_{44} = [387,\ 396]$	$u_{63} = [558,\ 567]$
$u_7 = [54,\ 63]$	$u_{26} = [225,\ 234]$	$u_{45} = [396,\ 405]$	$u_{64} = [567,\ 576]$
$u_8 = [63,\ 72]$	$u_{27} = [234,\ 243]$	$u_{46} = [405,\ 414]$	$u_{65} = [576,\ 585]$
$u_9 = [72,\ 81]$	$u_{28} = [243,\ 252]$	$u_{47} = [414,\ 423]$	$u_{66} = [585,\ 594]$
$u_{10} = [81,\ 90]$	$u_{29} = [252,\ 261]$	$u_{48} = [423,\ 432]$	$u_{67} = [594,\ 603]$
$u_{11} = [90,\ 99]$	$u_{30} = [261,\ 270]$	$u_{49} = [432,\ 441]$	$u_{68} = [603,\ 612]$
$u_{12} = [99,\ 108]$	$u_{31} = [270,\ 279]$	$u_{50} = [441,\ 450]$	$u_{69} = [612,\ 621]$
$u_{13} = [108,\ 117]$	$u_{32} = [279,\ 288]$	$u_{51} = [450,\ 459]$	$u_{70} = [621,\ 630]$
$u_{14} = [117,\ 126]$	$u_{33} = [288,\ 297]$	$u_{52} = [459,\ 468]$	$u_{71} = [630,\ 639]$
$u_{15} = [126,\ 135]$	$u_{34} = [297,\ 306]$	$u_{53} = [468,\ 477]$	$u_{72} = [639,\ 648]$
$u_{16} = [135,\ 144]$	$u_{35} = [306,\ 315]$	$u_{54} = [477,\ 486]$	$u_{73} = [648,\ 657]$
$u_{17} = [144,\ 153]$	$u_{36} = [315,\ 324]$	$u_{55} = [486,\ 495]$	$u_{74} = [657,\ 666]$
$u_{18} = [153,\ 162]$	$u_{37} = [324,\ 333]$	$u_{56} = [495,\ 504]$	$u_{75} = [666,\ 675]$
$u_{19} = [162,\ 171]$	$u_{38} = [333,\ 342]$	$u_{57} = [504,\ 513]$	–

zero and one according to Equation (1):

$$T(x;a,b,c) = \begin{cases} 0 & x \leq a, \\ \dfrac{x-a}{b-a} & a \leq x \leq b, \\ \dfrac{c-x}{c-b} & b \leq x \leq c, \\ 0 & x \geq c. \end{cases} \tag{1}$$

In the piecewise function of Equation (1), parameters a and b define the points in U where the function T reaches its lowest value: zero. Furthermore, parameter b represents the point in U where T reaches its largest value: one. Typically, this parameter is placed in the middle of the membership function, i.e., $b = (a+c)/2$.

The fuzzification model adopted in this research considers $n + 1 = 76$ fuzzy sets to entirely cover the universe of discourse. Each fuzzy set $A_1, \ldots, A_{76}$ has a corresponding triangular membership function $T_{A_1}, \ldots, T_{A_{76}}$ with its own parameter values. Table 2 shows the parameter values for each membership function.

With the fuzzification model fully defined, the next step consists in fuzzifying all of the 910 observations of the time series. The fuzzification process is performed by computing the degrees of membership of all the observations to each fuzzy set according to Equation (1). Thus, each observation belongs to fuzzy sets $A_1, \ldots, A_{76}$ with a certain level of membership. The observations are fuzzified to the fuzzy sets for which their level of membership is maximum [10]. Mathematically:

$$A_j^{\star} = \underset{A_i:\ i=1,\ldots,76}{\arg\max} \{\mu_{A_i}(Y(t))\} \qquad \forall t = 1, \ldots, 910,$$

Table 2. Parameter values for the triangular membership functions $T_{A_1}, \ldots, T_{A_{76}}$.

