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The Data-Driven Fuzzy System with Fuzzy Subtractive Clustering for Time Series Modeling

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Abstract*: *The paper aims to identify input variables of fuzzy systems, generate fuzzy rule bases by using the fuzzy subtractive clustering, and apply fuzzy system of Takagi Sugeno to predict rice stocks in Indonesia. The monthly rice procurement dataset in the period January 2000 to March 2017 are divided into training data (January 2000 to March 2016 and testing data (April 2016 to March 2017). The results of identification of the fuzzy system input variables are lags as system input including $Y_{t-1}, Y_{t-2}, Y_{t-6}, Y_{t-7}, Y_{t-11}, Y_{t-12}$ and Y_{t-13}. The Input-output clustering fuzzy subtractive and selecting optimal groups by using the cluster thigness measures indicator produced 4 fuzzy rules.The fuzzy system performance in the training data has a value of R^2 of 0.8582, while the testing data produces an R^2 of 0.7513.

Keywords : fuzzy system, generating rule bases, subtractive clustering. System performance

I. INTRODUCTION

Modern life presents many facilities and conveniences. Advanced infrastructure and sophisticated technology have dominant support. The demand for accurate and timely information is a very decisive factor for surviving or winning in the pressing of rivals with competitors. In this case the science of statistics, especially the analysis of industrial statistics and forecasting has an important role. Time series analysis is widely used in various sectors of life to get a predictive value of future events [1-3], but unfortunately, the time series modeling is not the simplicity of work. In addition, there are several assumptions in time series modeling that in reality are not easily fulfilled [4] Fuzzy clustering is applied more in object labeling than Euclid's distance-based hierarchical clustering method. Fuzzy clustering is considered to group objects more fairly because each entity has a degree of membership in each cluster. [5]. Basically there are 2 types of fuzzy clustering methods, namely Fuzzy C-Means (FCM) and Fuzzy Subtractive Clustering (FSC).

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The FCM takes the number of clusters as input parameter arguments, while the FSC requires a large radius value as the input parameter argument. Recently Handoyo and Efendi [6] applied FCM to generate a fuzzy rules base that is able to produce several fuzzy rules. Marji et al [7] investigated the relationship between the large data variance and the large radius value at the FSC which recommends that the greater the data variance, the greater the radius value used to be close to one, conversely the smaller the data variance the radius value should be chosen close to zero in order to obtain the optimal number cluster. The application of both FCM and FSC for decision making has been carried out by many researchers including Rao et al [8], Singh et al [9], and Gupta et al [10] with satisfying results. To get the optimal number of clusters in health facility data by hybridizing the FSC and FCM methods, Handoyo et al [11] have done it. Human beings in communication use verbal language that is composed of words or terms that are often referred to as linguistic terms. The use of linguistic value as an observation value is found in the fuzzy system which is generally divided into the fuzzy system Mamdani model and Sugeno model [12].

The main difference between the two fuzzy system models lies in the fuzzy rules component, namely the consequent part of the fuzzy rules in the form of linguistic values (Mamdani model) or a linear equation (Sugeno model). Some researchers have implemented the Mamdani model for various problem solving including Mohammad et al [13], Pourjavad, & Shahin [14], while the implementation of the Sugeno model for prediction was carried out by Wang et al [15], Liu et al [16]. Specifically, the implementation of the first-order Sugeno model for data-driven modeling was carried out by Handoyo and Marji [17], Handoyo et al [18], Handoyo and Kusdarwati [19].

The linear function on the consequent part of the fuzzy rules is also a research focus by several researchers including Cai et al [20], Chen & Chen [21], and also Arief et al [22]. The hybrid model yielded by the injection model approach of the classical regression model to the consequent part of the Sugeno fuzzy model as done by Arief et al [22] still faces many obstacles. One assumption about independence among predictors variables is still ignored. This paper aims to implement the Sugeno fuzzy model which is carried out early identification of the data patterns used, and also the establishment of a rule base through the subtractive fuzzy method. The seasonal time series data will be used as a case study in this article.

II. LITERATURE REVIEW

A. Time series identification model

Model identification is carried out through ACF and PACF plots on the seasonal ARMA model for seasonally patterned time series data that has been stationary for variety, average and seasonal. The characteristics of ACF and PACF from the seasonal ARMA stationary process are listed in Table 1 as follows [1] :

Table 1. Characteristics of ACF and PACF in the Seasonal ARMA Model.

