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Submission date: 13-Jun-2023 11:49AM (UTC+0700)
Submission ID: 2115008846
File name: 28Vol100No22_jatit.pdf (3.86M)
Word count: 6524
Character count: 32365

Journal of Theoretical and Applied Information Technology
30th November 2022. Vol.100. No 22

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

FUZZY INFERENCE SYSTEM FOR CLASSIFICATION WITH DIMENSION REDUCTION OF ROUGH SET

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ABSTRACT

Data obtained from various measurements will have different characteristics. Different data sets can be classified according to the characteristics of each data. One of the classification methods is the Takagi Sugeno Kang (TSK) fuzzy inference system, where the fuzzy TSK output is a constant, linear or polynomial. However, one of the obstacles in fuzzy TSK is regarding the dimensions of the data. Therefore, we propose a dimension reduction using the rough set in this study. Then, the results of the rough set will be used as input to the fuzzy TSK, and each rule will be optimized using MBGD and SGD. This study compares TSK's accuracy and computational time results using MBGD and SGD. The results indicate that the average time of the MBGD-UR produces the shortest time. In addition, MBGD-UR has a time that tends to be more stable than other methods. Then, the BCA value shows that MBGD-A has the most significant BCA value. Therefore, MBGD-A has the best performance compared to other methods.
Keywords: *Fuzzy TSK, Dimension reduction, MBGD, SG, Rough set.*

1. INTRODUCTION

Classification is a data processing technique using the type of unsupervised learning where each data has been entered into a predetermined class **[1].** One of the classification methods is a fuzzy inference system. A fuzzy inference system is a computational framework based on fuzzy set theory and rules in the form of IF-THEN, where IF is the input (antecedent) and THEN is the output (consequent) **[2], [3].**

The basic idea of fuzzy set theory is to model phenomena in the real world that are not clear or ambiguous. One application of fuzzy set theory and fuzzy logic is a rule-based fuzzy system. In this application, fuzzy sets and fuzzy logic represent knowledge about the problem being solved and model the relationship between input and output variables **[4]**. The main components of the fuzzy system are the rule base, membership function, and fuzzy inference that convert input values into outputs. The input variables in the rules are converted to fuzzy form, and the resulting output depends on the type of fuzzy system used **[5].** In this case, the output in question can be a fuzzy set, constant, linear or polynomial.

Several fuzzy inference systems can be used, namely Tsukamoto, Mamdani, and Takagi Sugeno Kang (TSK). The Tsukamoto method has input and output from fuzzy sets with monotonous membership **[6]**. Meanwhile, the Mamdani and TSK methods have almost the same reasoning, only the output of the Mamdani fuzzy is a fuzzy set, and the output of the fuzzy TSK is a constant, linear or polynomial. Therefore, TSK has fuzzy logic control, which is more concise and efficient in terms of computation because the output is in the form of constants, linear or polynomial **[7], [8].**

The consequence in the fuzzy TSK, which is a linear function, has a constant that must be determined. The constants in question are $b_0, b_1, \ldots, b_n$ where n is the number of input variables, one method that can be used to determine these constants is the gradient descent method, which is used to find the minimum function **[9].** There are several gradient descent methods, including MBGD and SGD. MBGD is a type of gradient descent that applies the mini-batch concept to update parameters, while the concept in SGD is

to update parameters with each data **[10].** Several studies discussing MBGD were carried out by **[11]** to train the ANN equalizer efficiently. MBGD is used by **[12]** to optimize the IoT 4.0 industry. In addition, **[13]** used MBGD to predict IncRNA disease associations. Then, several studies related to SGD include research conducted by **[14]–[16]** to make the classification.

In a study by **[17],** TSK was used for classification problems using MBGD. However, this TSK will have complications if the data dimensions are large. Large data dimensions can be overcome by making dimension reduction. One of the dimension reduction methods that can be used is a rough set. The rough set was introduced by Pawlak in 1982 and is an extension of set theory, a subset of the universe described by a pair of original sets called the upper and lower approximation sets. The main thing in the rough set model is equivalence relations, namely reflexive, symmetrical and transitive relations **[18]**.

Rough set theory can be applied to classification **[19]–[23]** and predictions **[24]–[27].** The main advantage of the rough set is that the method does not require initial information or additional information about the data, such as probability in statistics, membership level, or probability value in fuzzy set theory **[28].** Several studies have been conducted for rough set applications. First, research by **[29]** rough set was applied for feature selection in classification by genetic algorithm. The data set shows that the proposed method gives good results regarding the number of selected features and computational time. In addition, **[30]** used a rough set to make decisions.

Balanced Classification Accuracy (BCA) is one of the methods used in classification to measure the level of true positive and true negative [31]. A higher overall accuracy value or BCA indicates good performance [32].

Based on some of the explanations above, the researcher will classify with fuzzy Takagi Sugeno Kang (TSK) using the rough set as a dimension reduction. Then, each generated rule will be optimized using MBGD and SGD with modifications to Uniform Regularization, Batch Normalization, and AdaBound.

2. METHODOLOGY

The method used in this research is the fuzzy TSK method which will reduce its dimensions with a rough set and optimize it using MBGD and SGD. Pawlak first introduced the rough set in 1982. The principle of the rough set model is equivalence relations, namely reflexive, symmetrical, and transitive relations **[18]**. This method is one of the methods to perform dimension reduction. Research by **[33]** carried out a dimension reduction with the attribute data set using as many as 2 attributes. One of the advantages of using a rough set is that it does not require any preliminary and additional information about the data in conducting data analysis **[34].** In addition, this method also does not require a random function to select candidate attributes randomly, which is done when selecting attributes using a random forest **[35]**.

In the rough set, an information system can be represented as a table **[36]**. The table can be described as $S=(U, A)$, where *You* is a non-empty finite set of objects, and A is a non-empty finite set of attributes. The information system has a decision system, namely the outcome of the general classification. The decision system can be written as $S=(U,A \cup\{d\})$, 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. Suppose $S=(U,A)$ is an information system and $B \subseteq A$. An indiscernibility relation of objects according to attribute B denoted by $IND]\_s\ (B)$ can be defined as follows:

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

where $IND_S(B)$ is $B - indiscrenibility\ relation$.

