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Implementation of Takagi Sugeno Kang (TSK) Fuzzy with Rough Set Theory and Mini-Batch Gradient Descent Uniform Regularization (MBGD-UR)

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Abstract Takagi Sugeno Kang (TSK) is a fuzzy method often used because its output is in the form of a constant or a function. The input used in TSK fuzzy usually affects the number of rules generated such that the use of larger dimensions of data normally leads to more rules, thereby causing complexity for the rule. It is possible to overcome this problem using dimension reduction methods which minimize the number of existing dimensions in the data. An example of this method is rough set theory introduced by Palwak in 1982. Moreover, Mini-Batch Gradient Descent (MBGD) which is an optimization method modified using Uniform Regularization (UR) was also applied. The body fat data of 252 respondents were used as input while the output was evaluated using Mean Absolute Percentage Error (MAPE). The results showed MAPE value was 37% and this is included in the reasonable category.

Keywords Rough set. Takagi Sugeno Kang fuzzy. Mini batch gradient descent, uniform regularization

1. Introduction

The dimensions in each data set have different sizes with those in large data often observed to have a high level of complexity which affects the number of rules generated when used in a fuzzy inference system. This is indicated by the fact that the use of large data dimensions as input normally leads to the generation of more rules.

One of the studies conducted by [1] uses Takagi Sugeno Kang (TSK) fuzzy which was observed to be limited when the input used was large. This TSK is a type of inference fuzzy introduced by Takagi and Sugeno in 1985 [2] which is often used for classification or prediction [3]–[5].

TSK was used by [6] to perform the AP-TSK-PID scheme in dealing with stochastic and non-stochastic uncertainties of nonlinear dynamic systems. It has also been applied in the health sector by [7] to predict the adequacy of dialysis in hemodialysis

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patients and [8] to treat the problem associated with the control of glucose levels for type-1 diabetes.

TSK fuzzy can be optimized using Gradient Descent (GD) to ensure better operating time performance [9]. This GD is one of the optimization algorithms normally used to minimize the cost function in machine learning and usually conducted by updating each parameter based on previous steps [10], [11].

The three types of GD are batch, stochastic, and Mini-Batch. The batch type has been previously used for classification by [12], [13] and the stochastic type by [14]–[16]. This present study used Mini-Batch Gradient Descent (MBGD) because it tends to have a smaller computational load and a faster convergence due to the involvement of only the data in a batch in each iteration [17], [18].

Several studies have been conducted on MBGD such as its use by [19] to efficiently train the ANN equalizer, [20] to optimize the IoT 4.0 industry while [21] combined it with MMLDA to predict lncRNA disease association. Moreover, the regularization technique was used to avoid overfitting and increase generalization due to its ability to promote the generalization of the algorithm by avoiding coefficients in order to fit the training sample data [22]. According to Goodfellow [23], regularization is defined as "any modification made to a learning algorithm intended to reduce generalization errors and not training errors". This technique is believed to be needed to stabilize numerical calculations [24].

Rough set is a dimension reduction method introduced by Palwak in 1982. It was conducted by [25] to perform feature selection in genetic algorithms and observed to have provided good results for the selected features. Another study by [26] also used this method for decision-making.

Previous explanation showed that [1] has limitations related to the large data dimensions. Therefore, this present study used rough set to reduce the dimension of the large data.

2. Preliminaries

2.1 Rough Set

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 [27]. It was applied to analyze the data in this present study in accordance with a study conducted by [28].

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, fuzzy set with membership function of $\mu_A(x)$ is:

$$\mu_A(x): X \rightarrow [0,1] \quad (1)$$

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

$$A = \{(x, \mu_A(x) | x \in X)\} \quad (2)$$

where, $\mu_A(x)$ is the membership function x in fuzzy set A which lies on the interval [0,1] [29].

