WATER CONSUMPTION PREDICTION USING FUZZY TIME SERIES - A CASE STUDY IN PRIVATE COMPANY OF TANGERANG DISTRICT INDONESIA

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Abstract

Consumption of water in the Tangerang Regency continuously increases from year to year due to the increasing population and birth rates an average increase of 3% every year. So, the water demand prediction to be important to meet customer or community needs. The private water utility company needs to use a new method for predicting future monthly water consumption values and improves accuracy when forecasting time series using a visibility graph and presents to make more accurate predictions. In this study, we aim to measure the trend analysis volume of water consumption prediction by Fuzzy Time Series versus actual usage volume. Fuzzy Time Series (FTS) is a concept plan method that uses fuzzy logic that is able to provide predictions (estimates) of time series data analysis for the next several periods. Mean Absolute Percentage Error (MAPE) is obtained for different configurations of the input sets and of the FTS model structure. From the results of the average value error accuracy was only 4.5% using FTS Chen Method and included in the low category and water consumption actual versus prediction with the FTS Chen method shown related stable.

Keywords*: water consumption; water demand; fuzzy time series; MAPE; FTS Chen method; forecasting*

1. Introduction

Estimation future of water consumption is the most important for the planning of a regional water-supply system. Furthermore, the planning of operating water the distribution system with adequate water quality in volume at a reasonable pressure and a reliable so that an increase of satisfying consumer demand (Zhou, McMahon, Walton, & Lewis, 2002). Increasing population, as well as economic and industrial activities in Tangerang Regency, especially in 8 Sub-districts, needs to be supported by an adequate clean water provision and services. The limited supply and service of clean water in those sub-district areas has led to excessive groundwater exploitation, causing high economic costs and declining environmental quality.

Based on the interview of the internal clerk the consumption of water in the Tangerang Regency in continually to increase from year to year due to the increasing population and birth rates in the area. And based on Central Bureau of Statistics that number of population by Sub district with an average increase of 3% every year. Forecasting can be basic for short-term planning and to be required to minimize the errors in it. Models forecasting for water utility or water consumption have been developed and implemented towards the needs of one-day-ahead. For the short-term forecast such as Artificial Neural Networks and Econometric models with simulation or scenario-based forecasting tends to be used for long-term strategic decisions. (Donkor, Mazzuchi, Soyer, & Alan Roberson, 2014)

For the water demand forecast, various methods have been developed and tested. Water consumption can be done based on the base consumption, seasonal consumption. And evaluated with and without using weather inputs, in order to assess the performance improvement of using weather data (Bakker, Van Duist, Van Schagen, Vreeburg, & Rietveld, 2014). Several research prediction of water demand such as a new hybrid approach based on structure optimization learning algorithm for Fuzzy Cognitive Maps (FCM), Artificial Neural Network (ANN) (Jenitha, 2017; Papageorgiou, Poczęta, & Laspidou, 2016). Using an FCM learning algorithm to Prediction capabilities in the problem of water demand forecasting by calculating the known prediction errors (Papageorgiou et al., 2016). Multivariate analysis methods such as ARIMA, ANN, winters, and hybrid were applied for urban water demand forecasting of the island of Skiathos (Kofinas, Mellios, Papageorgiou, & Laspidou, 2014; Laspidou, 2014). The other paper using ANN (Artificial Neural Network) and Multiple Linear Regression (MLR) combined with MAPE for the future daily forecast of water consumption and humidity forecast(Piasecki,

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Jurasz, & Kaźmierczak, 2018). Combine method of ANFIS and Mamdani fuzzy inference system (MFIS) models and can be successfully applied for prediction of water consumption time series (Firat, Turan, & Yurdusev, 2009)

To predict water demand using several methods, one the so-called fuzzy time series (FTS) where this method is usually used for predicting data with the historical of water consumption (Cai, Zhang, Wu, & Leung, 2013). PDAM Malang Using the method of Fuzzy Time Series with a genetic algorithm and a MAPE (Mean Absolute Percentage Error) for measuring errors that can be generated by forecasting methods. It results in applying parameters with best testing results and effectively results in more be value predictive accurate (Istiqara dkk, 2018).