Attributes in the rough set can be omitted without losing their actual value because there are redundant attributes that will not affect the classification results if they are omitted. Suppose $S=(U,A), B \subseteq A$, and $a \in B$ then a is dispensable in attribute B if $IND]\_S\ (B)=[IND]\_S\ (B-\{a\})$ and if a is indispensable then a is indispensable in B. A set B is considered independent if all its attributes are indispensable. Any subset $B^{\wedge\prime}$ of B is called a reduct of B if $B^{\wedge\prime}$ is independent and $IND]\_S\ (B')=[IND]\_S\ (B)$. So reduction is the set of attributes that can produce the same classification as if all attributes were used. Meanwhile, non-reduct attributes are attributes that are not useful in the classification process **[36]**. Suppose $B \subseteq A$ and core of B is the set of all dispensable attributes of B, then core can be defined as follows *[37]:*

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

A fuzzy set theory is needed because all *crisp* numbers will be converted to fuzzy numbers.

Definition 1 The fuzzy set A, in universe X can be defined as a set of ordered pairs as follows

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

Journal of Theoretical and Applied Information Technology
30th November 2022. Vol.100. No 22

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

with $\mu_A(x)$ membership function x in fuzzy set A located in the interval interval $[0,1]$ [38]. Takagi Sugeno Kang fuzzy system with one input x_1 and x_2 and output y is explained by r fuzzy inference rules as follows [37]

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

where $j = 1,2,\dots,r, F_j(x_1), G_j(x_2)$ is fuzzy set and $P_j(x_1,x_2)$ is degree polynomial d. In addition to the fuzzification stage, defuzzification aims to convert fuzzy numbers to crisp numbers. The defuzzification value (Z*) can be calculated using the following equation:

$$Z^* = \frac{\sum_{i=1}^{N} a_i z_i}{\sum_{i=1}^{N} z_i}; i = 1,2,\dots,N \quad (4)$$

where α_i is the value of *alfa-cut* output in the rule number i and z_i = output value in rule number i.

The fuzzy inference system can be optimized using MBGD to handle large-scale data sets by reducing computational complexity in each iteration. The rules obtained from the fuzzification results can be optimized for each rule using MBGD. Parameter update by using $\theta = \theta - \eta \cdot \nabla_\theta J(\theta; x^{(i:i+n)}; y^{(i:i+n)})$, where $\eta > 0$ is the *learning rate* (*step size*) [40]. Meanwhile, SGD is a gradient descent method that performs parameter updates using each data [10]. Parameter update with SGD is done with $\theta = \theta - \eta \cdot \nabla_\theta J(\theta; x^{(i)}; y^{(i)})$, where $\eta > 0$ is *learning rate* (*step size*). [40], [41].

The UR method is a regularization technique that forces the rules to have a similar average ring level (degree of activation), minimizing losses. The UR function can be written as follows:

$$\mathcal{L} = \ell + \alpha \ell_2 + \lambda \sum_{n=1}^{n} \left(\frac{1}{N} \sum_{n=1}^{N} y'_i - y_i \right)^2 \quad (5)$$

where N is the number of experiment examples, τ is the *firing level* of each rule, y'_i is the output value of fuzzy, and y_i is actual data.

AdaBound is an optimization method that uses dynamic limits on the learning rate [42]. *AdaBound* limits the learning rate from above and below so that a learning rate that is too large or too small cannot occur. In addition, the constraints become stricter with increasing iterations, forcing the learning rate to be nearly constant. The function used to determine the upper limit is as follows [41]:

$$u(k) = 0.01 - \frac{0.01}{(1-\beta_2)k} \quad (6)$$

Meanwhile, to determine the lower limit, the following function is used:

$$l(k) = 0.01 - \frac{0.01}{(1-\beta_2)k+1} \quad (7)$$

When $k = 0$ or the start of training, the limit is $[0, +\infty)$. When training is in progress or k is approaching $+\infty$, then the limit is approaching $[0.01, 0.01]$.

Batch Normalization (BN) has an activation output of zero mean and one standard deviation. There are shifts and scales in the Batch Normalization (BN) algorithm to represent the identity of the batch transformation. The BN process can be defined as follows [43]:

$$BN(x_i) = \gamma \hat{x}_i + \beta \quad (8)$$

β = shift training parameter.
γ = scale training parameter.

The flowchart in this study is as follows:

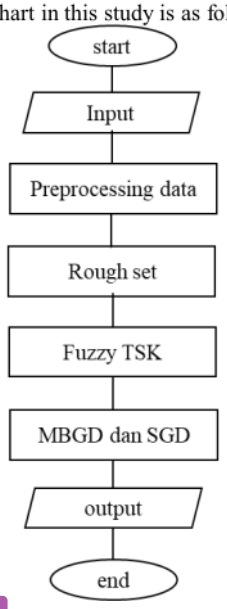

Figure 1. *Flowchart* of study

Figure 1 is a flowchart in this study, where the raw data will be preprocessed first. Then, the data that has been preprocessed will be used as input to the rough set to reduce its dimensions, and the output from the rough set will be used as input to the fuzzy TSK. The fuzzy TSK will produce several rules, each of which will be optimized with MBGD and SGD.

3. RESULTS AND DISCUSSION

In this study, the data used are body fat, anaemia, and air pollution data. The data set was obtained from Kaggle and the official website for data open Jakarta. The first data is body fat data used consisting of 14 variables, namely age (X_1), weight (X_2), height (X_3), density (X_4), neck

Journal of Theoretical and Applied Information Technology
30th November 2022. Vol.100. No 22

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

circumference (X_5), chest circumference (X_6), abdominal circumference (X_7) , hip circumference (X_8), thigh circumference (X_9), knee circumference (X_{10}), ankle circumference (X_{11}), bicep circumference (X_{12}), forearm circumference (X_{13}), wrist circumference (X_{14}), and body fat (Y). The first data set used is in Table 1.

Table 1. *Bodyfat* Data Set

X_1	X_2	X_3	⋯	Y
22	154.25	67.75	⋯	12.3
22	173.25	72.25	⋯	6.1
⋮	⋮	⋮	⋱	⋮
70	190.70	70.5	⋯	26

The dimensions of the data set in Table 1 will be reduced by using the rough set, and the results are obtained, as shown in Table 2.

Table 2. Bodyfat Data Set Reduction Results

X_1	X_2	X_3	Y
70	172	1070.8	12.3
78.6	183.5	1085.3	6.1
⋮	⋮	⋮	⋮
94	177.8	1027,1	26

Based on the results of the rough set, the data set, which has 14 variables, can be reduced to 3 variables, namely weight (X_1), height (X_2), and density (X_3). Then the second data is air pollution data in Jakarta, which consists of 7 variables, namely PM10 (X_1), PM25 (X_2), SO2 (X_3), CO (X_4), O3 (X_5), NO2 (X_6), and ISPU (Y). The data set of air pollution in Jakarta is shown in Table 3.