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 [30]:

$$R_j = IF\ x_1 \in F_j(x_1)\ AND\ x_2 \in G_j(x_2)\ THEN\ y = P_j(x_1, x_2) \quad (3)$$

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 [30]:

- 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:

$$Y^* = \frac{\sum_{i=1}^{N} a_i y_i}{\sum_{i=1}^{N} a_i}; i = 1,2,\ldots,N \quad (4)$$

Where,
y_i = output value in the i-th rule
y_i = output value in the i-th rule

2.4 Mini Batch Gradient Desccent (MBG)

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

$$\theta = \theta - \eta \cdot \nabla_\theta J\left(\theta; x^{(i;i+n)}; y^{(i;i+n)}\right) \quad (5)$$

Where, $\eta > 0$ is learning rate (step size) [31].

2.5 Uniform Regularization (UR)

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

$$\ell_{UR} = \sum_{r=1}^{R}\left(\frac{1}{N}\sum_{n=1}^{N}\bar{f}_r(x_n) - \tau\right)^2 \quad (6)$$

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

$$\mathcal{L} = \ell + \alpha\ell_2 + \lambda\sum_{r=1}^{R}\left(\frac{1}{N}\sum_{n=1}^{N}\bar{f}_r(x_n) - \frac{1}{R}\right)^2 \quad (7)$$

2.6 Mean Absolute Percentage Error (MAPE)

MAPE is one of the methods normally used to evaluate a model and its value can be determined using the following equation [32]:

$$MAPE = \frac{\sum_{i=1}^{n}\frac{|y_i - y'_i|}{y_i}}{n} \times 100\% \quad (8)$$

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 [32] are as follows:

Table 1. MAPE Criteria

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

3. Results

The body fat data from a database known as Kaggle 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:

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

$$= \frac{\sum_{i=1}^{n} \frac{|12.3-18.2045|}{12.3} + \frac{|6.1-19.7421|}{6.1} + \ldots + \frac{|31.9-20.6161|}{31.9}}{252} \times 100\%$$

$$= 36.5510\% \approx 37\%$$

4. Discussion

This study used 252 data with 14 independent variables and 1 dependent variable, and the results of the dimension reduction using 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.

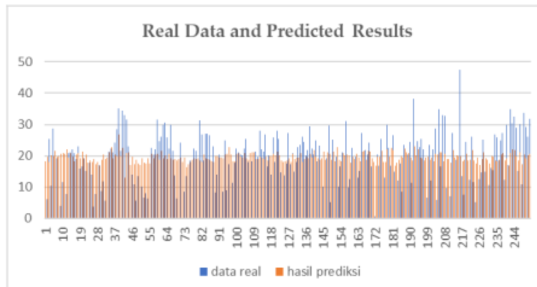

Figure 1. Real data and predicted results

Figure 1 was used to compare the data from the predicted results and the real data. Moreover, MAPE value was calculated using Equation (8) to determine the accuracy of the model obtained and the value was found to be 37% which is classified as a reasonable category as indicated in Table 1.

5. Conclusion

This study applied rough test dimension reduction method TSK fuzzy to body fat data after which the rule from TSK fuzzy was optimized through MBGD modified using UR. Moreover, MAPE was used for evaluation and its value was recorded to be 37%, thereby indicating the model is included in the reasonable category. Therefore, it is recommended that further studies use other dimension optimization and reduction methods.