In this paper, related time series model reviews will be carried on only as we chose to forecast of water consumption by time series model approach FTS method is able to provide predictions (*estimates*) of time series data analysis for the next several periods for prediction of water consumption due to water demand prediction to be important to meet customer or community needs and MAPE for measurement of error level from the result of prediction calculation. We use actual data of consumption water for about three years in the private company, Tangerang Regency.

To explain the details of methods, this paper is organized as follows; section I explained of research of background; section II presents the related framework of research, instrument data with FTS methods and data analysis technique; section III result of water consumption analysis using step of Fuzzy Time Series method.

2. Research Methodology

A. Fuzzy Time Series Algorithm

According to Chen, the Fuzzy time series is one of the soft computing methods to predict data using a fuzzy basis. In predicting or forecasting with the fuzzy time series method using the value in the fuzzy set that has been obtained from real numbers. Fuzzy set in this method is used as a substitute for previous data into expected data (Chen, 1996). Developing a fuzzy time series method with a combination of Zadeh's work and time series as well as Chen and Chissom (Song & Chissom, 1993)(Song & Chissom, 1994). Using fuzzy time series from Chen Method more be simplify for this research to get better forecasting(Chen, 1996). The steps to make predictions using fuzzy time series begins with the determination of average-based intervals are as follows:

- **Determine the Universe of Discourse**

  For universe is:

  U = {U1,U2, U3, ….. , Un}............................. (1)

  Ui: The amount of distance at U, for i = 1,2,….,n

  We can use universe of discourse and divide it itu class using:

  Where:

  U: Universe

  U = [Xmin - D1, Xmax + D2] .... (2)

  Where:

  Xmin: Minimum monthly transaction data

  Xmax: Maximum monthly transaction data

  We can use universe of discourse and divide it itu class using:

  Where:

  U: Universe

  U = [Xmin - D1, Xmax + D2] .... (2)

  Where:

  Xmin: Minimum monthly transaction data

  Xmax: Maximum monthly transaction data

- Determine the interval length based on its Universe

  We can form a number of linguistic values to represent a fuzzy set from set of universes using sturges work.

  1 + 3,322 log10 (n) ....(3)

  Where:

  n: Observable data

B. Research Framework

To build forecasting for water demand in Tangerang Regency we need 2 important components which are training set and the other one would be forecasting algorithm that can compute and simulate data. **Figure 1** shows research framework.

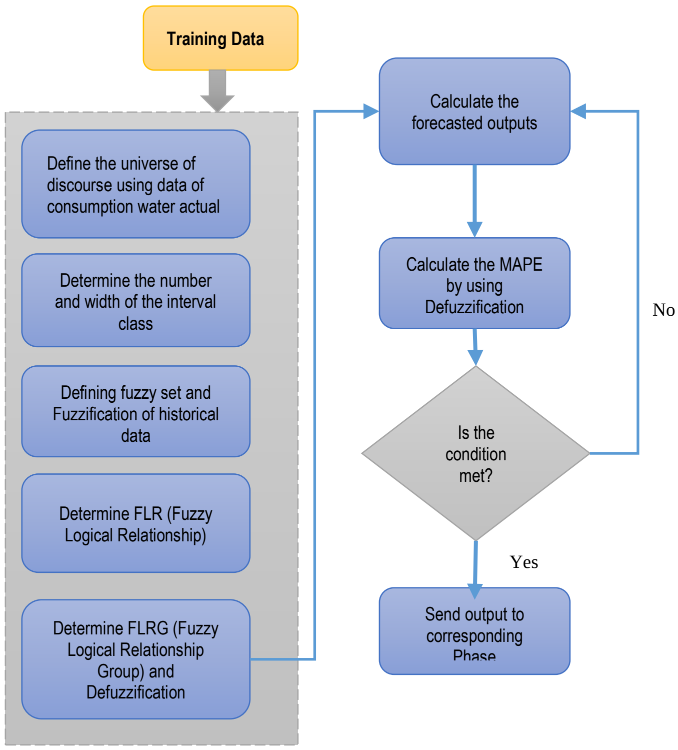

Figure 1. Framework of Research

3. Result and Analysis

Determine the Universe of Discourse

D1 and D2 are positive (arbitrary) numbers to determine the universal set of historical data sets determined by the researcher. Using this equation we show universe of discourse on **Table 1**.