Table 3. Data Set of Air Pollution

X_1	X_2	X_3	X_4	X_5	X_6	Y
26	42	22	11	13	19	42
41	54	27	11	17	19	54
15	42	20	8	18	22	42
⋮	⋮	⋮	⋮	⋮	⋮	⋮
78	140	32	18	29	39	140
75	121	37	12	50	21	121
53	80	29	6	34	13	80

Furthermore, the following results are obtained in the same way in the rough set steps.

Table 4. Reduction Results of Air Pollution Data Set

X_1	X_2	X_3	X_4	Y
42	22	11	13	42
54	27	11	17	54
42	20	8	18	42
⋮	⋮	⋮	⋮	⋮
140	32	18	29	140
121	37	12	50	121
80	29	6	34	80

The rough set results in Table 4 consist of 5 variables, namely PM25 (X_1), SO2 (X_2), CO (X_3), O3 (X_4), and ISPU (Y). The third data is anaemia data which consists of 6 variables, namely age (X_1), RBC (X_2), MCV (X_3), MCH (X_4), MCHC (X_5), and HGB (X_6). The anaemia data set is in Table 5.

Table 5. Anemia Data Set

X_1	X_2	X_3	X_4	X_5	Y
40	4.65	89.5	28.8	32.2	13.4
20	4.14	89.1	27.8	31.2	11.5
28	4.98	84.9	24.9	29.3	12.4
⋮	⋮	⋮	⋮	⋮	⋮
25	4	93.7	32.3	34.5	12.9
21	4.47	88.7	29.3	33	13.1
35	4.75	86.7	27.9	32.1	13.2

The data set in Table 5 will be processed in the same way in the rough set steps in 2.4 and the following results are obtained.

Table 6. Reduction Results of Anemia Data Set

X_1	X_2	X_3	Y
4.65	89.5	28.8	13.4
4.14	89.1	27.8	11.5
4.98	84.9	24.9	12.4
⋮	⋮	⋮	⋮
4	93.7	32.3	12.9
4.47	88.7	29.3	13.1
4.75	86.7	27.9	13.2

The rough set results in Table 6 consist of 4 variables, namely RBC(X_1), MCV (X_2), MCH (X_3), and HGB (Y).

Then, the results of the rough set will be used as input to the fuzzy TSK. The first stage in the fuzzy TSK is the fuzzification process, where this result is a fuzzy number that will be used

for further calculation. Fuzzification results for each data variable can be seen in Table 7.

Table 7. Results of Bodyfat Data Fuzzification

X_1	X_2	X_3	Y
0	0.2714	0	0
0.3438	0.9824	0.7408	0
⋮	⋮	⋮	⋮
0.6494	0.6106	0.3145	0

Table 7 shows the results of fuzzification in the form of fuzzy numbers on each body fat data. The first data on the first variable has a membership value of 0, the first data on the second variable has a membership value of 0.2714, and so on.

Table 8. Anemia Data Fuzzification Results

X_1	X_2	X_3	Y
0,3333	0,9500	0,4500	0,7778
0,2097	0,9100	0,0000	0,1667
0,9667	0,4900	0,3415	0,6667
⋮	⋮	⋮	⋮
0,3226	0,6300	0,5667	0,9444
0,1167	0,8700	0,5750	0,9444
0,5833	0,6700	0,0000	0,8889

Based on Table 8, the results of the first data fuzzification on the first variable are 0.3333, the first data on the second variable is 0.9500, and so on.

Table 9. Air Pollution Data Fuzzification Results

X_1	X_2	X_3	Y
0.9600	0.9388	0.2857	0.2034
0.3600	0.4490	0.8000	0.2712
1.0000	0.9388	0.6667	0.2881
⋮	⋮	⋮	⋮
0.8800	0.2381	0.1111	0.4746
1.0000	0.6905	0.5714	0.8305
0.1200	0.3488	0.4000	0.5593

Table 9 is the result of the fuzzification of each air pollution data variable. The fuzzification of the first data on the first variable is 0.9600, the first data on the second variable is 0.9388, and so on.

After obtaining the fuzzification results, the second stage of fuzzy TSK is the formation of basic rules that aim to formulate rules in the form of fuzzy implications that state the relationship between input variables and output variables. The basic rules formed from bodyfat data are as follows:

[R1] If X_1 is not standard and X_2 is not standard and X_3 is high, then Y is obese
[R2] If X_1 is not standard and X_2 is not standard and X_3 is moderate, then Y is overweight
[R3] If X_1 is standard and X_2 is not standard and X_3 is high, then Y is obese
[R4] If X_1 is not standard and X_2 is not standard and X_3 is low, then Y is obese
[R5] If X_1 is standard and X_2 is not standard and X_3 is moderate, then Y is overweight
[R6] If X_1 is standard and X_2 is not standard and X_3 is moderate, then Y is normal
[R7] If X_1 is standard and X_2 is nonstandard and X_3 is high, then Y is athletic
[R8] If X_1 is standard and X_2 is not standard and X_3 is high, then Y is normal
[R9] If X_1 is not standard and X_2 is not standard and X_3 is high, then Y is normal
[R10] If X_1 is not standard and X_2 is not standard and X_3 is moderate, then Y is normal
[R11] If X_1 is not standard and X_2 is not standard and X_3 is high, then Y is athletic

Similar to the basic rules for body fat data, some basic rules for anaemia data are as follows:

[R1] If X_1 is lacking and X_2 is not normal and X_3 is moderate, then Y is excessive
[R2] If X_1 is normal and X_2 is normal and X_3 is low, then Y is excessive
[R3] If X_1 is lacking and X_2 is normal and X_3 is moderate, then Y is normal
[R4] If X_1 is normal and X_2 is normal and X_3 is moderate, then Y is excessive
[R5] If X_1 is lacking and X_2 is normal and X_3 is high, then Y is normal
[R6] If X_1 is normal and X_2 is low and X_3 is low, then Y is normal

