FUZZY SUBTRACTIVE CLUSTERING FOR INDUSTRIAL MAPPING IN BREBES REGENCY

Sri Anjarwati
Bachelor's Degree in Informatics Engineering, STMIK YMI Tegal
Jl.Pendidikan No.1 Pesurungan Lor Kota Tegal
Indonesia
sri.anjarwati007@gmail.com

Amrulloh Surya Aji
Bachelor's Degree in Informatics Engineering, STMIK YMI Tegal
Jl.Pendidikan No.1 Pesurungan Lor Kota Tegal
Indonesia
amrulloh.suryaaji@gmail.com

***Abstract*— Industrial mapping in Brebes Regency is performed by the Central Administration of Statistics (CAS) and the Department of Trade and Industry (DTI) in Brebes Regency. According to the CAS of Brebes Regency, the Industrial Mapping is based on the classification of a number of workers while it is based on the classification of a number of investments according to the DTI. There are some methods to overcome these mapping problems, such as one which was introduced by the fuzzy set theory which is known as fuzzy clustering with fuzzy subtractive clustering. However, the industrial mapping based on the classification by using fuzzy subtractive clustering is not sufficiently accurate. Research on this, Fuzzy Subtractive clustering is used for industrial mapping based on the classification of parameters with the radii of 0.8, 0.5, and 0.3 The results and explanations of industrial mapping by using fuzzy subtractive clustering with the radius of 0.8 is 4 clusters and the percent accuracy is 70.73 percent , the radius of 0.5 is 8 clusters and the percent accuracy is 92.68 percent, and the radius of 0.3 is 20 clusters and the percent accuracy is 95.93 percent. And therefore, fuzzy subtractive clustering can be used for industrial mapping based on the classification of the parameters becomes more accurate.**

Keywords—component; industrial mapping, fuzzy clustering, fuzzy subtractive clustering

I. INTRODUCTION

Since the concept of industrial mapping was popularized for the first time by Porter in 1990, many countries have been trying it to improve their competitiveness through an industrial sector. Not only companies that take part in the cluster but also academic institutions, government agencies, associations, and supporting industries [1]. Industrial mapping services have played an important role in an economic system of a region. The core competence of the evaluation of modern industrial mapping services has been becoming a theoretical and practical problem which is very significant from research on industrial mapping [2].In recent conditions, there is a lot of industrial mapping formed in developing and developed countries as the economic global develops, thus mapping on industrial feature characteristics have been formed. Those are the United States, Germany, France, and China [3]. It is widely believed that the competitiveness of a country or area comes from industrial mapping [4]. Industrial mapping influences a magnetic field, the concept of the magnetic field for teaching protocols in a talent grouping on industrial mapping in which quantity, quality, and human resource structure scan be altered through a magnetic effect which has a reciprocal attraction and symbiotic effect which is caused by a talent grouping so as to encourage more economic development than industrial mapping [5]. Creative industrial mapping can also attract certain interests as the result of bigger potential economic growth. It can also be of use for partner selections for industries which enhances the economic efficiency [6]. Meanwhile, there are also industrial mapping developments which is the network of corporations of industries, research and academic institutions and others supporting institutions which are tied one another in activities to increase the values of productions which can be the core of assignments, development, making use of science and technology for the economy of a country. The increasing values of production aim at the impression and market targets of the domestic products in the global market can be strengthened. Eventually, the position of national economy in global economy system can be strengthened and the nation can obtain bigger and bigger incomes and revenues [7].

The book of Brebes Regency in 2009 was a corporation between the Provincial Development Planning Agency (PDPA) and the CAS which provides a series of data. There is statistical information from the mapping and industrial classification about how many productions and its values in Brebes Regency in 2009 [8], by knowing the number of productions, thus we will know the results of the industrial productions in 2009 as the number of productions is the number of assignments which can be done during a certain amount of time [9]. There are a few kinds of industrial classifications; it is based on the number of workers according to CAS while it is based on the number of investments according to the DTI. The success of mapping depends on how far industrial mapping creates, provides, and implement knowledge through a community which develops an ecological mapping with charm and effectiveness that develops from time to time. The development of innovation and industrial competitiveness can be achieved through industrial mapping developments [11].

