HASIL CEK_Implementation of Takagi Sugeno Kang Fuzzy

by Implementation Of Takagi Sugeno Kang Fuzzy Naskah

Implementation of Takagi Sugeno Kang Fuzzy with Rough Set Theory and Mini-Batch Gradient Descent Uniform Regularization

Sugiyarto Surono [1,*], Zani Anjani Rafsanjani HSM [1], Deshinta Arrova Dewi [2], Annisa Eka Haryati [3], Tommy Tanu Wijaya [4]

[1] *Department of Mathematics, Ahmad Dahlan University, Yogyakarta, Indonesia*

[2] *Faculty of Data Science and Information Technology, INTI International University, Nilai, Malaysia*

[3] *Master of Mathematics Education, Ahmad Dahlan University, Yogyakarta, Indonesia*

[4] *School of Mathematical Sciences, Beijing Normal University, China.*

Abstract

The Takagi Sugeno Kang (TSK) fuzzy approach is popular since its output is either a constant or a function. Parameter identification and structure identification are the two key requirements for building the TSK fuzzy system. The input utilized in fuzzy TSK can have an impact on the number of rules produced in such a way that employing more data dimensions typically results in more rules, which causes rule complexity. This issue can be solved by employing a dimension reduction technique that reduces the number of dimensions in the data. After that, the resulting rules are improved with MBGD (Mini-Batch Gradient Descent), which is then altered with uniform regularisation (UR). UR can enhance the classifier's fuzzy TSK generalization performance. This study looks at how the rough sets method can be used to reduce data dimensions and use Mini Batch Gradient Descent Uniform Regularization (MBGD-UR) to optimize the rules that come from TSK. 252 respondents' body fat data were utilized as the input, and the mean absolute percentage error was used to analyze the results (MAPE). Jupyter Notebook software and the Python programming language are used for data processing. The analysis revealed that the MAPE value was 37%, falling into the moderate area.

1- Introduction

Each data set contains a variety of dimensions, ranging in size from small to large, with large dimensions frequently being observed to have a high level of complexity, which has an impact on the number of rules produced when employed in a fuzzy inference system. This is demonstrated by the fact that using large data dimensions as input typically results in the creation of more rules. The Takagi Sugeno Kang (TSK) fuzzy used in one of the studies [1] was found to have limitations when the input used was large. This TSK, which Takagi and Sugeno first developed in 1985 [2], is a form of inference fuzzy that is frequently employed for prediction or classification [3]-[5].

TSK was utilized by [6] in order to carry out the AP-TSK-PID method while dealing with stochastic and non-stochastic uncertainties of nonlinear dynamic systems. In the field of medicine, it has also been used by [7] to forecast how well hemodialysis patients will respond to their treatment and [8] to address the issue of type 1 diabetes's difficulty controlling their blood glucose levels.

To achieve improved operating time performance, TSK fuzzy can be tuned using Gradient Descent (GD) [9]. This GD is one of the techniques typically employed in optimization to reduce the cost function in machine learning, and it is typically carried out by updating each parameter depending on previous steps [10], [11]. GD can be divided into three

categories: batch, stochastic, and mini-batch. Prior to this, [12, 13] and [14–16] employed the batch type and stochastic type, respectively, for classification. Due to its tendency to have a lesser computing load and a faster convergence because only the data from a batch are used in each iteration, the Mini-Batch Gradient Descent (MBGD) method was adopted in this work [17], [18].

MBGD has been the subject of numerous studies, including its application by [19] to effectively train the ANN equalizer, [20] to maximize the IoT 4.0 market, and [21] to combine it with MMLDA to predict lncRNA illness association. Additionally, the regularization strategy was employed to prevent overfitting and boost generalization because it can help the algorithm become more universal by preventing coefficient from being used to match the training sample data [22]. Regularization is described by Goodfellow [23] as "any change made to a learning system intended to reduce generalization mistakes and not training errors." It is thought that this method is necessary to stabilize numerical calculations [24].

The rough set is a set theory extension that Pawlak first proposed in 1982. It is a subset of the universe that is characterized by two original sets known as the upper and lower approximation sets. Equivalence relations, specifically reflexive, symmetrical, and transitive relations, are the primary component of the rough set model [25]. This was carried out by [26] to carry out feature selection in the genetic algorithm, and it was observed that the picked features produced good results. This technique for making decisions was also employed in [27]'s study, and [28] used it to categorize leukemia by identifying prominent traits.