[R7] If X_1 is lacking and X_2 is normal and X_3 is low, then Y is normal
[R8] If X_1 is lacking and X_2 is normal and X_3 is high, then Y is excessive
[R9] If X_1 is lacking and X_2 is normal and X_3 is low, then Y is excessive
[R10] If X_1 is lacking and X_2 is low and X_3 is low, then Y is less
[R11] If X_1 is lacking and X_2 is low and X_3 is low, then Y is excessive
[R12] If X_1 is normal and X_2 is low and X_3 is low, then Y is excessive
[R13] If X_1 is normal and X_2 is normal and X_3 is high, then Y is excessive
[R14] If X_1 is lacking and X_2 is low and X_3 is low, then Y is normal
[R15] If X_1 is normal and X_2 is normal and X_3 is low, then Y is normal

Whereas the results of the rules formed from the pollution data are as follows:
[R1] If X_1 is moderate and X_2 is not healthy and X_3 is not healthy and X_4 is good then Y is moderate.
[R2] If X_1 is moderate and X_2 is not healthy and X_3 is moderate and X_4 is good, then Y is moderate
[R3] If X_1 is moderate and X_2 is not healthy and X_3 is not healthy and X_4 is good, then Y is not healthy
[R4] If X_1 is moderate and X_2 is not healthy and X_3 is very unhealthy and X_4 is good, then Y is moderate
[R5] If X_1 is good and X_2 is not healthy and X_3 is moderate and X_4 is good, then Y is moderate
[R6] If X_1 is moderate and X_2 is not healthy and X_3 is very unhealthy and X_4 is good, then Y is not healthy
[R7] If X_1 is moderate and X_2 is not healthy and X_3 is moderate and X_4 is good, then Y is not healthy
[R8] If X_1 is good and X_2 is moderate and X_3 is and X_4 is good, then Y is moderate
[R9] If X_1 is good and X_2 is not healthy and X_3 is not healthy and X_4 is good, then Y is
[R10] If X_1 is good and X_2 is moderate and X_3 is not healthy and X_4 is good, then Y is moderate
[R11] If X_1 is moderate and X_2 is not healthy and X_3 is good and X_4 is good, then Y is moderate
[R12] If X_1 is moderate and X_2 is moderate and X_3 is and X_4 is good, then Y is moderate
[R13] If X_1 is good and X_2 is moderate and X_3 is and X_4 is good, then Y is good
[R14] If X_1 is good and X_2 is moderate and X_3 is good and X_4 is good, then Y is good
[R15] If X_1 is moderate and X_2 is very unhealthy and X_3 is not healthy and X_4 is good, then Y is not healthy
[R16] If X_1 is moderate and X_2 is moderate and X_3 is not healthy and X_4 is good, then Y is moderate
[R17] If X_1 is good and X_2 is moderate and X_3 is good and X_4 is good, then Y is moderate

The third stage of fuzzy TSK is making fuzzy inferences from several rules obtained from the collection and correlation between rules. The method used in performing fuzzy system inference is the Min (Minimum) method. The composition of the rules is as follows:

[$R1$] If X_1 is not standard and X_2 is not standard and X_3 is high, then Y is obese

$$\mu_{predicate1} = \mu_{X_1 not\ standard} \cap \mu_{X_2 not\ standard} \cap \mu_{X_3 high}$$
$$= min(\mu_{X_1 not\ standard}[83.80], \mu_{X_1 not\ standard}[83.57], \dots, \mu_{X_1 not\ standard}[86.52],$$
$$min(\mu_{X_2 not\ standard}[183.52], \mu_{X_2 not\ standard}[180.98], \dots, \mu_{X_2 not\ standard}[179.07],$$
$$min(\mu_{X_3 high}[1075.10], \mu_{X_3 high}[1034], \dots, \mu_{X_3 high}[1039,90],$$
$$= min(0.4393, 0.4393, \dots, 0.4966;\ 0.9824, 0.8141, \dots, 0.7463; 0.2139, 0, \dots, 0)$$
$$= 0$$

[$R2$] If X_1 not standard and X_2 not standard and X_3 moderate, then Y is *overweight*

$$\mu_{predicate2} = \mu_{X_1 not\ standard} \cap \mu_{X_2 not\ standard} \cap \mu_{X_3 moderate}$$
$$= min(\mu_{X_1 not\ standard}[82.10], \mu_{X_1 not\ standard}[83.35], \dots, \mu_{X_1 not\ standard}[76.54],$$
$$min(\mu_{X_2 not\ standard}[177.17], \mu_{X_2 not\ standard}[1054.90], \dots, \mu_{X_2 not\ standard}[171.45],$$
$$min(\mu_{X_3 moderate}[1054.90], \mu_{X_3 moderate}[1062.20], \dots, \mu_{X_3 moderate}[1056.30],$$
$$= min(0.4202, 0.4393, \dots, 0.3056;\ 0.6106, 0.2714, \dots, 0.2035; 0.8925, 0.4710, \dots, 0.7871)$$
$$= 0.1357$$

By using the same method, the alpha predicate value of each rule is obtained, as shown in the table below.

Table 10. Alpha Predicate

Bodyfat Data	Anemia Data	Air Pollution Data
0	0,0323	0
0.1357	0	0
0	0,0300	0
⋮	⋮	⋮
0	0	0.0594
0.0495	0	0
0.2865	0	0

Table 10 is the alpha value of the predicate of the composition of the rules for each data. In body fat data, the first rule has an alpha value of 0, and the second rule has an alpha predicate of 0.1357, and so on. Then, for anaemia data, the first rule has an alpha predicate of 0.0323, the second rule has an alpha predicate of 0, and so on. Meanwhile, for air pollution data, the first rule has an alpha predicate of 0, the second rule has an alpha predicate of 0, and so on.