Industrial competitiveness enhancement strategy requires a priority approach through which the hoped industrial mapping will create an interactivity attraction pattern in both the industrial sector itself and inter sectors and the entire related production network and distribution [12]. The methods used in both industrial and classification mappings are as follow: Rough3Sets-Artificial Neural Network (RS-ANN) with the attribute value of continues discretization using fuzzy clustering algorithms based on Maximum Discernibility Value (MDV) and entropy information. An empiric result shows that fuzzy clustering algorithm based on MDV and entropy information can enhance effective discretization performance and the integration of Rough Sets (RS) modeland Artificial Neural Network (ANN). A high accuracy in predicting is an efficient and practical tool to identify industry clusters life cycle [13]. The next method is the one done by Xiang Wei; YeiFeian who implemented the optimization of Ant Colony Algorithms for a partner selection on a creative industry based on forming the multi-goal decision-making using integer 0-1 programming model and provided an example for describing the validity algorithm which was proposed to select creative industry partners [14]. Mapping is a process for a data partition into groups or classes where the same data have been submitted to the same cluster whereas different data must be owned by different clusters [15]. The purpose of mapping for a collected record partition is to make several groups so as the same records are in the same location according to the similarity function with the similar data subpopulations [16]. Another purpose of mapping is to find similar cases which are grouping among data according a new observation which must be classified. This can be done based on a feature or combination of features [17].

An Industrial mapping problem occurs when the mapping based on classifications of parameters are not accurate yet. To create industrial mapping as the core assignments, developments, making use of science and technology for the economy of a country as well as to find out a amount of work which can be done during a certain amount of time. Thus, industrial mapping in Brebes Regency is based on the number of workers, investments, productions and the value of them by using a logic model Fuzzy Clustering with Fuzzy Subtractive Clustering [19].

II. RESEARCH METHODOLOGY

The research methodology used is the experimental research with the research stages as follow [18]:

Data feature selection

Data used for industrial mapping in Brebes Regency comes from industrial data which is made up of small-scale industries and household industries that are recorded by the DTI of Brebes Regency. Most of the raw industrial data which will be clustered is not complete yet, there are also data duplications and noisy by which data cannot be processed [23]. To avoid such stuff, the data needs preprocessing by cleaning and transforming data on industrial data in Brebes Regency. From the result of reprocessing, the data which will be used for industrial mapping based on such variables: the number of workers, the number of investments, the number of productions and the values of them along with the data sample as many as 123 pieces of data.

Clustering algorithm design

A clustering algorithm which is used for the industrial mapping in Brebes Regency is fuzzy subtractive clustering algorithm. Here is the design phase of the clustering or selection algorithm [19]:

Step 1 Enter data which will be clustered: Xij, with I = 1, 2, ..., n; and j = 1, 2, …, m

Step 2 Determine a value:

- r_j(a radius of each data attribute); j = 1,2,…,m
- q (squash factor)
- Accept ratio
- Reject ratio
- Xmin (minimum data)
- Xmax (maximum data)

Step 3 Normalization

Step 4 Determining initial potential for each data node

Step 5 Finding the highest potential node

Step 6 Determining the central cluster and subtracting its potential from nodes around it

Step 7 Reversing the central cluster from its normalized form to the earliest form

Step 8 Counting the value of cluster sigma resulting a membership function/ membership cardinality using the parameter values of the Gauss membership function.

Testing

On testing accuracy, testing and analyzing the comparison with different radii from clustering results using fuzzy subtracting clustering on industrial empiric data in Brebes Regency. The cluster validation uses Blackbox and Whitebox tests. This kind of testing has already been included for testing the whole program thoroughly. This system uses a web-based test, to ensure that the fuzzy subtracting clustering algorithm can be used for the industrial mapping and components or elements of a system have worked well as it is expected.