This study builds on earlier work by Cui et al. [1] on the fuzzy TSK system with optimization based on Mini Batch Gradient Descent (MBGD) on classification issues. To enhance the TSK fuzzy classification's generalization performance and prevent overfitting, researchers utilize uniform regularisation (UR), as in [1]. Further, the researcher suggests applying the rough set method. The following are the primary contributions of this study:
1. The rough set technique is utilized to minimize the data's dimensions. The experimental findings demonstrate that the rough set enhances the rules produced by TSK fuzzy classification.
2. Additional researchers who used the rough set and UR approach found that the model falls into the reasonable category.

2- Methodology

2-1- Rough Set

The rough set is one of the dimension reduction techniques developed by Pawlak in 1982 with its principle associated with a reflexive, symmetrical, and transitive equivalence relation [25]. In the rough set, there is an information system that can be represented in the form of a table $S = (U, A)$, where U is a non-empty finite set of objects and A is a non-empty finite set of attributes [29]. If the information table is added with the output of the classification, it will become a decision system table denoted by $S = (U, A \cup \{d\})$, where $d \notin A$ is the decision attribute. Indiscernibility relation is a relationship that cannot be separated because an object can have the same value for a condition attribute. This can happen at the time of the decision system. Suppose $S = (U, A)$ is an information system and $B \subseteq A$. The indiscernibility relation of objects according to attribute B is denoted by $IND_S(B)$ can be defined as follows:

$$IND_S(B) = \{(X, X') \in U^2 | \forall a \in Ba(x) = a(x')\} \quad (1)$$

Attributes in the rough set can be removed without losing their true value by using core and reduct. Reduct is the set of attributes that can produce the same classification as if all attributes were used. While attributes that are not reducts are attributes that are not useful in the classification process [29]. Core is the intersection of all reducts, so the core is in every reduction, that is, every core attribute is included in every reduction. Suppose $B \subseteq A$ and core of B is the set of all dispensable attributes of B then core can be defined as follows [30]:

$$Core(B) = \cap Red(B) \quad (2)$$

2-2- Fuzzy Set

Definition 1: Let X represent the universe of discourse, x is a member of the universe while X and A represent fuzzy sets. Therefore, a fuzzy set with the membership function of $\mu_A(x)$ is:

$$\mu_A: X \to [0,1] \quad (3)$$

Definition 2: The fuzzy set A in universe X can be defined as a set of ordered pairs as indicated in the following equation:

$$A = \{x, \mu_A(x) | x \in X\} \quad (4)$$

where, $\mu_A(x)$ is the membership function x in the fuzzy set A which lies on the interval [0,1] [31].

2-3- Takagi Sugeno Kang (TSK) Fuzzy

TSK fuzzy system with one input x_1 and x_2 as well as output y is described by fuzzy inference rules as follows [32]:

$$R_j = IF\ x_1 \in F_j(x_1)\ AND\ x_2 \in G_j(x_2)\ THEN\ y = P_j(x_1, x_2) \qquad (5)$$

Where, $j = 1, 2, \ldots, r, F_j(x_1), G_j(x_2)$ is a fuzzy set and $P_j(x_1, x_2)$ is a degree polynomial d.

Definition 3: TSK system in line with rules (2.3) is defined as follows [32]:

- The order is zero if $P_j(x_1, x_2) = b_j$, where $b_j \in \mathbb{R}$, and this means the consequent function is a constant (degree polynomial d is equal to zero).

- The order is one if $P_j(x_1, x_2) = w_{1j}x_1 + v_{1j}x_2 + b_j$, where, $w_{1j}, v_{1j} \in \mathbb{R}$, and this means the consequent functions are linear (a degree polynomial d is equal to one).

- The order is high if $P_j(x_1, x_2) = w_{mj}x_1^m + \ldots + w_{1j}x_1 + v_{mj}x_2^m + \ldots + v_{1j}x_2 + b_j$, where, $m \geq 2, w_{kj}, v_{kj} \in \mathbb{R}$ and $k = 2, 3, \ldots, m$ and this means the consequent function is nonlinear (a degree polynomial d is greater than one).