T_{A_j}	a	b	c	T_{A_j}	a	b	c	T_{A_j}	a	b	c
T_{A_1}	-18	0	18	$T_{A_{27}}$	216	234	252	$T_{A_{53}}$	450	468	486
T_{A_2}	-9	9	27	$T_{A_{28}}$	225	243	261	$T_{A_{54}}$	459	477	495
T_{A_3}	0	18	36	$T_{A_{29}}$	234	252	270	$T_{A_{55}}$	468	486	504
T_{A_4}	9	27	45	$T_{A_{30}}$	243	261	279	$T_{A_{56}}$	477	495	513
T_{A_5}	18	36	54	$T_{A_{31}}$	252	270	288	$T_{A_{57}}$	486	504	522
T_{A_6}	27	45	63	$T_{A_{32}}$	261	279	297	$T_{A_{58}}$	495	513	531
T_{A_7}	36	54	72	$T_{A_{33}}$	270	288	306	$T_{A_{59}}$	504	522	540
T_{A_8}	45	63	81	$T_{A_{34}}$	279	297	315	$T_{A_{60}}$	513	531	549
T_{A_9}	54	72	90	$T_{A_{35}}$	288	306	324	$T_{A_{61}}$	522	540	558
$T_{A_{10}}$	63	81	99	$T_{A_{36}}$	297	315	333	$T_{A_{62}}$	531	549	567
$T_{A_{11}}$	72	90	108	$T_{A_{37}}$	306	324	342	$T_{A_{63}}$	540	558	576
$T_{A_{12}}$	81	99	117	$T_{A_{38}}$	315	333	351	$T_{A_{64}}$	549	567	585
$T_{A_{13}}$	90	108	126	$T_{A_{39}}$	324	342	360	$T_{A_{65}}$	558	576	594
$T_{A_{14}}$	99	117	135	$T_{A_{40}}$	333	351	369	$T_{A_{66}}$	567	585	603
$T_{A_{15}}$	108	126	144	$T_{A_{41}}$	342	360	378	$T_{A_{67}}$	576	594	612
$T_{A_{16}}$	117	135	153	$T_{A_{42}}$	351	369	387	$T_{A_{68}}$	585	603	621
$T_{A_{17}}$	126	144	162	$T_{A_{43}}$	360	378	396	$T_{A_{69}}$	594	612	630
$T_{A_{18}}$	135	153	171	$T_{A_{44}}$	369	387	405	$T_{A_{70}}$	603	621	639
$T_{A_{19}}$	144	162	180	$T_{A_{45}}$	378	396	414	$T_{A_{71}}$	612	630	648
$T_{A_{20}}$	153	171	189	$T_{A_{46}}$	387	405	423	$T_{A_{72}}$	621	639	657
$T_{A_{21}}$	162	180	198	$T_{A_{47}}$	396	414	432	$T_{A_{73}}$	630	648	666
$T_{A_{22}}$	171	189	207	$T_{A_{48}}$	405	423	441	$T_{A_{74}}$	639	657	675
$T_{A_{23}}$	180	198	216	$T_{A_{49}}$	414	432	450	$T_{A_{75}}$	648	666	684
$T_{A_{24}}$	189	207	225	$T_{A_{50}}$	423	441	459	$T_{A_{76}}$	657	675	693
$T_{A_{25}}$	198	216	234	$T_{A_{51}}$	432	450	468	–	–	–	–
$T_{A_{26}}$	207	225	243	$T_{A_{52}}$	441	459	477	–	–	–	–

where:

- $Y(t)$ stands for the observation at time t in the time series,
- $\mu_{A_i}(Y(t))$ is the degree of membership of $Y(t)$ to fuzzy set A_i, and
- $A_j^\star$ represents the fuzzy set for which the membership level of $Y(t)$ is the largest.

Given the large number of observations in the time series, we only show the first and last five fuzzified observations in Table 3.

2.5 Fuzzy Logical Relationships

The fuzzy logical relationship $A_i \to A_j$ establishes the following. If the value at time $t-1$ is A_i then the value at time t is A_j. Thus, in this fuzzy rule, A_i is the antecedent and A_j is the consequent. In order to obtain the fuzzy logical relationships (FLRs) for our FTSM, we must relate all consecutive pair of fuzzified observations. For instance, the fuzzy logical relationship of observations $Y(906)$ and $Y(907)$ is $A_{17} \to A_{10}$ (see Table 3).

Table 3. First and last five fuzzified values of the time series under study.

t	$Y(t)$	fuzzy set	t	$Y(t)$	fuzzy set
1	0	A_1	906	141	A_{17}
2	0	A_1	907	79	A_{10}
3	0	A_1	908	77	A_{10}
4	0	A_1	909	251	A_{29}
5	0	A_1	910	224	A_{26}

Table 4. First and last four fuzzy logical relationships for the time series under study.

$A_1 \rightarrow A_1$	$A_1 \rightarrow A_1$	$A_1 \rightarrow A_1$	$A_1 \rightarrow A_1$	$\cdots$
$\cdots$	$A_{17} \rightarrow A_{10}$	$A_{10} \rightarrow A_{10}$	$A_{10} \rightarrow A_{29}$	$A_{29} \rightarrow A_{26}$

Since there are 910 observations, there will be 909 FLRs. Due to the large number of relations, we show the first and last four FLRs for our fuzzy time series model in Table 4.

Sometimes when dealing with large time series, there are $k > 1$ fuzzy logical relationships with the same antecedent, i.e., $A_i \rightarrow A_{j1}, A_i \rightarrow A_{j2}, \ldots, A_i \rightarrow A_{jk}$. In this case, the k fuzzy logical relationships can be grouped into one single fuzzy logical relationship group (FLRG), that is, $A_i \rightarrow A_{j1}, A_{j2}, \ldots, A_{jk}$.