Then, each rule generated from each data will be optimized using MBGD and SGD. The results of MBGD and SGD are in the form of values of b_0, b_1, b_2, and b_3 as follows:

Table 11. Results of b_0, b_1, b_2, and b_3 with MBGD on bodyfat data

UR				Adabound				BN			
b_0	b_1	b_2	b_3	b_0	b_1	b_2	b_3	b_0	b_1	b_2	b_3
−0.3673	0.7797	0.6938	0.4711	0.5356	0.4288	0.1579	−0.3190	0.5358	0.4287	0.1579	−0.3191
−0.0398	0.0671	0.0644	0.0536	0.0383	0.0365	0.0402	−0.0293	0.3807	0.3502	0.4052	−0.2763
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
0.5141	−0.0765	0.0343	−0.0113	0.0371	0.0539	0.0153	0.0124	0.3723	0.0539	0.1524	0.0127

The values of b_0, b_1, b_2, and b_3 Table 11 will be arranged into the following equation:

$z_1 = -0.3673 + 0.7797X_1 + 0.6938X_2 + 0.4711X_3$
$z_2 = -0.0398 + 0.0671X_1 + 0.0644X_2 + 0.0536X_3$
⋮
$z_{11} = -0.5141 - 0.0765X_1 + 0.0343X_2 - 0.0113X_3$

Table 12. Results of b_0, b_1, b_2, and b_3 with SGD on bodyfat data

UR				Adabound				BN			
b_0	b_1	b_2	b_3	b_0	b_1	b_2	b_3	b_0	b_1	b_2	b_3
−0.1092	0.9830	0.9466	0.9676	−0.0068	0.9989	0.9967	0.9980	−0.1092	0.9830	0.9466	0.9676
−0.1906	0.0929	0.0916	0.0940	−0.0187	0.0993	0.0992	0.0994	−0.1906	0.0929	0.0916	0.0940
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
0.3394	0.1000	0.1000	0.1000	0.2759	0.1000	0.1000	0.1000	0.3617	0.1000	0.0110	0.1000

Based on the results of b_0, b_1, b_2, dan b_3 from SGD, they will also be arranged in the form of an equation as follows:

$z_1 = -0.1092 + 0.9830X_1 + 0.9466X_2 + 0.9676X_3$
$z_2 = -0.1906 + 0.0929X_1 + 0.0916X_2 + 0.0940X_3$
⋮
$z_{11} = -0.3394 + 0.1000X_1 + 0.1000X_2 + 0.1000X_3$

Journal of Theoretical and Applied Information Technology
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ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Table 13. Results of b_0, b_1, b_2, and b_3 with MBGD on anaemia data

UR				Adabound				BN			
b_0	b_1	b_2	b_3	b_0	b_1	b_2	b_3	b_0	b_1	b_2	b_3
−0,5466	0,7639	0,5205	0,8562	−0,4085	0,8446	0,3235	0,6189	−0,4086	0,8445	0,3235	0,6188
−0,5943	0,7634	0,6616	0,6612	−0,5288	0,9120	0,5438	0,5742	−0,5288	0,9120	0,5437	0,5743
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
−0,6481	0,4037	0,6260	0,9583	−0,6439	0,4597	0,6518	0,9171	0,3235	−0,6325	0,4537	0,6447

Values of b_0, b_1, b_2, and b_3 Table 13 will be arranged in the form of an equation as follows:

$z_1 = -0.5466 + 0.7639X_1 + 0.5205X_2 + 0.8562X_3$

$z_2 = -0.5943 + 0.7634X_1 + 0.6616X_2 + 0.6612X_3$

⋮

$z_{15} = -0.6482 + 0.4037X_1 + 0.6260X_2 + 0.9583X_3$

Table 14. Results of b_0, b_1, b_2, and b_3 with SGD on anaemia data

UR				Adabound				BN			
b_0	b_1	b_2	b_3	b_0	b_1	b_2	b_3	b_0	b_1	b_2	b_3
0,3323	−0,3734	0,6802	0,7112	−0,0683	0,9415	0,9471	0,9921	−0,3734	0,6802	0,7112	0,9569
0,2906	−0,4710	0,9144	0,6703	−0,1265	0,9770	0,9114	0,9158	−0,4710	0,9144	0,6703	0,6864
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
0,3667	−0,3496	0,8835	1,0000	−0,3496	0,8835	1,0000	0,8411	−0,3496	0,8835	1,0000	0,8411

Based on the results of b_0, b_1, b_2, dan b_3 from SGD, they will also be arranged in the form of an equation as follows:

$z_1 = -0.0683 + 0.9415X_1 + 0.9471X_2 + 0.9921X_3$

$z_2 = -0.1265 + 0.9770X_1 + 0.9114X_2 + 0.9158X_3$

⋮

$z_{15} = -0.3496 + 0.8835X_1 + 1.000X_2 + 0.8411X_3$

Table 15. Results of b_0, b_1, b_2, b_4, and b_4 with MBGD on air pollution data

b_0	b_1	b_2	b_3	b_4	b_0	b_1	b_2	b_3	b_4	b_0	b_1	b_2	b_3	b_4
−0,4667	0,9804	0,9591	0,7183	0,9507	−0,2030	0,3453	0,8750	0,2030	0,1771	−0,2035	0,3467	0,8756	0,2038	0,1765
−0,6119	0,7580	0,7025	0,4113	0,6587	−0,5205	0,7179	0,6994	0,4061	0,6665	−0,5206	0,7179	0,6994	0,4060	0,6665
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
−0,4657	0,8133	0,6671	0,2707	0,4084	−0,5259	0,4937	0,6126	0,2638	0,4819	−0,4817	0,5466	0,6133	0,2325	0,4761

Values of b_0, b_1, b_2, dan b_3 Table 15 will be arranged in the form of an equation as follows:

$z_1 = -0.4667 + 0.9804X_1 + 0.9591X_2 + 0.7183X_3 + 0.9507X_4$

$z_2 = -0.6119 + 0.7580X_1 + 0.7025X_2 + 0.4113X_3 + 0.6587X_4$

⋮

$z_{17} = -0.4657 + 0.8133X_1 + 0.6671X_2 + 0.2707X_3 + 0.4084X_4$

Journal of Theoretical and Applied Information Technology
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ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Table 16. Results of b_0, b_1, b_2, b_4, and b_4 with SGD on air pollution data

UR					Adabound					BN				
b_0	b_1	b_2	b_3	b_4	b_0	b_1	b_2	b_3	b_4	b_0	b_1	b_2	b_3	b_4
1,0000	0,9797	0,8751	0,9557	1,0000	1,0000	0,9994	0,9962	0,9987	1,0000	−0,2498	1,0000	0,9797	0,8751	0,9557
0,7753	0,7046	0,7472	0,5939	0,7753	0,9875	0,9836	0,9860	0,9774	0,9875	−0,5056	0,7753	0,7046	0,7472	0,5939
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
0,8892	0,5570	0,5570	0,7342	0,8892	0,8992	0,5968	0,5968	0,7581	0,8992	−0,4430	0,8892	0,5570	0,5570	0,7342

Based on the results of b_0, b_1, b_2, b_3, dan b_4 from SGD, they will also be arranged in the form of an equation as follows:

$z_1 = -0.2498 + 1.0000X_1 + 0.9797X_2 + 0.8751X_3 + 0.9557X_4$
$z_2 = -0.5056 + 0.7753X_1 + 0.7046X_2 + 0.7472X_3 + 0.5939X_4$
⋮
$z_{17} = -0.4430 + 0.8892X_1 + 0.5570X_2 + 0.5570X_3 + 0.7342X_4$

Next, the fourth stage of fuzzy TSK is defuzzification. Defuzzification is a process in fuzzy where data in the form of fuzzy numbers will be converted into firm numbers. The defuzzification value can be calculated as follows:

$$Z^* = \frac{(\mu_1 \times z_1) + (\mu_1 \times z_1) + \cdots + (\mu_{11} \times z_{11})}{\mu_1 + \mu_2 + \cdots + \mu_{11}}$$

$$= \frac{9.9968}{0.4717}$$

$$= 21.1936$$

By using the same method, the results of the defuzzification are obtained as below.