Defuzzification is a fuzzy process aimed at converting fuzzy numbers to crisp numbers. Therefore, the defuzzification value (Y^*) was calculated using the following equation

$$Y^* = \frac{\sum_{i=1}^{\infty} a_i y_i}{\sum_{i=1}^{N} a_i}; i = 1, 2, \ldots, N \qquad (6)$$

Where,

a_i = output value in the i-th rule

y_i = output value in the i-th rule

2-4- Mini Batch Gradient Desacent (MBGD)

MBGD is Gradient Descent (GD) method that uses the concept of Mini-Batch to update parameters. Meanwhile, the updated parameter can be defined as follows [17]:

$$\theta = \theta - \eta \cdot \nabla_\theta J\left(\theta; x^{(i;i+n)}; y^{(i;i+n)}\right) \qquad (7)$$

Where $\eta > 0$ is the learning rate (step size) [33].

2-5- Uniform Regularization (UR)

UR is a regularization method that forces the rules to have firing levels by minimizing losses [1]. It can be calculated as follows:

$$\ell_{UR} = \sum_{r=1}^{R} \left(\frac{1}{N} \sum_{n=1}^{N} \bar{f_r}(x_n) - \tau\right)^2 \qquad (8)$$

Where N is the number of training samples and τ is the firing level of each rule. Furthermore, ℓ_{UR} is added to the loss function in MBGD-based TSK classification training using Mini-Batch with N training samples and this is represented as follows

$$\mathcal{L} = \ell + \alpha \ell_2 + \lambda \sum_{r=1}^{R} \left(\frac{1}{N} \sum_{n=1}^{N} \bar{f_r}(x_n) - \frac{1}{R}\right)^2 \qquad (9)$$

2-6- Mean Absolute Percentage (MAPE)

MAPE is one of the methods normally used to evaluate a model and its value can be determined using the following equation [34]:

$$MAPE = \frac{\sum_{i=1}^{n} \frac{|y_i - y'_i|}{y_i}}{n} \times 100\% \qquad (10)$$

Where, y_i is the i-th data, y'_i is the i-th data for forecasting, and n is the total data. The prediction criteria for MAPE as indicated by [34] are as follows:

Table 1. MAPE Criteria.

MAPE	Prediction Criteria
<10%	Excellent
10% - 20%	Good
20% - 50%	Reasonable
>50%	Bad

2-7- Flowchart

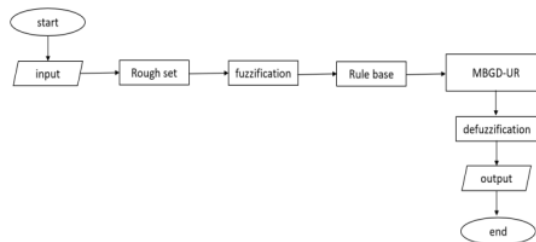The flowchart in this study can be seen in Figure 1:

Figure 1. Flowchart Rough Set TSK-MBGDUR.

First, a rough set method is utilized to process the data in Figure 1. Afterward, a method known as "fuzzification" is used to transform the rough set's results into fuzzy numbers. The creation of the fundamental rules, IF-THEN, where IF is the antecedent and THEN is the consequent, comes next once the fuzzification phase has been completed. The established rules will be improved using Mini Batch Gradient Descent Uniform Regularization (MBGD-UR). The next and last stage is the defuzzification procedure, which involves converting the fuzzy set back to the crisp set.

3- Results

The body fat data from a database known as Kaggle (https://www.kaggle.com/datasets/fedesoriano/body-fat-prediction-dataset) was used in this study. It consists of data for 252 respondents with 14 independent variables and 1 dependent variable as indicated in the following Table 2.

Table 2. Data from PCA Dimension Reduction.

X_1	X_2	X_3	...	Y
23	154.25	67.75	...	12.3
22	173.25	72.25	...	6.1
⋮	⋮	⋮	...	⋮
72	190.75	70.5	...	26
74	207.5	70	...	31.9

The dimensions of the data set were reduced using a rough set and the results are presented in Table 3.

Table 3. Body fat data reduction results.

X_1	X_2	X_3	Y
154.25	67.75	1.0708	12.3
173.25	72.25	1.0853	6.1
⋮	⋮	⋮	⋮
190.75	70.5	1.0399	26
207.5	70	1.0271	31.9

The data in Table 3 were further converted into fuzzy numbers, and the results are presented in the following table

Table 4. Body fat membership value.