Interpretation results

Interpretation results are the main aim of clustering which is for providing users with useful knowledge from industrial data so that the users can develop the clear understanding from data mapping and can solve mapping problem effectively.

Relevant research

Pieces of research that have the connection with this one are:

1. Fuzzy Model Identification Based on cluster estimation [24] (Stephen L. Chiu, 1994) implementing cluster estimation method for an input-output data collection, with each of the central cluster which is basically a prototypical data node which shows the behavior of the characters of a system. And therefore, each of the central clusters can be

used as a basic protocol that describes the system behavior.

2. Extracting Fuzzy Rules from Data function Approximation and Pattern Classification [25] some methods for extracting fuzzy rules for a function approach use clustering for determining a number of rules and initial rule parameters. A clustering method called subtractive clustering forming a basic classification approach to illustrate the rules of extracting method and implement its function and approach on a classification problem pattern.
3. An Efficient Method for Extracting Fuzzy Classification Rules from High Dimensional data [26] Stephen L. Chiu provides an efficient method for extracting fuzzy classification rules of high dimensional data. A cluster estimation method called subtractive clustering used to extract efficiently the rules of high dimensional feature space. Subtractive clustering to extract the rules for a high approximation and algorithms for classification purposes provided in Fuzzy Logic Toolbox Software for MATLAB.

Fuzzy Clustering (Fuzzy Subtractive Clustering)

Fuzzy clustering is a partition out of data sets becoming fuzzy subsets or clusters based upon the similarity between data. A clustering method develops a fuzzy estimation model for predicting an output which has been given by an input. Cluster algorithms with data trainings which use the closest neighbor for a fuzzy system [27]. Unlike Fuzzy C-Means (FCM) which is a supervised algorithm cluster as we need to know the number of clusters that will be formed. On Fuzzy Subtractive Clustering, an unsupervised algorithm cluster based on density (potential) data nodes within some space (variables) [19]. So that, it can be usedto find clusters when we do not want to determine the number of cluster itself. These are fast algorithms use for predicting the number of cluster and the central cluster within a data collection [15]. This method enhances a subtractive clustering conventional batch version in online cases which is a revised version of a clustering mountain version and applied in graphical methods known in MATLAB™ fuzzy logic toolbox. The basic concept of this method is by using a data sample as a candidate to become a cluster prototype (central), not grid nodes like what we do in mountain clustering [28].

Fuzzy Subtractive Clustering Algorithms [19]:

Step 1clustered data input : Xij, with i=1, 2, ...,n; and j=1, 2, ..., m

Step 2 assign a value :

a. rj(a radius of each data attribute); j=1, 2, ...,m
b. Q (squash factor);
c. Accept_ratio;
d. Reject_ratio;
e. XMin (minimum data)
f. XMax (maximum data)

Step 3 Normalization

$$X_{ij} = \frac{X_{ij}-XMin_j}{XMax_j-XMin_j}; i = 1,2,..n; j = 1,2 ..., m \quad (1)$$

Step 4 Specify the initial potential of each data :

a. $i = 1$
b. doing until
   1) $T_j = X_{ij}; j = 1,2, ..., m \quad (2)$
   2) Finding a data distance forwards T :
   $$Dist_{kj} = \left(\frac{T_j - X_{kj}}{r}\right); j = 1,2, ..., m; \ k = 1,2, ..., n \quad (3)$$
   3) Initial Potential :
   i. If , then
   $$D_i = \sum_{k=1}^{n} e^{-4\,(Dist_{kl}^2)}; \quad (4)$$
   If , then
   $$D_i = \sum_{k=1}^{n} e^{-4\left(\sum_{j=1}^{m} Dist_{kl}^2\right)}; \quad (5)$$
   4) $i = i + 1$

Step 5 Finding a node with the highest potential

a. $M = max\,[D_i | i = 1,2, ..., n];$ (6)
b. $h = i$, so $Di = M$;

Step 6 Finding a central cluster and subtracting its potential by nodes around it.