Table 17. Defuzzification of *bodyfat* data

No	Z^*					
	MBGD-UR	MBGD-A	MBGD-BN	SGD-UR	SGD-A	SGD-BN
1	21.1936	12.7523	28.4223	23.5580	24.0561	19.7775
2	21.7707	13.5790	33.0524	25.4964	26.0380	21.2502
3	20.6311	12.5227	28.3115	23.1761	23.6669	19.4016
⋮	⋮	⋮	⋮	⋮	⋮	⋮
250	20.2425	13.2431	31.7807	24.5361	25.0658	19.9591
251	20.8344	13.6866	35.1146	25.8232	26.3782	21.1481
252	20.4810	13.9951	36.9043	26.4268	26.9999	21.3411

In Table 17, the results of the MBGD-UR TSK defuzzification for the first data are 21.1936, and the second data is 21.7707, and so on. Then, the MBGD-A TSK defuzzification for the first data is 12.7523, and the second data is 13.5790, and so on. Meanwhile, the result of TSK SGD-UR defuzzification for the first data is 23.5580; the second data is 25.4964, and so on. The results of TSK SGD-A defuzzification for the first data are 24.0561, and the second data are 26.0380, and so on.

Table 18 shows the results of the defuzzification of anaemia data. The result of the MBGD-UR TSK defuzzification for the first data is 19.4083; the second data is 19.0598, and so on. Then, the defuzzification of TSK MBGD-A for the first data is 7.5087, and the second data is

7.3533, and so on. Meanwhile, the result of TSK SGD-UR defuzzification for the first data is 28.5058; the second data is 28.0567, and so on. The result of defuzzification of TSK SGD-A for the first data is 30.8138, and the second data is 30.3419, and so on. In addition, the TSK SGD-BN defuzzification results were 28.0567 for the second data, 28.5058 for the first data, and so on.

Table 18. Defuzzification of anaemia data

No	Z^*					
	MBGD-UR	MBGD-A	MBGD-BN	SGD-UR	SGD-A	SGD-BN
1	19.4083	7.5087	17.2666	28.5058	30.8138	28.5058
2	19.0598	7.3533	16.9459	28.0567	30.3419	28.0567
3	18.0945	7.0200	16.1271	26.5820	28.7673	26.5820
⋮	⋮	⋮	⋮	⋮	⋮	⋮
250	20.5393	7.9174	18.2381	30.1869	32.6025	30.1869
251	19.3541	7.4844	17.2124	28.4179	30.7091	28.4179
252	18.8638	7.3086	16.7914	27.6824	29.9240	27.6824

Table 19. Defuzzification of air pollution data

No	Z^*					
	MBGD-UR	MBGD-A	MBGD-BN	SGD-UR	SGD-A	SGD-BN
1	59,7839	60,6693	60,6515	82,2045	87,5700	82,2045
2	81,7450	82,3955	82,3249	110,3638	117,2378	110,3638
3	60,3545	61,5103	61,5158	83,1285	88,4210	83,1285
⋮	⋮	⋮	⋮	⋮	⋮	⋮
250	176,7872	186,1775	185,8947	236,2693	251,6983	236,2693
251	171,0981	176,3479	176,2568	231,0712	245,2846	231,0712
252	115,2295	118,5489	118,4704	155,0350	164,4745	155,0350

Table 19 shows the results of defuzzification from air pollution data. The results of the MBGD-UR TSK defuzzification for the first data were 59.7839; the second data was 81.7450, and so on. Then, the defuzzification of TSK MBGD-A for the first data is 60.6693, and the second data is 82.3955, and so on. Meanwhile, the result of TSK SGD-UR defuzzification for the first data is 82.2045; the second data is 110.3638, and so on. The results of TSK SGD-A defuzzification for the first data are 87.5700, and the second data are 117.2378, and so on. Defuzzification of TSK SGD-BN yielded different results of 82.2045 for the first data, 110.3638 for the second data, and so on.

After the defuzzification results are obtained, the results will be classified based on the existing classes. The classification results will look for the accuracy value using the Balanced Classification Accuracy (BCA). Based on the results of bodyfat defuzzification, the BCA value is obtained, as shown below.

Figure 2 is a comparison of BCA values between MBGD and SGD. The result of BCA scores for MBGD-UR is 0.2000, MBGD-A is 0.2098, and MBGD-BN is 0.1971. Meanwhile, SGD-UR has a BCA value of 0.2078, SGD-A of 0.1991, and SGD-BN of 0.2029. Based on [17], the most significant BCA value indicates the best performance of a method. Therefore, the MBGD-A method has the best BCA value compared to other methods.

Based on Figure 3, the BCA value for MBGD-UR is 0.1595, MBGD-A is 0.3702, and MBGD-BN is 0.3107. Meanwhile, the BCA values for SGD-UR, SGD-A, and SGD-BN, respectively, are 0.3253, 0.3039, and 0.2891. Based on [17], the largest BCA value indicates the best performance of a method. Therefore, the MBGD-A method has the best BCA value compared to other methods.