X_1	X_2	X_3	Y
0	0.2713	0	0
0.3437	0.9823	0	0
⋮	⋮	⋮	⋮
0.4965	0.7462	0	0
0.6493	0.6105	0	0

The input in Table 4 was used to obtain the following rules:

[R1] If X1 is nonstandard2, X2 is high nonstandard2, X3 is high, then Y is athletic.

[R2] If X1 is standard, X2 is high nonstandard2, X3 is high, then Y is athletic.

[R3] If X1 is nonstandard2, X2 is high nonstandard2, X3 is high, then Y is good.

[R4] If X1 is nonstandard2, X2 is high nonstandard2, X3 is high, then Y is normal.

[R5] If X1 is nonstandard2, X2 is high nonstandard2, X3 is high, then Y is overweight.

[R6] If X1 is standard, X2 is high nonstandard2, X3 is high, then Y is good.

[R7] If X1 is nonstandard1, X2 is high nonstandard2, X3 is high, then Y is athletic.

The similarities in each rule were later determined using MBGD-UR, and the results are indicated as follows:

$$
\begin{aligned}
y_1 &= -0.1515 + 0.9664X_1 + 0.9201X_2 + 0.6203X_3 \\
y_2 &= -0.2981 + 0.8369X_1 + 0.8939X_2 + 0.7895X_3 \\
y_3 &= -0.5750 + 0.6356X_1 + 0.6385X_2 + 0.6492X_3 \\
y_4 &= -0.6431 + 0.8585X_1 + 0.6853X_2 + 0.5158X_3 \\
y_5 &= -0.5017 + 0.7990X_1 + 0.4268X_2 + 0.6014X_3 \\
y_6 &= -0.3812 + 0.7074X_1 + 1.1365X_2 + 0.4482X_3 \\
y_7 &= -0.3093 + 0.9108X_1 + 0.6590X_2 + 0.7610X_3
\end{aligned}
\tag{9}
$$

Defuzzification was conducted on the rules obtained, and the results are indicated in Table 5.

Table 5. Body fat defuzzification results.

Y'	Y
12.3	18.2045
6.1	19.7421
⋮	⋮
26	20.0780
31.9	20.6161

MAPE value was determined as follows:

$$
\begin{aligned}
MAPE &= \frac{\sum_{i=1}^{n} \frac{|y_i - y'_i|}{y_i}}{n} \times 100\% \\
&= \frac{\sum_{i=1}^{n} \frac{|12.3-18.2045|}{12.3} + \frac{|6.1-19.7421|}{6.1} + \ldots + \frac{|31.9-20.6161|}{31.9}}{252} \times 100\% \\
&= 36.5510\% \approx 37\%.
\end{aligned}
$$

4- Discussion

This study used 252 data with 14 independent variables and 1 dependent variable, and the results of the dimension reduction using the rough set method are presented in Table 3. The 14 variables were discovered to be reduced to 4 variables including weight (X_1), height (X_2), density (X_3), and body fat (Y).

Rough set results were subsequently used as input in TSK with each variable subjected to a fuzzification process to convert the data to fuzzy numbers using membership functions. This led to the generation of 7 rules which are in the

form of IF-THEN as in Equation (3). Moreover, the consequences for each rule were optimized using MBGD-UR, and the constants generated for each rule were arranged into Equation (8).

The defuzzification process was later used to obtain output in the form of firm numbers. It is important to know that the defuzzification value was determined by multiplying the y value with the predicate alpha in each rule and dividing it by the total predicate alpha. The defuzzification (Y') was calculated using Equation (4) and the results are shown in Table 5.
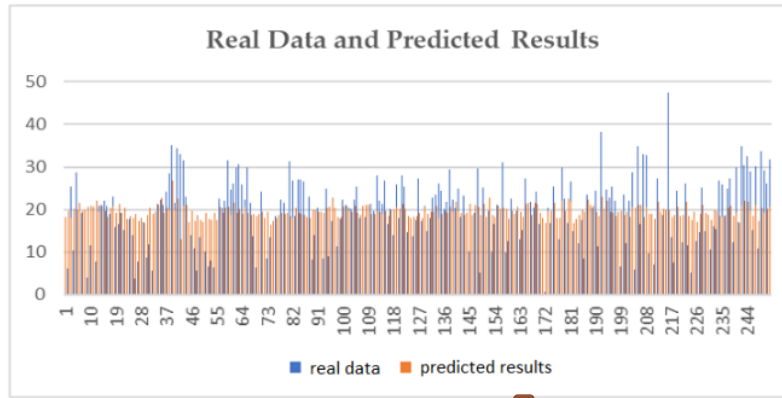

Figure 2. Real data and predicted results.