Process	AR(*p*)	MA(*q*)
SAR $(1)^s$	Significantly different of the first seasonal lag	Decreases exponentially in seasonal lags
SAR $(P)^s$	Significantly different on *lag* P^s	Decreases exponentially in seasonal lags
SMA $(1)^s$	Decreases exponentially in seasonal lags	Significantly different of the first seasonal lag
SMA $(Q)^s$	Decreases exponentially in seasonal lags	Significantly different of *lag* Q^s
$SAR(1)^sAR(1)$/ SARMA(1,0,0)(1,0,0)	Significantly different in lag 1 and lag s (seasonal), s-1, and s + 1	Decreases exponentially
$SMA(1)^sMA(1)$/ SARMA(0,0,1)(0,0,1)	Decreases exponentially	Significantly different in lag 1 and lag s (seasonal), s-1, and s + 1

Table 1 explains how to identify models based on the characteristics of the autocorrelation value and the partial autocorrelation value. The first column of table 1 states possible time series models, the second column states the characteristics of the autocorrelation value of the lag p, and the third column states the characteristics of the partial autocorrelation value of the lag q. Suppose a data that are stationary have the characteristics of the autocorrelation value in row 1 and column 1, while the characteristics of partial autocorrelation values in row 1 and column 2, then the data has the model of Seasonal Autoregressive (SAR) order one or SAR (1).

B. The fuzzy subtractive clustering me

In Fuzzy Subtractive Clustering (FSC), an object or record can be a member of several existing clusters that are indicated by the degree of membership in the each cluster centers [8]. An object becomes a cluster member if the object has the highest degree of membership on the center of the cluster. The difference of FSC with other cluster methods is that many clusters to be formed are obtained through a number of iterations. In classical cluster analysis, the cluster number is determined by the greatest distance change on the dendogram, all possible cluster members are already formed, while in FSC, the cluster number will be calculated one by one starting at the beginning of the iteration.

According to Gupta et al [10], the initial step of clustering with FSC is to determine the object or record that has the highest potential value to the object around it. Suppose there are *n* objects or records $x_1, x_2, \ldots, x_n$, potential value of an object can be calculated by the formula:

$$P_k = \sum_{j=1}^{n} e^{-\frac{4}{r_a^2}\|x_k - x_j\|^2} \qquad (1)$$

P_k is the potential value of k-record, x_k is the k-record, and x_j is the j-record, notation ‖.‖ is the Euclidean distance, n is the amount of data, r_a is a positive constant known as the radius. An object has a high potential if the object has the largest number of neighbors. After calculating the potential of each object, the object with the highest potential is selected as the center of the group. Suppose x_{c1} is the object selected as the center of the first group, while P_{c1} is a measure of the potential of the cluster center in the first group. Furthermore, the potential of the object around it is determined by the formula[10]

$$P'_k = P_k - P_{c1} e^{-\frac{4}{r_b^2}\|x_k - x_j\|^2} \qquad (2)$$

P'_k is the new potential value of object k-th, r_b is a positive constant. This means that objects near the center of the group will experience great potential reductions. The constant r_b causes the object around the center of the group to diminish its potential value. Usually r_b is greater when compared to r_a, ie: $r_b = q * r_a$ where q is squash factor. Once the potential of all objects in a group is reduced, the object with the highest potential is selected as the center of the second group. Furthermore, after obtaining the center of the second group, the potential value of each object is reduced again, and so on.

The center of the cluster is determined by using two comparative factors namely the accept ratio and reject ratio [10]. Accept ratio is the lower bound of an object that becomes a candidate cluster center accepted as the center of the cluster, while the reject ratio is the upper limit of an object that becomes the candidate center group is not accepted as the center of the cluster. At an iteration, if it is found an object with the highest potential, then proceed by calculating the potential ratio of the object to the highest potential of an object in the first iteration. There are 3 conditions that may occur in an iteration that is:

a. If the ratio> accept ratio, then the object is accepted as a new group center.
b. If the reject ratio <ratio≤ accept ratio, then the object is accepted as a new group center if and only if the sum between the ratio and the object's nearest distance to the other existing group center ≥1.
c. If the ratio≤ reject ratio, then no more objects can be considered as a candidate for group center, iteration is stopped [9].