Table 1. Universe of Discourse Water Consumption

Min	Max
1,475,481	2,173,437
D1	**D2**
481	63
Min 1	**Max 2**
1,475,000	2,173,500
Class Quantity	**Class Interval**
6	115,559.54

Determine the interval length based on its Universe

Using equation 3, we can divide the set of universes into several intervals with the same distance. Table 2 shows several class intervals with the same length.

Table 2. Class Interval

Class	Lower Limit	Upper Limit	Median
A1	1,475,000	1,590,559	1,532,779
A2	1,590,560	1,706,118	1,648,339
A3	1,706,119	1,821,678	1,763,898
A4	1,821,679	1,937,237	1,879,458
A5	1,937,238	2,052,797	1,995,017
A6	2,052,798	2,168,356	2,110,577

Based on class interval table we have fuzzy linguistic set also in **Table 2**. Using table 2 we can perform fuzzification on Water Consumption. **Table 3** shows fuzzification Water Consumption table.

Determine Fuzzy Logical Relationsip (FLR) and Fuzzy Logical Relationship Group (FLRG)

To determine FLR, we are using the first order fuzzy logical relationships. To do this we need to pair the current month water consumption data to the next month water consumption data. After FLR done we grouping the FLR based on current month group, for example was for FLR A1->A2, A1->A3, and A1->A6 to become G1 group. Therefore we in table 5 we have FLR and FLRG shown.

Table 3. Water Consumption Fuzzification

Month	Volume (m^3)	Fuzzification
Jan'17	1,542,323	A6
Feb'17	1,531,075	A6
Mar'17	1,482,550	A6
Apr'17	1,674,524	A6
Mei'17	1,552,133	A6
Jun'17	1,628,890	A6
Jul'17	1,475,481	A6
Ags'17	1,693,114	A6
Sep'17	1,738,058	A6
Okt'17	1,712,688	A6
Nov'17	1,804,072	A6
Des'17	1,753,580	A6
Jan'18	1,755,638	A6
Feb'18	1,760,083	A6
Mar'18	1,705,896	A6
Apr'18	1,738,713	A6
Mei'18	1,794,671	A6
Jun'18	1,716,302	A6
Jul'18	1,753,834	A6
Ags'18	1,835,558	A6
Sep'18	1,902,058	A6
Okt'18	1,968,283	A6
Nov'18	2,100,222	A6
Des'18	1,978,579	A6
Jan'19	1,861,209	A6
Feb'19	2,021,665	A6
Mar'19	1,950,961	A6
Apr'19	1,961,783	A6
May'19	2,021,682	A6
Jun'19	1,782,517	A6
Jul'19	2,083,732	A6
Ags'19	2,173,437	A6
Sep'19	2,125,508	A6

Table 4. Water Consumption FLR and FLRG

Month	Volume (m^3)	Fuzzification	FLR1	LH	RH	FLRG
Jan'17	1,542,323	A1				
Feb'17	1,531,075	A1	A1->A1	A1	A1	G1
Mar'17	1,482,550	A1	A1->A1	A1	A1	G1
Apr'17	1,674,524	A2	A1->A2	A1	A2	G1
Mei'17	1,552,133	A1	A2->A1	A2	A1	G2
Jun'17	1,628,890	A2	A1->A2	A1	A2	G1
Jul'17	1,475,481	A1	A2->A1	A2	A1	G2
Ags'17	1,693,114	A2	A1->A2	A1	A2	G1
Sep'17	1,738,058	A3	A2->A3	A2	A3	G2
Okt'17	1,712,688	A3	A3->A3	A3	A3	G3
Nov'17	1,804,072	A3	A3->A3	A3	A3	G3
Des'17	1,753,580	A3	A3->A3	A3	A3	G3
Jan'18	1,755,638	A3	A3->A3	A3	A3	G3
Feb'18	1,760,083	A3	A3->A3	A3	A3	G3
Mar'18	1,705,896	A2	A3->A2	A3	A2	G3
Apr'18	1,738,713	A3	A2->A3	A2	A3	G2
Mei'18	1,794,671	A3	A3->A3	A3	A3	G3
Jun'18	1,716,302	A3	A3->A3	A3	A3	G3
Jul'18	1,753,834	A3	A3->A3	A3	A3	G3
Ags'18	1,835,558	A4	A3->A4	A3	A4	G3
Sep'18	1,902,058	A4	A4->A4	A4	A4	G4
Okt'18	1,968,283	A5	A4->A5	A4	A5	G4
Nov'18	2,100,222	A6	A5->A6	A5	A6	G5
Des'18	1,978,579	A5	A6->A5	A6	A5	G6
Jan'19	1,861,209	A4	A5->A4	A5	A4	G5
Feb'19	2,021,665	A5	A4->A5	A4	A5	G4
Mar'19	1,950,961	A5	A5->A5	A5	A5	G5
Apr'19	1,961,783	A5	A5->A5	A5	A5	G5
May'19	2,021,682	A5	A5->A5	A5	A5	G5
Jun'19	1,782,517	A3	A5->A3	A5	A3	G5
Jul'19	2,083,732	A6	A3->A6	A3	A6	G3
Ags'19	2,173,437	A6	A6->A6	A6	A6	G6
Sep'19	2,125,508	A6	A6->A6	A6	A6	G6