Figure 2 shows the results of the representation of table 5 which compares the predicted defuzzification data with the actual data. In addition, the MAPE value is calculated using Equation (8) to determine the accuracy of the model obtained, and a value of 37% is obtained which belongs to the fair category as shown in Table 1.

5- Conclusion

In order to transform data with big enough dimensions into those with small enough dimensions, the rough set method is employed in this study. The rules are then enhanced in the fuzzy TSK classification process using MBGD modification and UR to get better results. The classification prediction result after MBGD-UR model modification is more reliable. This is so that the MBGD method's parameters can be updated using the mini-batch idea. By reducing losses, the role of UR in this study can push the rules to have a firing level. Additionally, MAPE (Mean Absolute Percent Error), which is a crucial component in assessing the forecast's accuracy, is employed based on the size of the forecasting variable. The MAPE value is recorded at 37%, indicating that the model is included in the reasonable category. MAPE measures how large the forecast error is in comparison to the actual value of the series. Further study is advised to compare other reduction techniques, such as using a decision tree and the Raw Classification Accuracy (RCA) accuracy, and to determine the minimum variable limit for dimensional reduction based on the analysis findings and conclusions.

6- References

[1] Cui, Y., Wu, D., & Huang, J. (2020). Optimize TSK Fuzzy Systems for Classification Problems: Minibatch Gradient Descent with Uniform Regularization and Batch Normalization. IEEE Trans. Fuzzy Syst., 28(12), 3065-3075. doi: 10.1109/TFUZZ.2020.2967282.

[2] Suryatini, F., Maimunah, M., & Fauzandi, F.I. (2019). Implementasi Sistem Kontrol Irigasi Tetes Menggunakan Konsep IoT Berbasis Logika Fuzzy Takagi-Sugeno. JTERA (Jurnal Teknologi Rekayasa), 4(1), 115. doi: 10.31544/jtera.v4.i1.2019.115-124.

[3] Muhajirah, A., Safitri, E., Mardiana, T., Hartina, H., & Setiawan, A. (2019). Analisis Tingkat Akurasi Metode Neuro Fuzzy dalam Prediksi Data IPM di NTB. JTAM (J. Teor. dan Apl. Mat.), 3(1), 58. doi: 10.31764/jtam.v3i1.769.

[4] Hajar, S., Badawi, M., Setiawan, Y.D., Noor, M., & Siregar, H. (2020). Prediksi Perhitungan Jumlah Produksi Tahu Mahanda dengan Teknik Fuzzy Sugeno. J. Sains Komput. Inform., 4(1), 210-219.

[5] Hu, Z. (2021). Uncertainty Modeling for Multicenter Autism Spectrum Disorder Classification Using Takagi-Sugeno-Kang Fuzzy Systems. IEEE Trans. Cogn. Dev. Syst., 1-10. doi: 10.1109/TCDS.2021.3073368.

[6] Shaheen, O., El-Nagar, A.M., El-Bardini, M., & El-Rabaie, N.M. (2020). Stable adaptive probabilistic Takagi-Sugeno-Kang fuzzy controller for dynamic systems with uncertainties. ISA Trans., 98(xxxx), 271-283. doi: 10.1016/j.isatra.2019.08.035.

[7] Du, A. (2021). Assessing the Adequacy of Hemodialysis Patients via the Graph-Based Takagi-Sugeno-Kang Fuzzy System. Comput. Math. Methods Med., 2021(Ml), doi: 10.1155/2021/9036322.

[8] Pan, J., Kang, Z., Zhang, W., Zhang, B., & Zhang, P. (2020) A Glucose Control Approach for Type-1 Diabetes via Takagi-Sugeno Fuzzy Models," Proc. 32nd (CDDC) Chinese Control Decision Conference, 2441–2446, 2020, doi: 10.1109/CCDC49329.2020.9163827.

[9] Buele J., Rios-Cando, P., Brito, G., Moreno-P, R., & Salazar, F.W. (2020). Temperature Controller Using the Takagi-Sugeno-Kang Fuzzy Inference System for an Industrial Heat Treatment Furnace. Comput. Sci. Its Appl. – ICCSA 2020, 351-366, doi: 10.1007/978-3-030-58799-4_75.

[10] Bisong, E. (2019). Building Machine Learning and Deep Learning Models on Google Cloud Platform.