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References

1. Y. Cui, D. Wu, and J. Huang, "Optimize TSK Fuzzy Systems for Classification Problems: Minibatch Gradient Descent with Uniform Regularization and Batch Normalization," *IEEE Trans. Fuzzy Syst.*, vol. 28, no. 12, pp. 3065–3075, 2020, doi: 10.1109/TFUZZ.2020.2967282.
2. F. Suryatini, M. Maimunah, and F. I. Fauzandi, "Implementasi Sistem Kontrol Irigasi Tetes Menggunakan Konsep IoT Berbasis Logika Fuzzy Takagi-Sugeno," *JTERA (Jurnal Teknol. Rekayasa)*, vol. 4, no. 1, p. 115, 2019, doi: 10.31544/jtera.v4.i1.2019.115-124.
3. A. Muhajirah, E. Safitri, T. Mardiana, H. Hartina, and A. Setiawan, "Analisis Tingkat Akurasi Metode Neuro Fuzzy dalam Prediksi Data IPM di NTB," *JTAM | J. Teor. dan Apl. Mat.*, vol. 3, no. 1, p. 58, 2019, doi: 10.31764/jtam.v3i1.769.
4. S. Hajar, M. Badawi, Y. D. Setiawan, M. Noor, and H. Siregar, "Prediksi Perhitungan Jumlah Produksi Tahu Mahanda dengan Teknik Fuzzy Sugeno," *J. Sains Komput. Inform.*, vol. 4, no. 1, pp. 210–219, 2020.
5. Z. Hu *et al.*, "Uncertainty Modeling for Multi center Autism Spectrum Disorder Classification Using Takagi-Sugeno-Kang Fuzzy Systems," *IEEE Trans. Cogn. Dev. Syst.*, pp. 1–10, 2021, doi: 10.1109/TCDS.2021.3073368.
6. O. Shaheen, A. M. El-Nagar, M. El-Bardini, and N. M. El-Rabaie, "Stable adaptive probabilistic Takagi–Sugeno–Kang fuzzy controller for dynamic systems with uncertainties," *ISA Trans.*, vol. 98, no. xxxx, pp. 271–283, 2020, doi: 10.1016/j.isatra.2019.08.035.
7. A. Du *et al.*, "Assessing the Adequacy of Hemodialysis Patients via the Graph-Based Takagi-Sugeno-Kang Fuzzy System," *Comput. Math. Methods Med.*, vol. 2021, no. Ml, 2021, doi: 10.1155/2021/9036322.
8. J. Pan, Z. Kang, W. Zhang, B. Zhang, and P. Zhang, "A Glucose Control Approach for Type-1 Diabetes via Takagi-Sugeno Fuzzy Models," *Proc. 32nd Chinese Control Decis. Conf. CCDC 2020*, pp. 2441–2446, 2019, doi: 10.1109/CCDC49329.2020.9163827.
9. J. Buele, P. Rios-Cando, G. Brito, R. Moreno-P, and F. W. Salazar, "Temperature Controller Using the Takagi-Sugeno-Kang Fuzzy Inference System for an Industrial Heat Treatment Furnace," *Comput. Sci. Its Appl. – ICCSA 2020*, pp. 351–366, 2020, doi: 10.1007/978-3-030-58799-4_75.
10. E. Bisong, *Building Machine Learning and Deep Learning Models on Google Cloud Platform*. 2019.
11. H. Xie, F. Yang, M. Hua, S. Liu, J. Hu, and Y. He, "Grounding grid corrosion detection based on mini-batch gradient descent and greedy method," *AIP Adv.*, vol. 11, no. 6, pp. 1–11, 2021, doi: 10.1063/5.0051678.
12. Z. Si, S. Wen, and B. Dong, "NOMA Codebook Optimization by Batch Gradient Descent," *IEEE Access*, vol. 7, pp. 117274–117281, 2019, doi: 10.1109/ACCESS.2019.2936483.
13. Y. Chen and C. Shi, "Network Revenue Management with Online Inverse Batch Gradient Descent Method," *SSRN Electron. J.*, 2019, doi: 10.2139/ssrn.3331939.
14. A. Hanifa, S. A. Fauzan, M. Hikal, and M. B. Ashfiya, "Perbandingan Metode LSTM dan GRU (RNN) untuk Klasifikasi Berita Palu Berbahasa Indonesia," *Din. Rekayasa*, vol. 17, no. 1, 2021.
15. B. Y. Hsueh, W. Li, and I. C. Wu,