a. Center = [];
b. $V_j = X_{hj}; \ j = 1, 2, ..., m;$ (7)
c. C = 0 (a number of clusters);
d. Condition = 1;
e. Z = M
f. Doing this if (condition ≠ 0) & (z ≠ 0) :
   1. (No more a new central candidate) ;
   Ratio = Z/M;
   2. if, then condition = 1; (there is a new central candidate). Else,

      a) if , (the new candidate will be acccepted as the centre if the existence balances data where its location far enough from the existed central cluster)
      b) MD= -1;
      c) do for i = 1 to i = C
         i. $G_{ij} = \frac{V_j - Center_{ij}}{r}; \ r = 1,2, \ldots, m$ (8)
         ii. $Sd_i = \sum_{j=1}^{m} (G_{ij})^2;$ (9)
         iii. *If (Md < 0) atau (Sd < Md), then Md = Sd*
         - $Smd = \sqrt{Md};$ (10)

         - **If (Ratio + Smd) ≥ 1, then the condition = 1**
         (The data is accepted as the central cluster)

         - **If (Ratio + Smd) < 1, then the condition = 2**
         (The data will no longer be considered anymore as the central cluster)

d) If the condition = 1 (The new centre candidate is accepted as the new center), doing:

i. $C = C + 1;$ .... (11)

ii. $Center_C = V;$ .... (12)

iii. Subtracting the potential from nodes near thecentral cluster

– $S_{ij} = \frac{V_j - X_{ij}}{r_j * q};\ j = 1, 2, \ldots, m;\ i = 1, 2, \ldots, n;$ (13)

– $De_i = M * e^{-4[\sum_{j=1}^{m}(S_{ij})^2]};\ i = 1,2, \ldots, n$........ (14)

– $D = D - Dc;$ .... (15)

- **If $Di \leq 0$, then $Di = 0$; $i = 1, 2, \ldots, n$**

– $Z = \max[D_i |\ i = 1, 2, \ldots, n];$ .... (16)

- **Select h=1, so $Di = Z$;**

e) If the condition = 2 (the new candidate will not be accepted as the new center), then

i. $Dh = 0;$ .... (17)

ii. $Z = max[Di | i = 1,2, \ldots, n];$............................... (18)

iii. Select h = 1, until $Di = Z$;

Step 7 Reversing the central cluster from the normalized from to the earliest one

$Center_{ij} = Center_{ij} * (XMax_j - XMin_j) + XMin_j;$.................. (19)

Step 8 Finding the cluster sigma value

$\sigma_j = r_j * (XMax_j - XMin_j)/\sqrt{8};$ .... (20)

The result of subtractive clustering algoritma is the central cluster (C) in the form of a matrix and sigma (σ) which will be used to determine the function parameter value of gauss membership as it is show below

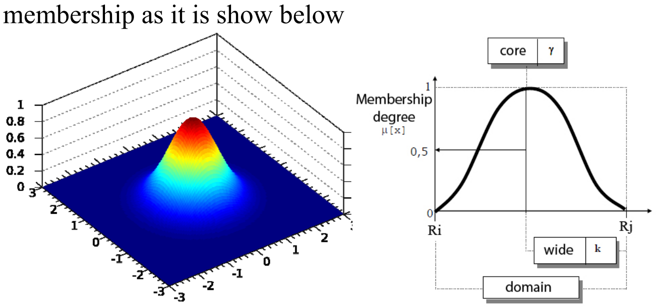

Figure 1st Gauss Curve

With gauss curve, the membership degree of a node at data X_i at the cluster to k is :

$$\mu_{ki} = e^{-\sum_{j=1}^{m}\frac{(Xij - Ckj)^2}{2\sigma_j^2}};\ \ldots\ (21)$$

III. The Result of the Research

From the result of the industrial mapping with the radii of 0.8, 0.5 and 0.3 respectively, there are some different membership degrees. The testing use a few industrial classifications that have been done in Brebes Regency are as follow :

Table 1st Industrial Clasification in Brebes Regency

Industry	Worker (W)	Investment (NI)	Number of Productions (NP)	Value of Productions (VP)
Household Industry (HI)	1-4	1-4	1-5	1-24
Small Scale Industry (SCI)	5-20	5-20	6-10	25-40

Explanation: There are four classifications of the industrial mapping for household and small-scale industries in Brebes Regency.