For example, from Table 4 we can observe that $A_{10} \rightarrow A_{10}$ and $A_{10} \rightarrow A_{29}$. In this example both relations have the same antecedent (A_{10}). Thus, the (incomplete) FLRG for this antecedent is $A_{10} \rightarrow \cdots, A_{10}, A_{29}$. In fact, this group has 28 fuzzy sets in its consequent. It is important to mention that there will be one group for each fuzzy set $A_1, \ldots, A_{76}$.

Therefore, our FTSM has 76 FLRGs. Due to the large numbers of groups and fuzzy sets in their consequent, we only show 15 FLRGs in Table 5. Notice that some groups do not have any fuzzy set in their consequent (e.g., Group 70), some groups have one fuzzy set (e.g., Group 19), and some groups have two or more fuzzy sets (e.g., Group 12).

2.6 Defuzzification and Accuracy

Defuzzification obtains a crisp value from a fuzzy value. In the context of fuzzy time series models, defuzzification computes the forecasted value from the fuzzy logical relationship groups. In this study, we use the three principles proposed by Chen [3]:

1. If the fuzzy logical relationship has exactly one fuzzy set in the consequent, i.e., $A_i \rightarrow A_j$, then the output value is the middle point of A_j.
2. If the fuzzy logical relationship has $k \geq 2$ fuzzy sets in the consequent, i.e., $A_i \rightarrow A_{j1}, \ldots, A_{jk}$, then the output value is the average of the middle points of the fuzzy sets in the consequent.
3. If the fuzzy logical relationship does not have any fuzzy set in the consequent, i.e., $A_i \rightarrow \emptyset$, then the output value is the middle point of the antecedent A_i.

In order to illustrate the defuzzification process under the previous principles, let us consider three different scenarios, one for each principle.

The first scenario consists in predicting the number of pregnant women with COVID–19 on January 30,2022 (forecasted output) knowing that there were 166 pregnant women positive for COVID–19 on January 29, 2022.

Table 5. Some fuzzy logical relationship groups for the time series under study.

	$\vdots$
Group 12:	$A_{12} \to A_9, A_{12}, A_{12}, A_{15}, A_{12}, A_{13}, A_{11}, A_{11}, A_5, A_{13}, A_{10}, A_{24}, A_{12}, A_{12}, A_5, A_9$
Group 13:	$A_{13} \to A_{12}, A_{14}, A_6, A_{15}, A_{12}, A_{14}, A_{11}$
Group 14:	$A_{14} \to A_{13}, A_{15}, A_7, A_9, A_{25}, A_{13}, A_{21}$
Group 15:	$A_{15} \to A_6, A_6, A_{16}, A_{17}, A_9, A_{14}, A_{14}$
Group 16:	$A_{16} \to A_{17}, A_{11}, A_{13}, A_{15}$
Group 17:	$A_{17} \to A_{16}, A_{20}, A_{20}, A_{17}, A_8, A_{17}, A_8, A_{17}, A_{10}$
Group 18:	$A_{18} \to A_7, A_{10}, A_{15}, A_{52}$
Group 19:	$A_{19} \to A_{18}$
	$\vdots$
Group 70:	$A_{70} \to \emptyset$
Group 71:	$A_{71} \to \emptyset$
Group 72:	$A_{72} \to \emptyset$
Group 73:	$A_{73} \to A_{73}, A_{73}, A_{74}$
Group 74:	$A_{74} \to A_{62}, A_{61}$
Group 75:	$A_{75} \to \emptyset$
Group 76:	$A_{76} \to \emptyset$

Firstly, we must fuzzify the crisp value $Y(760) = 166$. The fuzzy set associated to this observation is A_{19} since the degree of membership $\mu_{A_{19}}(166) = 0.778$ is the largest. According to Table 5, the FLRG for A_{19} (Group 19) has one fuzzy set in the consequent: A_{18}. Thus, the first principle must be applied.

This principle states that the forecasted value is the middle point of A_{18}, which is the value of parameter b for $T_{A_{18}}$ (see Table 2). Therefore, the forecasted output is 153. It is important to mention that the actual value is $Y(761) = 149$. Thus, the predicted output had an absolute error of only 4 units.

In the second scenario we consider observation $Y(751) = 653$ corresponding to January 20, 2022. The fuzzy set associated to this observation is A_{74} since $\mu_{A_{74}}(653) = 0.778$ is the largest. In this case the FLR to be used is $A_{74} \to A_{62}, A_{61}$ (Group 74). Since the consequent has two fuzzy sets, the second principle applies. Thus, the forecasted output is the average of the middle points of A_{62} and A_{61}, which is $\lfloor(549 + 540)/2\rfloor = 544$. Therefore, our FTSM predicts 544 pregnant women positive for COVID–19 on January 21, 2022. According to official data, the actual value is $Y(752) = 552$, which implies a relatively low error of 8 units.