Table 5. Water Consumption FLR and FLRG

FLRG	Median	Current State	Next State	Total	FTS Chen
G1	1,532,779	A1	A1, A2	5	1,602,115
G2	1,648,339	A2	A1, A3	4	1,648,339
G3	1,763,898	A3	A2, A3, A4, A6	11	1,795,415
G4	1,879,458	A4	A4, A5	3	1,956,498
G5	1,995,017	A5	A3, A4, A5, A6	6	1,956,498
G6	2,110,577	A6	A5, A6	3	2,072,057

Defuzzification

If the result of fuzzification in month t is Aj and Aj has several FLRs on FLRG, for example Ai → Aj1, Aj2, ..., Ajk where Ai, Aj1, Aj2, ..., Ajk is the fuzzy set and the maximum value of the function the membership of Aj1, Aj2, ..., Ajp is at the interval of uj1, uj2, .., ujk and mj1, mj2, ..., mjk, then the predicted results of Ft + 1 are as follows:

$$Ft+1 = (mj1 + mj2 + \cdots + mjk)/ k \qquad (4)$$

Table 5 shows defuzzification Water Consumption table based on FLRG on **Table 4**.

Analysis of FTS

To assess the forecasting performance and accuracy of the models created using MAPE (Mean Absolute Percentage Error) methods. The mean absolute percentage error (MAPE) is one of the most widely used measures of forecast accuracy, due to its advantages of scale-independency and interpretability and the most popular measures from the most textbooks (Kim & Kim, 2016). **Table 6** and **Figure 2** shown accuracy error testing using MAPE for Water Consumption versus Water Consumption prediction using FTS Chen methods.