Classification 1 which is based on the number of workers (NW)

- The number of workers is made up of between 1 to 4 people, which is a household industry (HI).
- The number of workers is made up of between 5 to 20 people, which is a small-scale industry (SCI).

Classification 2 which based of the number of investments (NI)

- The number of investments that is worth between 1 to 4 million rupiahs is a household industry (HI).
- The number of investments that is worth between 5 to 20 million rupiahs is a small-scale industry (SCI).

Classification 3 which based on the number of productions (NP)

- The number of productions that weighs between 1 to 5 tons is a household industry (HI).
- The number of productions that weighs between 6 to 10 tons is a small-scale industry (SCI).

Classification 4 which based on the value of the production (VP)

- The number of productions that weighs between 1 to 24 tons is a household industry (HI).
- The number of productions that weighs between 25 to 40 tons is a small-scale industry (SCI).

The result of the industrial mapping using the radius of 0.8

Table 2nd The result of clusters with the radius of 0.8 based on each industrial classification in Brebes Regency

Cluster	Class 1		Class 2		Class 3		Class 4	
	W	C1	I	C2	NP	C3	VP	C4
1	4	HI	6	SCI	7	SCI	26	SCI
2	4	HI	4	HI	4	HI	22	HI
3	8	SCI	5	SCI	6	SCI	31	SCI
4	7	SCI	4	HI	6	SCI	18	HI

Explanation: Clustering is classified by each parameter.

For example: the first cluster

Class 1: There are 4 workers, and therefore the worker classification (C1) is a household industry (HI)

Class 2: The number of investments (NI) that is worth Rp. 6,000,000.00 and therefore it belongs into a small-scale industry (SSI) with the number of classification 2 (C2).

Class 3: The number of production (NP) that is 7 tons, and therefore it belongs into a small-scale industry (SSI) with the number of classification 3 (C3).

Class 4: The value of production (VP) that is 26 tons, and therefore it belongs to a small-scale industry (SSI) with the industrial value (C4).

The result of the industrial mapping with the radius of 0.5

Table 3rd The result of the cluster with the radius of 0.5 based on each industrial classification in Brebes Regency.

Cluster	Classifications 1		Classifications 2		Classifications 3		Classifications 4	
	W	C1	I	C2	NP	C3	VP	C4
1	4	HI	7	SCI	7	SCI	27	SCI
2	4	HI	4	HI	4	HI	22	HI
3	8	SCI	5	SCI	6	SCI	31	SCI
4	6	SCI	4	HI	4	HI	19	HI
5	4	HI	5	SCI	7	SCI	26	SCI
6	3	HI	3	HI	3	HI	19	HI
7	3	HI	4	HI	6	SCI	23	HI
8	7	SCI	5	SCI	6	SCI	21	HI

Explanation: Clustering is classified based on each parameter.
For example: the first cluster

Classification 1: The number of workers (NW) is 4 people, and therefore it belongs into a household industry (HI) with the classification of workers (C1).

Classification 2: The number of investments that is worth Rp 7,000,000.00, and therefore it belongs into a small-scale industry (SSI) with the classification of the number of investments (C2).

Classification 3: The number of production that is 7 tons, and therefore it belongs into a small-scale industry (SSI) with the classification of the number of productions (C3).

Classification 4: The value of productions that is 27 tons, and therefore it belongs into a small-scale industry (SSI) with the classification of the value of the industry (C4).

The result of the industrial mapping with the radius of 0.3

Table 4th The result of the cluster with the radius of 0.3 based on the industrial classification in Brebes Regency.