"Stochastic gradient descent with hyperbolic-tangent decay on classification," *2019 IEEE Winter Conf. Appl. Comput. Vision, WACV 2019*, pp. 435–442, 2019, doi: 10.1109/WACV.2019.00052.
16. F. Mignacco, F. Krzakala, P. Urbani, and L. Zdeborová, "Dynamical mean-field theory for stochastic gradient descent in Gaussian mixture classification," *Adv. Neural Inf. Process. Syst.*, vol. 2020-Decem, pp. 1–16, 2020.
17. S. Ruder, "An overview of gradient descent optimization algorithms," pp. 1–14, 2017, [Online]. Available: http://arxiv.org/abs/1609.04747.
18. S. Khirirat, H. R. Feyzmahdavian, and M. Johansson, "Mini-batch gradient descent: Faster convergence under data sparsity," *2017 IEEE 56th Annu. Conf. Decis. Control. CDC 2017*, vol. 2018-Janua, no. Cdc, pp. 2880–2887, 2018, doi: 10.1109/CDC.2017.8264077.
19. P. Gou and J. Yu, "A nonlinear ANN equalizer with mini-batch gradient descent in 40Gbaud PAM-8 IM/DD system," *Opt. Fiber Technol.*, vol. 46, no. May, pp. 113–117, 2018, doi: 10.1016/j.yofte.2018.09.015.
20. S. Messaoud, A. Bradai, and E. Moulay, "Online GMM Clustering and Mini-Batch Gradient Descent Based Optimization for Industrial IoT 4.0," *IEEE Trans. Ind. Informatics*, vol. 16, no. 2, pp. 1427–1435, 2020, doi: 10.1109/TII.2019.2945012.
21. J. Hu, Y. Gao, J. Li, and X. Shang, "Deep Learning Enables Accurate Prediction of Interplay Between lncRNA and Disease," *Front. Genet.*, vol. 10, no. October, pp. 1–7, 2019, doi: 10.3389/fgene.2019.00937.
22. P. Murugan and S. Durairaj, "Regularization and Optimization strategies in Deep Convolutional Neural Network," pp. 1–15, 2017, [Online]. Available: http://arxiv.org/abs/1712.04711.
23. ian Goodfellow, "Regularization for Deep Learning: A Taxonomy," 2017, [Online]. Available: http://arxiv.org/abs/1710.10686.
24. Y. Gong, "Bernstein Filter: A New Solver For Mean Curvature Regularied Models," *Icassp 2016*, pp. 1701–1705, 2016.
25. Q. Wang, Y. Qian, X. Liang, Q. Guo, and J. Liang, "Local neighborhood rough set," *Knowledge-Based Syst.*, vol. 153, pp. 53–64, 2018, doi: 10.1016/j.knosys.2018.04.023.
26. J. Zhan, Q. Liu, and T. Herawan, "A novel soft rough set: Soft rough hemirings and corresponding multicriteria group decision making," *Appl. Soft Comput. J.*, vol. 54, pp. 393–402, 2017, doi: 10.1016/j.asoc.2016.09.012.
27. B. Davvaz, I. Mukhlash, and S. Soleha, "Himpunan Fuzzy dan Rough Sets," *Limits J. Math. Its Appl.*, vol. 18, no. 1, p. 79, 2021, doi: 10.12962/limits.v18i1.7705.
28. N. Listiana, W. Anggraeni, and A. Mukhlason, "Dan Penanganan Dini Penyakit Sapi," 2010.
29. H. J. Zimmermann, *Fuzzy Set Theory and Its Applications, Third Edition*. USA: Kluwer Academic Publisher, 1996.
30. K. Wiktorowicz and T. Krzeszowski, "Approximation of two-variable functions using high-order Takagi–Sugeno fuzzy systems, sparse regressions, and metaheuristic optimization," *Soft Comput.*, vol. 24, no. 20, pp. 15113–15127, 2020, doi: 10.1007/s00500-020-05238-3.
31. D. Wu, Y. Yuan, J. Huang, and Y. Tan, "Optimize TSK Fuzzy Systems for Regression Problems: Minibatch Gradient Descent with Regularization, DropRule, and AdaBound (MBGD-RDA)," *IEEE Trans. Fuzzy Syst.*, vol. 28, no. 5, pp. 1003–1015, 2020, doi: 10.1109/TFUZZ.2019.2958559.
32. mimin F. Rohmah and L. Ardiantoro,

"Meramal Indeks Harga Konsumen Kabupaten di Jawa Timur dengan Metode Support Vector Regression Data Mining," no. x, pp. 30–36, 2019.

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