According to Gupta et al [10], the specification of accept ratio = 0.5 and reject ratio = 0.15, whereas the radius is a vector that determines how much influence the cluster center on each variable.

C. Cluster tightness mesuare (CTM)

Optimization of clustering results can be assessed using Ctm, which is formulated as follows [7]:

$$CTM = M^{-1} \sum_{m=1}^{M} (K^{-1} \sum_{k=1}^{K} \frac{\sigma_k^m}{\sigma_k}) \qquad (3)$$

M is the number of groups, K is the number of variables, σ_k^m is the standard deviation of the k-th variable in the m-th group, and $\sigma_k$is the standard deviation of the k-th variable. The value of Ctm is closer to zero, the better of the clusters result obtained

D. The first order Takagi-Sugeno model

Consicer L as the number of rules on the fuzzy rule bases (l = 1,2, ..., L) shows the rule index, and k (k = 1,2, ..., p) indicates the input index. According to Liu et al [16], the inference process on Fuzzy Takagi-Sugeno model is divided into 2 stages. The first stage calculates the degree of activation (fire strength) for each rule on a fuzzy rule basis. The second stage is the calculation of the output of crisp values calculated using the average defuzzification method. In general, the order rule of the first order Fuzzy Takagi-Sugeno model is as follows:

$$IF\ (y_{t,1}\ is\ A_1^l)\ AND\ ...\ AND\ (y_{t,p}\ is\ A_p^l)$$
$$THEN\ y_t^l = \theta_0^l + \theta_1^l y_{t,1} + \cdots + \theta_p^l y_{t,p}\ ,fo \qquad (4)$$

where $y_{t,k}$ is the value of the k-th input variable, y_t^l is the local output (output produced by the l-th rule), θ_0^l, θ_k^l is the consequent parameter in rule l, and A_k^l is the fuzzy set of k-input variables for the l-th rule represented by a membership function $\mu_{A_k^l}(y_{t,k})$. In this research is used the Gaussian membership function (gaussmf) expressed in (4) as follows:

$$\mu_{A_k^l}(y_{t,k}) = exp\left(-\frac{1}{2}\left(\frac{y_{t,k} - c_k^l}{\sigma_k^l}\right)^2\right) \qquad (5)$$

where c_k^l and σ_k^l are the center and spread parameters of gaussmf corresponding to the antecedents part for the l-th rule. The fire strength of l-th rule for the t-observation is calculated by the multiplication operator as follows

$$\alpha_t^l = \prod_{k=1}^{p} \mu_{A_k^l}(y_{t,k}) \qquad (6)$$

where p is the number of input variables. Then fire strength is normalized by using equation (6) to compute the output in the form of a crisp value:

$$\bar{\alpha}_t^l = \frac{\alpha_t^l}{\sum_{l=1}^{L} \alpha_t^l} = \frac{\prod_{k=1}^{p} \mu_{A_k^l}(y_{t,k})}{\sum_{l=1}^{L} \prod_{k=1}^{p} \mu_{A_k^l}(y_{t,k})} \qquad (7)$$

the output of the system in the form of a crisp number $\hat{y}_t$ is the predicted value of the t-observation calculated by the formula:

$$\hat{y}_t = \sum_{l=1}^{L} \bar{\alpha}_t^l y_t^l$$
$$= \sum_{l=1}^{L} \bar{\alpha}_t^l(\theta_0^l + \theta_1^l y_{t,1} + \cdots + \theta_p^l y_{t,p}) \qquad (8)$$

The equation (8) is used for the defuzzification process by the weighted average method. The weights used in the Takagi-Sugeno model are normalized fire strength $(\bar{\alpha}_t^l)$. The consequent part (y_t^l) is a linear equation. Parameters of linear equations in consequent part are estimated using the Ordinary Least Squares (OLS) method [17]

III. RESULT AND ANALYSIS

The data used in the paper are monthly rice procurement or the period January 2000 to March 2017 which is a seasonal time series data. The data plot is stated in Figure 1 that shows that the data has a seasonal trend where data starts to rise after January. This happens because during the rainy season there is still the beginning of rice cultivation so that rice production tends to decrease, while in the dry season rice production will increase due to the harvest. When the rainy season with high rainfall intensity, the production of rice will be greatly decreased and when the intensity of the rain begins to decline or begins to enter the dry season, the rice production will increase.