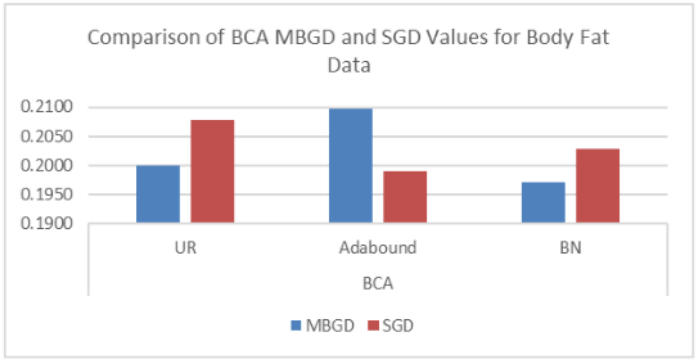

Figure 2. Comparison of BCA MBGD and SGD Values for Body Fat Data

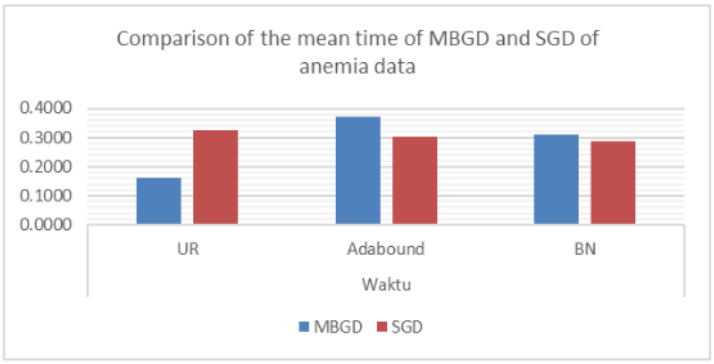

Figure 3. Comparison of BCA MBGD and SGD values for anemia data

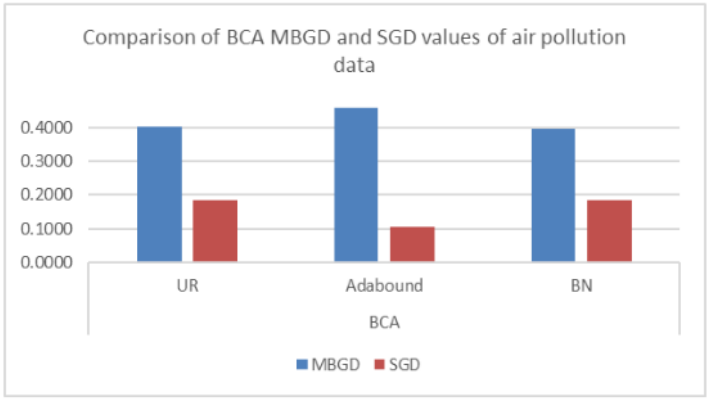

Figure 4. Comparison of BCA MBGD and SGD values of air pollution data

In Figure 4, the BCA value for MBGD-UR is 0.4031, MBGD-A is 0.4576, and MBGD-BN is 0.3972. Meanwhile, the BCA values for SGD-UR, SGD-A, and SGD-BN are 0.1829, 0.1053, and 0.1829, respectively. Based on [17], the largest BCA value indicates the best performance of a method. Therefore, the MBGD-A method has t best BCA value compared to other methods. In

addition to the BCA value, Table 20 also provides the duration between MBGD and SGD.

Table 20. MBGD and SGD time of bodyfat data

MBGD			SGD		
UR	Adabound	BN	UR	Adabound	BN
0.1088	0.5273	0.5469	0.8861	0.2960	0.5604
0.1093	0.5250	0.6841	0.6689	0.2740	0.3067
0.1076	0.3329	0.3508	0.3348	0.3221	0.3790
0.1019	0.4240	0.4421	0.3102	0.2759	0.4134
0.1104	0.3446	0.3728	0.3493	0.2861	0.3026
0.1002	0.3432	0.5855	0.3151	0.3044	0.5090
0.1018	0.7353	0.7151	0.3292	0.2747	0.3328
0.1029	0.7738	0.7280	0.3847	0.3040	0.3400
0.1029	0.3033	0.8556	0.3956	0.3162	0.2919
0.1098	0.3197	0.8440	0.4162	0.3748	0.2678

Table 20 shows the computational times for MBGD-UR, MBGGD-A, MBGD-BN, SGD-UR, SGD-A, and SGD-BN. The average time generated by MBGD-UR is 0.1105, MBGD-A is 0.4483, and MBGD-BN is 0.6331. Meanwhile, the average time produced by SGD-UR, SGD-A, and SGD-BN, respectively, is 0.4302, 0.3054, and 0.3749. Therefore, MBGD-UR has the smallest average time compared to other methods. The time graph of MBGD and SGD can be shown in Figure 5.

Figure 5 shows the time comparison between the MBGD-UR, MBGD-A, MBGD-BN, SGD-UR, SGD-A, and SGD-BN methods. Based on the picture above, it can be seen that MBGD-UR has a time that tends to be more stable than other methods.

Table 21 shows that the average time for MBGD-UR, MBGD-A, and MBGD-BN, respectively, is 0.1869, 0.3702, and 0.3107. Meanwhile, the average time generated by SGD-UR is 0.3253, SGD-A is 0.3039, and SGD-BN is 0.2891. Therefore, MBGD-UR has the shortest average time compared to other methods. The time graph of MBGD and SGD can be seen in Figure 6.

In Figure 6, we can see the time between MBGD and SGD between the methods of MBGD-UR, MBGD-A, MBGD-BN, SGD-UR, SGD-A, and SGD-BN. Based on the picture above, MBGD-UR and MBGD-BN tend to be stable compared to other methods. However, MBGD-UR has a faster time than MBGD-BN or other methods.

Table 22 shows that the average time for MBGD-UR, MBGD-A, and MBGD-BN, respectively, is 0.1505, 0.4645, and 0.4194. Meanwhile, the average time generated by SGD-UR is 0.3207, SGD-A is 0.2612, and SGD-BN is 0.2596. Therefore, MBGD-UR has the shortest average time compared to other methods. The time graph of MBGD and SGD can be seen in Figure 7.