[11] Xie, H., Yang, F., Hua, M., Liu, S., Hu, J., & He, Y. (2021). Grounding grid corrosion detection based on mini-batch gradient descent and greedy method. AIP Adv., 11(6), 1-11, doi: 10.1063/5.0051678.

[12] Si, Z., Wen, S., & Dong, B. (2019). NOMA Codebook Optimization by Batch Gradient Descent. IEEE Access, 7, 117274-117281, doi: 10.1109/ACCESS.2019.2936483.

[13] Chen, Y., & Shi, C. (2019). Network Revenue Management with Online Inverse Batch Gradient Descent Method. SSRN Electron. J., doi: 10.2139/ssrn.3331939.

[14] Hanifa, A., Fauzan, S.A., Hikal, M., & Ashfiya, M.B. (2021). Perbandingan Metode LSTM dan GRU (RNN) untuk Klasifikasi Berita Palu Berbahasa Indonesia. Din. Rekayasa, 17(1).

[15] Hsueh, B.Y., Li, W., & Wu, I.C. (2019). Stochastic gradient descent with hyperbolic-tangent decay on classification. IEEE Winter Conf. Appl. Comput. Vision (WACV 2019), 435-442, doi: 10.1109/WACV.2019.00052.

[16] Mignacco, F., Krzakala, F., Urbani, P., & Zdeborová, L. (2020). Dynamical mean-field theory for stochastic gradient descent in Gaussian mixture classification. Adv. Neural Inf. Process. Syst., 1-16, December 2020.

[17] Ruder, S. (2017). An overview of gradient descent optimization algorithms. 1-14, Available Online: http://arxiv.org/abs/1609.04747

[18] Khirirat, S., Feyzmahdavian, H.R., & Johansson, M. (2018). Mini-batch gradient descent: Faster convergence under data sparsity. IEEE 56th Annual Conference Decision Contorl (CDC 2017), January 2018, 2880-2887, doi: 10.1109/CDC.2017.8264077.

[19] Gou, P., & Yu, J. (2018). A nonlinear ANN equalizer with mini-batch gradient descent in 40Gbaud PAM-8 IM/DD system. Opt. Fiber Tech., 46(May), 113-117, doi: 10.1016/j.yofte.2018.09.015.

[20] Messaiud, S., Bradai, A., & Moulay, E. (2020). Online GMM Clustering and Mini-Batch Gradient Descent Based Optimization for Industrial IoT 4.0. IEEE Trans. Ind. Informatics, 16(2), 1427-1435, doi: 10.1109/TII.2019.2945012.

[21] Hu, J., Gao, Y, Li, J., & Shang, X. (2019). Deep Learning Enables Accurate Prediction of Interplay Between lncRNA and Disease. Front. Genet., 10(October), 1-7, doi: 10.3389/fgene.2019.00937.

[22] Murugan, P., & Durairaj, S. (2017). Regularization and Optimization strategies in Deep Convolutional Neural Network. 1-15, Available Online: http://arxiv.org/abs/1712.04711.

[23] Goodfellow, I. (2017). Regularization for Deep Learning: A Taxonomy. Available Online: http://arxiv.org/abs/1710.10686

[24] Gong, Y. (2016). Bernstein Filter: A New Solver For Mean Curvature Regularied Models. Icassp 2016, 1701-1705.

[25] Davvaz, B., Mukhlash, I., & Soleha, S. (2021). Himpunan Fuzzy dan Rough Sets. Limits J. Math. Its Appl., 18(1), 79, doi: 10.12962/limits.v18i1.7705.

[26] Wang, Q., Qian, Y., Liang, X., Guo, Q., & Liang, J. (2018). Local neighborhood rough set. Knowledge-Based Syst., 153, 53-64, doi: 10.1016/j.knosys.2018.04.023.

[27] Zhan, J., Liu, Q., & Herawan, T. (2017). A novel soft rough set: Soft rough hemirings and corresponding multicriteria group decision making. Appl. Soft Comput. J., 54, 393-402, doi: 10.1016/j.asoc.2016.09.012.

[28] Hannah, G.J.H., Ahmad, I., Azar, T., Devi, K.R. (2018). Rough set theory with Jaya optimization for acute lymphoblastic leukemia classification. Neural Comput. Appl., 7, doi: 10.1007/s00521-018-3359-7.