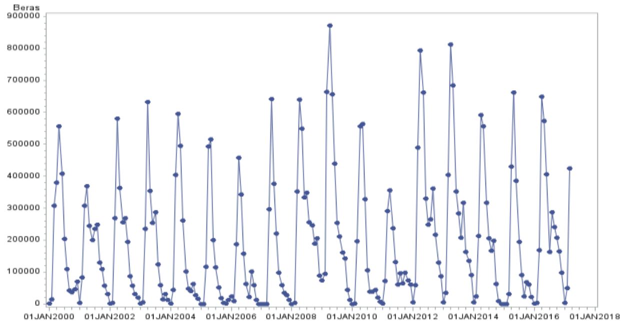

Figure 1. Monthly Rice Procurement Data Plot in the period of January 2000 to March 2017 in Indonesia

The identification model is done through a PACF plot of the stationary data to determine the Authorization of the q order model. The identification phase in this research is only carried out on the PACF which only involves the data lags and without considering the identified lags of the errors. The PACF plot of data of rice procurement is presented in Figure 2 as follows:

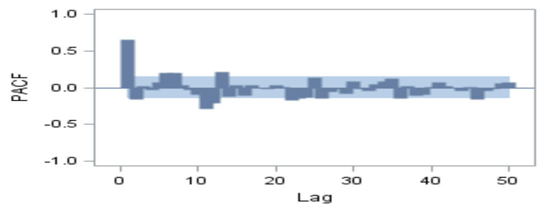

Figure 2. PACF plot of stationary rice procurement data

Figure 2 shows a PACF plot on rice procurement data where significant lags are used as the input variables of the FIS. Based on Figure 2, it is known that significant lags are $Y_{t-1}, Y_{t-2}, Y_{t-6}, Y_{t-7}, Y_{t-11}, Y_{t-12}$ *and* Y_{t-13}.Furthermore, the input and output data pairs formed are presented in Tabl

Table 1. the Input-Output data pairs of the results of PACF identification

Yt	Yt-1	Yt-2	Yt-6	Yt-7	Yt-11	Yt-12	Yt-13
83217,7	3433,9	70073,4	43022,2	108219,9	307930,1	14831,2	714,7
308306,4	83217,7	3433,9	36027,7	43022,2	380097,8	307930,1	14831,2
369272,9	308306,4	83217,7	45531,0	36027,7	555939,3	380097,8	307930,1
245419.4	369272,9	308306,4	70073,4	45531,0	408189,8	555939,3	380097,8
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
167949,8	4193,1	641,0	67358,9	22984,9	430558,6	30964,2	0,0

The data sets in the structure such as in Table 1 are divided into two parts that are training and testing data. The distribution of training and testing data is seasonal patterns that are almost the same so that the modeling carried out on the training data will have high compatibility with the testing data when the model is used as a predictive model. The testing data chosen in this research are one season period which consists of 12 points which are monthly observed value from April 2016 to March 2017. The analysis for building models is carried out on the training data, namely data from the rice procurement for the period from January 2000 to March 2016, the table 1 presents that the first column is the output or target of the system, while the other columns are the input system. Furthermore, the training data is clustered to be some groups by fuzzy subtractive clustering (Fsc) with trying some values of the radius including 261739.92, 348986.56, and so on as presented in the first column of Table 2. The cluster members of each record will be determined by calculating its membership degree by using the Gaussian membership function (Gauss_mf). The formation of group members on each radius is shown in detailly in Table 2.