Finally, in the third scenario we consider a hypothetical observation $x = 619$. This observation belongs to fuzzy set A_{70} with the maximum degree of membership, i.e., $\mu_{A_{70}}(619) = 0.889$. The fuzzy logical relationship to be used is $A_{70} \to \emptyset$ (Group 70).

Notice that there is no any fuzzy set in the consequent, and hence, the third principle applies. According to this principle, the forecasted output is the middle point of A_{70}. Therefore, the predicted number of pregnant women with COVID–19 for the following day is 621. Any prediction of time series can be assessed in terms of its accuracy.

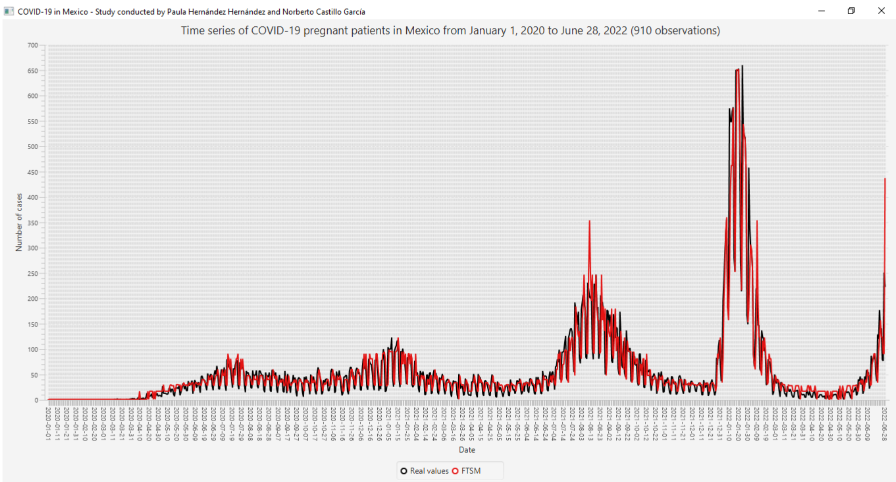

Fig. 2. Real values (black) against forecasted values (red) of the daily number of pregnant women with COVID–19 in Mexico (RMSE = 34.45).

In this paper, we assess the accuracy of our proposed Fuzzy Time Series Model by means of the well–known Root Mean Square Error (RMSE) according to Equation (2):

$$\text{RMSE} = \sqrt{\frac{\sum_{t=1}^{T}\left(Y(t) - \widehat{Y}(t)\right)^2}{T}}, \tag{2}$$

where:

– $Y(t)$ represents the value observed at time t in the time series (real value),
– $\widehat{Y}(t)$ stands for the value forecasted by the FTSM for time t, and
– T is the number of paired values (real and forecasted).

It is important to mention that low values of RMSE indicate a good accuracy while high values denote a poor accuracy.

3 Model Validation and Discussion

Our Fuzzy Time Series Model (FTSM) was implemented in Java (JDK 1.8.0_121) and executed on a workstation with an AMD Ryzen Threadripper 3960X 24–Core Processor at 3.80 GHz and 128 GB of RAM. Figure 2 depicts the actual and forecasted values for the time series under study.

From Figure 2, we can observe that the forecasted values fit relatively well to the original time series. This observation is numerically consistent with the RMSE value (34.45 units). This value is low since it is closer to the minimum RMSE value than the maximum. The minimum RMSE value is zero and is obtained when each pair of observations have the same value, i.e., $Y(t) = \widehat{Y}(t)$ for all t.

The maximum value is obtained when all the forecasted values are equal to the lower bound of the universe of discourse, i.e., $\widehat{Y}(t) = 0$ for all t. Thus, the maximum possible RMSE value for this time series is 103.08. Clearly, the RMSE value of our model is low, and hence, it has good accuracy.

4 Conclusions

In this paper, we developed a Fuzzy Time Series Model (FTSM) to forecast the daily number of pregnant women who tested positive for COVID–19 in Mexico. The raw data were collected from the official web site of the Mexican Government. The time series was obtained by computing the daily number of pregnant women with COVID–19 in Mexico from January 1, 2020 to June 28, 2022, totaling 910 observations.

The proposed FTSM uses the average–based method to partition the universe of discourse and the three principles of Chen to perform the defuzzification process. Our forecasting model was implemented in Java and its accuracy was assessed by the Root Mean Square Error (RMSE).

Our model obtained a RMSE value of 34.45 units. This value is low and therefore the accuracy of the model is high. According to the empirical results, we conclude that the FTSM proposed in this research produces reliable predictions and could be used in benefit of the important group of risk studied here.

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