Cluster	Classifications 1		Classifications 2		Classifications 3		Classifications 4	
	W	C1	I	C2	NP	C3	VP	C4
1	4	HI	7	SCI	7	SCI	27	SCI
2	8	SCI	5	SCI	6	SCI	31	SCI
3	3	HI	4	HI	4	HI	20	HI
4	6	SCI	4	HI	4	HI	19	HI
5	3	HI	4	HI	6	SCI	23	HI
6	4	HI	6	SCI	6	SCI	26	SCI
7	5	SCI	3	HI	4	HI	20	HI
8	4	HI	8	SCI	6	SCI	27	SCI
9	3	HI	3	HI	3	HI	19	HI
10	4	HI	5	SCI	7	SCI	27	SCI
11	7	SCI	5	SCI	6	SCI	33	SCI
12	4	HI	4	HI	4	HI	23	HI
13	7	SCI	5	SCI	6	SCI	21	HI
14	8	SCI	5	SCI	7	SCI	29	SCI
15	3	HI	6	SCI	7	SCI	24	HI
16	4	HI	8	SCI	8	SCI	27	SCI
17	4	HI	6	SCI	8	SCI	28	SCI
18	4	HI	3	HI	3	HI	21	HI
19	3	HI	8	SCI	7	SCI	25	SCI
20	4	HI	5	SCI	9	SCI	28	SCI

Explanation: Clustering is classified by each parameter.
For example: the first cluster

Classification 1: The number of workers (NW) is 4 people, and therefore it belongs into a household industry (HI) with the classification of the number of workers (C1).

Classification 2: The number of investments that is worth Rp 7,000,000.00, and therefore it belongs into a small-scale industry (SSI) with the classification of the number of investments (NI).

Classification 3: The number of productions (NP) is 7 tons, and therefore it belongs into a small-scale industry (SSI) with the classification of the number of productions (C3).

Classification 4: The value of productions (VP) is 27 tons, and therefore it belongs into a small-scale industry (SSI) with the classification of the value of the industry (VI).

Explanation

The accurate result is determined by the industrial classifications existed in BrebesRegency and the result of industrial mapping using Fuzzy Subtractive Clustering based on each parameter classification and the membership function. The result is accurate if the result of the industrial data classification corresponds to the result of the industrial mapping using fuzzy subtracting clustering.

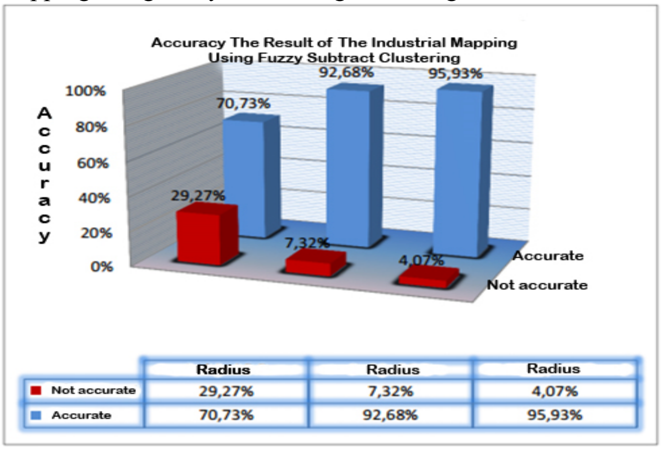

Figure 2nd Accuration Result

IV. Conclusion

Based upon the result of the industrial mapping in BrebesRegency using Fuzzy Subtractive Clustering with the samples as many pieces of 123 industrial data, we can conclude that:

1. Fuzzy Subtractive Clustering can be used for industrial mapping in Brebes Regency, which is based on its parameter classification, is accurate.
2. The accuracy results of each radius are as follow:
   a. The radius of 0.8 results 70.74%.
   b. The radius of 0.5 results 92.68%.
   c. The radius of 0.3 results 95.93%.
3. The smaller number of a radius in a computerized calculation for industrial mapping in Brebes Regency, the higher accuracy it can be trusted.

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