Table 2. Results of Fsc clustering and count of cluster Members

Radius	Cluster count	Record count on each cluster
261739.92	11	91, 13, 11, 11, 11, 11, 8, 7, 5, 10, 4
348986.56	7	60, 21, 19, 30, 22, 19, 11
434233.20	6	52, 23, 37, 28, 24, 18
523479.84	5	52, 45, 33, 24, 28
610726.48	5	70, 40, 29, 24, 19
697973.12	4	72, 52, 28, 30
785219.76	3	89, 65, 28

Based on the results in Table 2, it is known that the clustering yielded on the radius 261739.92 can not be used in the continuous process which the Gaussian parameters can not be estimated by using Ordinary Least Squared (OLS) because, in this radius value, there is one cluster, namely the 11th cluster that is only 4 records member. In other hand, the radius values including 261739.92, 348986.56, 436233.20, 523479.84 and 610726.48 can not be continued in estimation of Gaussian parameters because in the clustering process using the Gaussian membership function there are several records that have the membership degree is equal to 0, it means that the records can not be included in any clusters. Therefore, only in the both radius of 697973.12 and 785219.76, the further analysis can be carried out. The Gaussian parameter estimation is only done at the most optimum cluster formation to yield the better clustering. Therefore, to determine of the optimal cluster is calculated by using Cluster Tightness measure (CTM).

the CTM value of 39.84 resulting in the Fsc with a radius of 697973.12 is smaller than the CTM value of 41.72 resulting in the Fsc with a radius of 785219.76. The choosing of optimal clustering will consider the magnitude of the radius value that produces a small CTM value.

The cluster number of 4 is the optimal cluster number that also means that the number of rules produced by Fsc is 4 rules which it is equal to the optimal cluster number. The next step in the analysis is to estimate the parameters of a linear function in the consequent part of each rule in the Takagi Sugeno rule bases. Furthermore, the results of estimating parameters that are as the coefficient of linear equation by using the Ordinary Least Squared (OLS) where the magnitude radius is 697973.12 that are presented in table 2 as follows:

Table 3. The coefficients of linear equation resulting by OLS

Yt	Yt.1	Yt.2	Yt.6	Yt.7	Yt.11	Yt.12	Yt.13
57735.8	108550.7	128550.3	199107.8	245420.4	70074.4	45532	36028.7
205225.3	317739.2	557114.5	23685.6	4684	206819.7	284336.8	352595.6
43639.1	37880.8	39253.9	563567.4	555882.3	43616.6	142133.8	161478.4
234960.4	5508.1	1362.3	57756.1	87107.1	580047.8	268685.4	3005.3

The first order FIS of the Takagi Sugeno inference stage is the calculation of the output as the crisp values or the predictive values is calculated by using the weighted average defuzzification method of the linear equations. The numerator part is the sum of multiplications between fire strength and consequent values of each rule or cluster. The consequent values are obtained by entering input variables from each record into the rule bases established. For example, considering the first record value, the consequence value can be calculated as follows:

$$Z_1 = -5489{,}38 + 0{,}8982(108550{,}74) - 0{,}2268(128550{,}30) - 0{,}0021(199107{,}78) + 0{,}0051(245420{,}36) + 0{,}0984(70074{,}36) + 0{,}5281(45532{,}02) - 0{,}1597(36028{,}75)$$

$$Z_2 = 243310{,}70 + 0{,}6305(108550{,}74) - 0{,}4387(128550{,}30) - 0{,}2493(199107{,}78) + 1{,}2009(245420{,}36) + 0{,}1633(70074{,}36) + 0{,}0023(45532{,}02) - 0{,}1507(36028{,}75)$$

$$Z_3 = -51921{,}28 + 0{,}4935(108550{,}74) + 0{,}1360(128550{,}30) + 0{,}2050(199107{,}78) - 0{,}0213(245420{,}36) + 0{,}2472(70074{,}36) + 0{,}1829(45532{,}02) - 0{,}4687(36028{,}75)$$

$$Z_4 = 263495{,}20 + 1{,}03391(108550{,}74) - 0{,}9675(128550{,}30) + 0{,}6424(199107{,}78) + 0{,}0984(245420{,}36) - 0{,}3778(70074{,}36) + 0{,}4286(45532{,}02) - 0{,}1913(36028{,}75)$$

The denominator is the sum of the fire strengths obtained on each rule, so the first value of the defuzzification process is obtained by the following calculation,

$$\widehat{Y}_t = \frac{\alpha_{1,1}Z_1 + \alpha_{2,1}Z_2 + \alpha_{3,1}Z_3 + \alpha_{4,1}Z_4}{\alpha_{1,1} + \alpha_{2,1} + \alpha_{3,1} + \alpha_{4,1}}$$