[29] Listiana, N., Anggraeni, W., & Mukhlason, A. (2010). Dan Penanganan Dini Penyakit Sapi.

[30] Yao, Y., & Zhang, X. (2017). Class-specific attribute reducts in rough set theory. Inf. Sci. (Ny)., 418-419, 601-618, doi: 10.1016/j.ins.2017.08.038.

[31] Zimmermann, H.J. (1996). (3rd Edi.). Fuzzy Set Theory and Its Applications. Kluwer Academic Publisher, New York, United States of America.

[32] Wiktorowicz, K., & Krzeszowski, T. (2020). Approximation of two-variable functions using high-order Takagi–Sugeno fuzzy systems, sparse regressions, and metaheuristic optimization. Soft Comput., 24(20), 15113-15127, doi: 10.1007/s00500-020-

05238-3.

[33] Wu, D., Yuan, Y., Huang, J. & Tan, Y. (2020). Optimize TSK Fuzzy Systems for Regression Problems: Minibatch Gradient Descent with Regularization, DropRule, and AdaBound (MBGD-RDA). IEEE Trans. Fuzzy Syst., 28(5), 1003-1015, doi: 10.1109/TFUZZ.2019.2958559.

[34] Rohmah, M.F., & Ardiantoro, L. (2019). Meramal Indeks Harga Konsumen Kabupaten di Jawa Timur dengan Metode Support Vector Regression Data Mining. X, 30-36.

HASIL CEK_Implementation of Takagi Sugeno Kang Fuzzy

PRIMARY SOURCES

1	www.jatit.org Internet Source	3%
2	eprints.uad.ac.id Internet Source	2%
3	Submitted to AAB College Student Paper	2%
4	Lecture Notes in Computer Science, 2012. Publication	1%
5	"Rough Sets", Springer Science and Business Media LLC, 2019 Publication	1%
6	mdpi-res.com Internet Source	1%
7	"Fuzzy Systems and Data Mining VIII", IOS Press, 2022 Publication	1%
8	Yuqi Cui, Dongrui Wu, Jian Huang. "Optimize TSK Fuzzy Systems for Classification Problems: Mini-Batch Gradient Descent with	1%

Uniform Regularization and Batch Normalization", IEEE Transactions on Fuzzy Systems, 2020
Publication

9   Krzysztof Wiktorowicz, Tomasz Krzeszowski. "Approximation of two-variable functions using high-order Takagi–Sugeno fuzzy systems, sparse regressions, and metaheuristic optimization", Soft Computing, 2020
Publication   1 %

10   ijournalse.org
Internet Source   1 %

11   Krzysztof Wiktorowicz, Tomasz Krzeszowski, Krzysztof Przednowek. "Sparse regressions and particle swarm optimization in training high-order Takagi–Sugeno fuzzy systems", Neural Computing and Applications, 2020
Publication   <1 %

12   docplayer.net
Internet Source   <1 %

13   "Fuzzy Multi-criteria Decision-Making Using Neutrosophic Sets", Springer Science and Business Media LLC, 2019
Publication   <1 %

14   Submitted to RMIT University
Student Paper   <1 %

15 Sun, Xu, Wangshu Sun, Jianzhou Wang, Yixin Zhang, and Yining Gao. "Using a Grey–Markov model optimized by Cuckoo search algorithm to forecast the annual foreign tourist arrivals to China", Tourism Management, 2016.
Publication

<1%

16 Advanced Information and Knowledge Processing, 2014.
Publication

<1%

17 Omar Shaheen, Ahmad M. El-Nagar, Mohammad El-Bardini, Nabila M. El-Rabaie. "Stable adaptive probabilistic Takagi–Sugeno–Kang fuzzy controller for dynamic systems with uncertainties", ISA Transactions, 2020
Publication

<1%

18 insightsociety.org
Internet Source

<1%

19 nozdr.ru
Internet Source

<1%

20 Dongrui Wu, Ye Yuan, Jian Huang, Yihua Tan. "Optimize TSK Fuzzy Systems for Regression Problems: Mini-Batch Gradient Descent with Regularization, DropRule and AdaBound (MBGD-RDA)", IEEE Transactions on Fuzzy Systems, 2019
Publication

<1%

www.ijournalse.org

| 21 | Internet Source | <1 % |

| 22 | www.mdpi.com
Internet Source | <1 % |

Exclude quotes   On   Exclude matches   Off

Exclude bibliography   On