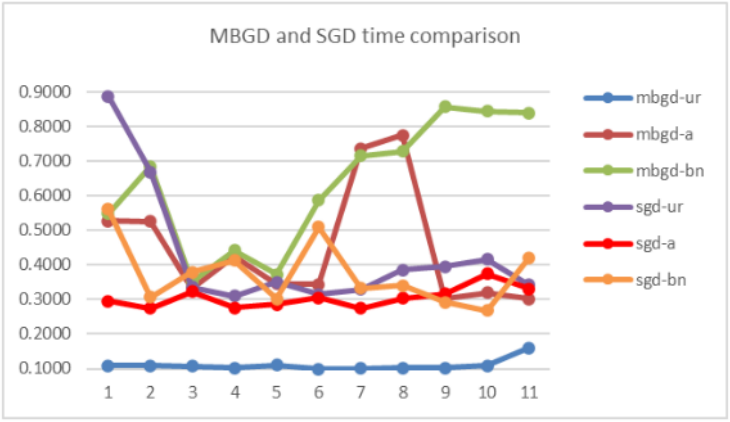

Figure 5. MBGD and SGD time comparison on *bodyfat* data

Table 21. MBGD and SGD time of anaemia data

MBGD			SGD		
UR	Adabound	BN	UR	Adabound	BN
0,1047	0,6857	0,3880	0,3323	0,2625	0,2443
0,1122	0,2942	0,3056	0,2906	0,2779	0,2260
0,1339	0,3466	0,2897	0,2715	0,2929	0,2472
0,2038	0,2845	0,2862	0,4065	0,3187	0,2385
0,2028	0,2759	0,2994	0,2865	0,3117	0,2420
0,1821	0,5120	0,3146	0,3343	0,2892	0,2497
0,2438	0,4189	0,2796	0,2860	0,2961	0,3201
0,2135	0,3491	0,2879	0,2821	0,2863	0,3051
0,2533	0,4201	0,2809	0,2720	0,3161	0,3100
0,1550	0,4365	0,3306	0,2705	0,3375	0,2376
0,2145	0,3959	0,3255	0,3397	0,3014	0,6460
0,2284	0,2866	0,3170	0,4833	0,2504	0,2335
0,2125	0,2750	0,3210	0,3487	0,3112	0,3067
0,4038	0,2815	0,3114	0,3083	0,3845	0,2385

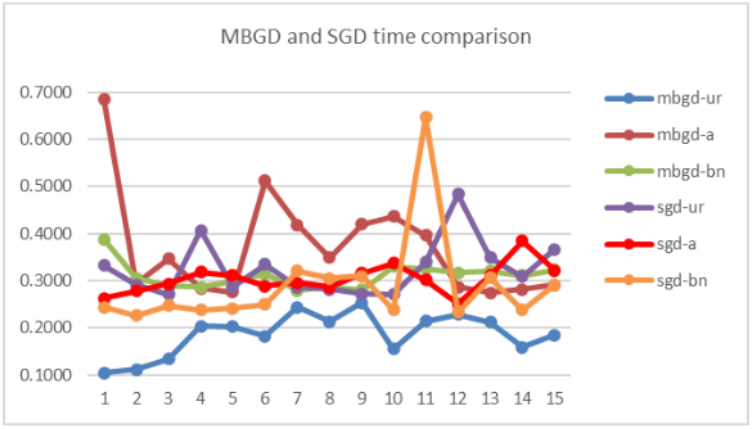

Figure 6. MBGD and SGD time comparison on anaemia data

In Figure 7, we can see the time between MBGD and SGD between the methods of MBGD-UR, MBGD-A, MBGD-BN, SGD-UR, SGD-A, and SGD-BN. Based on the picture above, MBGD-UR tends to be faster than other methods.

Based on the objectives of the study, the results obtained that the average MBGD-UR time resulted in the shortest time. Isn addition, MBGD-UR has a time that tends to be more stable than other methods. Then, the BCA value shows that MBGD-A has the most significant BCA value, which shows that MBGD-A has the best performance compared to other methods.

Table 22. MBGD and SGD time on air pollution data

MBGD			SGD		
UR	Adabound	BN	UR	Adabound	BN
0,11419	0,48410	0,49849	0,30392	0,27165	0,26311
0,24092	0,78463	0,55376	0,27468	0,25920	0,23584
0,14637	0,62246	0,55385	0,26471	0,27833	0,23799
0,10075	0,48969	0,47248	0,29837	0,26764	0,26160
0,19525	0,40071	0,43769	0,33674	0,25218	0,31685
0,10330	0,26502	0,37231	0,27936	0,23804	0,24630
0,10728	0,39761	0,26333	0,29730	0,24182	0,27463
0,11303	0,38788	0,61371	0,36092	0,24721	0,29813
0,18168	0,46139	0,52662	0,27795	0,27899	0,24179
0,21161	0,27248	0,44083	0,32224	0,24970	0,23176
0,20367	0,50240	0,30656	0,27492	0,25839	0,24929
0,12743	0,51434	0,54507	0,32593	0,27019	0,24854
0,12322	0,49653	0,37667	0,33315	0,26242	0,25308
0,11221	0,27164	0,26648	0,29530	0,25478	0,24676

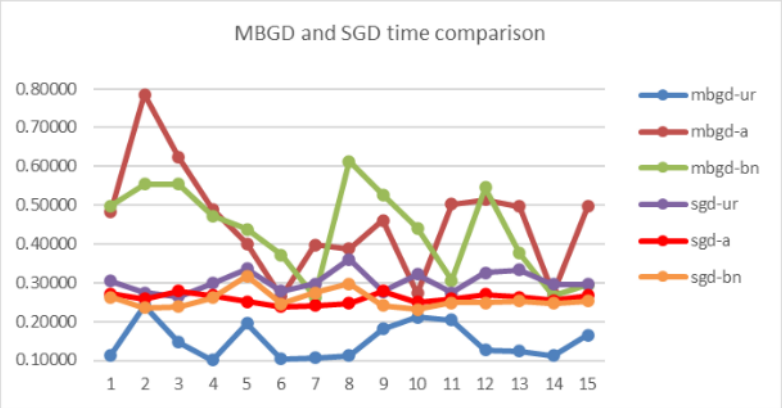

Figure 7. Time comparison between MBGD and SGD on air pollution data

4. CONCLUSION

The method used in this research is the reduction of rough set and fuzzy Takagi Sugeno Kang (TSK) dimensions applied to several data sets. Each generated rule will be optimized with MBGD and SGD modified with UR, Adabound, and BN. In this study, the rough set significantly reduces the dimensions of the data from 14 variables into three variables, six variables into four variables, and five into three variables. The use of UR, Adabound, and BN on MBGD and SGD resulted in different times. Based on testing on several data sets, the MBGD-UR average time produces the shortest time. In addition, MBGD-UR has a time that tends to be more stable than other methods. The classification results' accuracy

level is sought by using the BCA value. The most significant BCA value indicates that a method performs best. Based on the results obtained, the most significant BCA value is in the MBGD-A method. Therefore, based on the BCA score, MBGD-A has the best performance compared to other methods. Based on the results of the analysis and the conclusions that have been obtained, it is recommended for further research to use this type of accuracy and use other dimensional reduction methods.

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