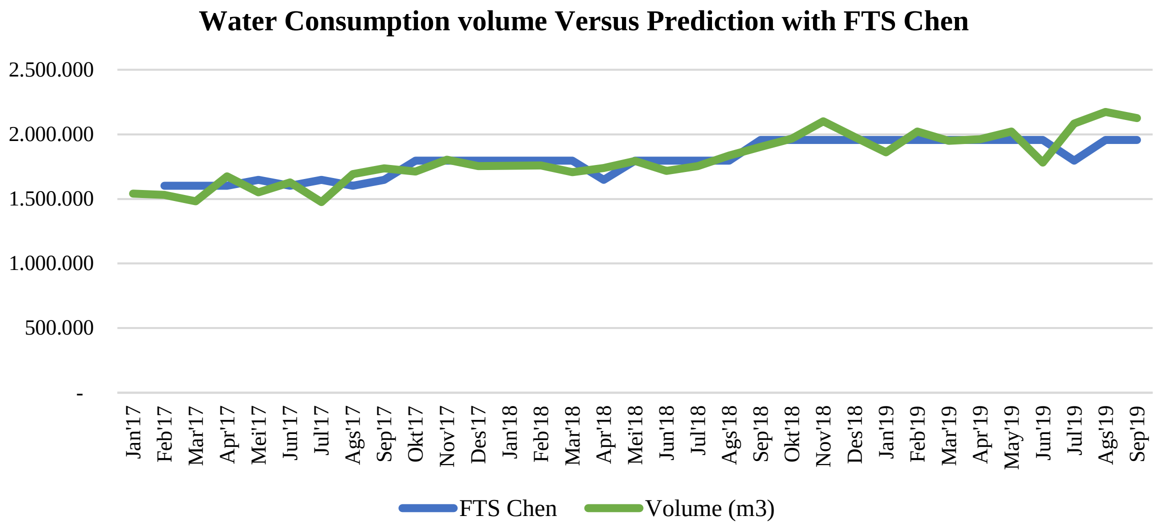

Figure 2. Forecast Water Consumption using Chen Method

Table 6. Water Consumption Prediction Using FTS Chen Methods and MAPE Value

Month	Volume (m^3)	Fuzzification	FLR	FLRG	Chen Forecast	MAPE	%
Jan'17	1,542,323	A1					
Feb'17	1,531,075	A1	A1->A1	G1	1,602,115	0.05	4.64
Mar'17	1,482,550	A1	A1->A1	G1	1,602,115	0.08	8.06
Apr'17	1,674,524	A2	A1->A2	G1	1,602,115	0.04	4.32
Mei'17	1,552,133	A1	A2->A1	G2	1,648,339	0.06	6.20
Jun'17	1,628,890	A2	A1->A2	G1	1,602,115	0.02	1.64
Jul'17	1,475,481	A1	A2->A1	G2	1,648,339	0.12	11.72
Ags'17	1,693,114	A2	A1->A2	G1	1,602,115	0.05	5.37
Sep'17	1,738,058	A3	A2->A3	G2	1,648,339	0.05	5.16
Okt'17	1,712,688	A3	A3->A3	G3	1,795,415	0.05	4.83
Nov'17	1,804,072	A3	A3->A3	G3	1,795,415	0.00	0.48
Des'17	1,753,580	A3	A3->A3	G3	1,795,415	0.02	2.39
Jan'18	1,755,638	A3	A3->A3	G3	1,795,415	0.02	2.27
Feb'18	1,760,083	A3	A3->A3	G3	1,795,415	0.02	2.01
Mar'18	1,705,896	A2	A3->A2	G3	1,795,415	0.05	5.25
Apr'18	1,738,713	A3	A2->A3	G2	1,648,339	0.05	5.20
Mei'18	1,794,671	A3	A3->A3	G3	1,795,415	0.00	0.04
Jun'18	1,716,302	A3	A3->A3	G3	1,795,415	0.05	4.61
Jul'18	1,753,834	A3	A3->A3	G3	1,795,415	0.02	2.37
Ags'18	1,835,558	A4	A3->A4	G3	1,795,415	0.02	2.19
Sep'18	1,902,058	A4	A4->A4	G4	1,956,498	0.03	2.86
Okt'18	1,968,283	A5	A4->A5	G4	1,956,498	0.01	0.60
Nov'18	2,100,222	A6	A5->A6	G5	1,956,498	0.07	6.84
Des'18	1,978,579	A5	A6->A5	G6	1,956,498	0.01	1.12
Jan'19	1,861,209	A4	A5->A4	G5	1,956,498	0.05	5.12
Feb'19	2,021,665	A5	A4->A5	G4	1,956,498	0.03	3.22
Mar'19	1,950,961	A5	A5->A5	G5	1,956,498	0.00	0.28
Apr'19	1,961,783	A5	A5->A5	G5	1,956,498	0.00	0.27
May'19	2,021,682	A5	A5->A5	G5	1,956,498	0.03	3.22
Jun'19	1,782,517	A3	A5->A3	G5	1,956,498	0.10	9.76
Jul'19	2,083,732	A6	A3->A6	G3	1,795,415	0.14	13.84
Ags'19	2,173,437	A6	A6->A6	G6	1,956,498	0.10	9.98
Sep'19	2,125,508	A6	A6->A6	G6	1,956,498	0.08	7.95

4. Conclusion

Based on the steps to make predictions water consumption using fuzzy time series begins with the determination of average-based intervals include fuzzification, develop FLR and FLRG, defuzzification, assess a value error with MAPE.

The result is shown:

- The data volume of water consumption actual versus prediction with FTS Chen method shown related stable in each of month (figure 2). There are no significant deviation of data.
- The result of the average value error accuracy was only 4.5% using FTS Chen Method. The error value obtained is included in the low category. If the accuracy error result of MAPE below 10% was included as a high accuracy (Anggrainingsih, Aprianto, & Sihwi, 2015).
- Refer to figure 2 and the average MAPE value shown that the previous actual volume of consumption water still on good and predicting using FTS Chen methods has not yet obtained an optimal volume prediction. And for the future estimation, FTS Chen methods can be used to get an increase in demand.

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