Based on Figure 3, the purple plot is the actual data and the orange plot is the output of the system or the result of defuzzification, visually it can be seen that the plot of data generated from the defuzzification process has a pattern similar to the actual data. Defuzzification results can model the actual data quite well even though it has a large enough difference. Therefore, to find out how big the measurement of the accuracy of the model can be done by calculating the value of R ^ 2. Based on the value of R ^ 2 which is the squared correlation between the actual data and the defuzzification result data produces a value of 0.8582, which means that the closeness of the relationship between defuzzification of data and actual data has a strong linear relationship closeness.

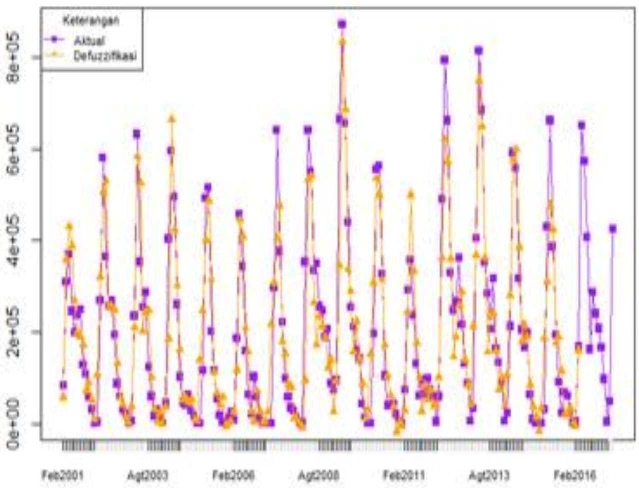

Figure 3. Plot both the actual output and the predicted value produced by the system

Figure 4 presents a plot of both the actual output and the predicted value of the data based testing on the FIS has been developed. It can be seen that the difference between the defuzzification result (the predicted value) and the actual output are quite large because the rule bases produced from the data are only 4 rules, the fewer rule bases are formed that influence only can capture the less complex patterns. In addition, the clustering method is generally used on data that has mutually independent input variables, but in this study, the input variables are formed from lags of time series data so that the input variables formed are not mutually independent due to the influence of lags between records.

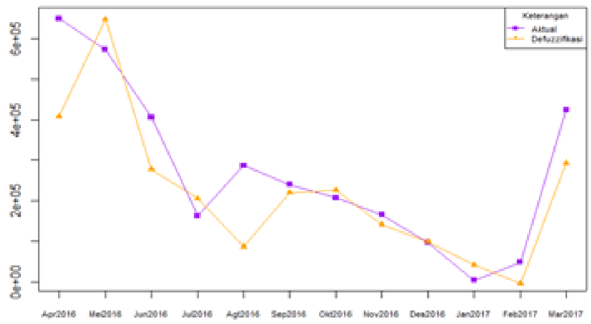

Figure 4. The plot is both the predicted output and the actual target on testing data

Figure 4. shown in the purple plot is the actual data and the orange plot is visually defuzzified output. It can be seen that the plot of data generated from the prediction results has a pattern similar to the actual data. Therefore, to find out how much the accuracy of the model can be done by calculating the value of R_squared. Based on the value of R_squared which is the squared correlation between the actual data and defuzzification result data produces a value of 0.7513 , which means that the closeness of the relationship between defuzzification of data and actual data on data testing has a strong linear relationship closeness.

IV. CONCLUSION

The clstering with fuzzy subtractive clustering forms the center of the group whose number will be the same as the number of base rules formed. Based on the results of fuzzy subtractive clustering, 4 groups are formed. Furthermore, each group member is suspected of using the MKT parameter to form the basis of the consequent part of the rule, so that 4 basic rules are formed by consequently a linear equation. Data modeling using Takagi-Sugeno FIS method based on fuzzy subtractive clustering performed on training data can explain 85.82% of the data while the rest is explained by other factors. While the testing data, shows that the data modeling on training data has a match of 75.13% in explaining testing data. The results of forecasting the data on the procurement of rice for the next 12 periods, namely the period April 2017 to March 2017 produce quite good results with a data pattern that is almost the same as the previous data pattern.

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