DISTRIBUTION RELIABILITY OF THE ENERGY SUPPLY CHAIN

Rachmad Hidayat[1], Sabarudin Akhmad[2]

[1,2]Industrial Engineering Department, University of Trunojoyo Madura, Indonesia
E-mail: rachmad.trunojoyo@gmail.com

ABSTRACT

Reliability of an oil fuel distribution system can be achieved by considering multiple attributes. Load-point indicators consisted of the frequency of failures, average duration of an outage and average annual outage time. Indicators of system performance were SAIFI and SAIDI and the method of the study was the Learning Vector Quantization (LVQ). Decisions were made by considering the multi-attribute oil fuel distribution system to determine high reliability, which was simulated on the agent. The use of agents in the simulation to determine the oil fuel distribution system reliability helped visualize the oil fuel distribution in meeting the quality of fuels received by consumers and made it easier to learn the problems faced by oil fuel distribution.

Keywords: oil fuel distribution, LVQ, agent, reliability

INTRODUCTION

Rising world oil prices have tremendous impacts on Indonesia's economy. The burden of oil fuel subsidy borne by the government is becoming increasingly high. This is compounded by the sub-optimal fuel distribution system. The risk of distribution fraud is very likely to occur at the level of distributor or retailer. Among those forms of fraud are misallocation of oil fuels, sales of oil fuels for households or individuals to industries and smuggling of subsidized oil fuels abroad. (Ardiansyah, *et.al.,* 2012). Oil fuels constitute a necessity which concerns the lives of many people. Oil fuel distribution requires transparency, necessitating public disclosure of distribution data as a form of the operator's accountability. A breakthrough should be found for smooth, transparent and traceable process of oil fuel distribution. The process of oil fuel distribution starts from the supply to the end user, the oil fuel consumers. The quality of oil fuels received by consumers is influenced the distribution system; therefore, a reliable oil fuel distribution system is required. Reliability of fuel distribution system is measured by the oil fuel availability and service level from the system to the end-users. (Simões, *et. al.,* 2011). The benchmark of distribution system reliability includes how often the distribution system experiences a delay, how long a delay occurs and how quickly is the distribution system to recover to its previous normal condition. (Portugal and Esteban, 2014). A highly reliable system will be able to distribute oil fuels any time as needed, while a system is said to be poorly reliable when it provides a low level of oil fuel availability.

A highly reliable distribution system is indicated by the load points and system performance, consisting of the frequency *of failures* (λ), *average duration of a failure* (*r*), *average annual outage time* (*U*). (González *et. al.,* 2009). Based on these indications, multiple attributes can be considered to achieve a highly reliable distribution system, such as the load points, SAIFI and SAIDI. Subsequently, the multiple attributes are subjected to learning by the use of Learning Vector Quantization (LVQ) in order to automatically classify the given input vectors. Among the advantages of LVQ is the method's ability to provide learning to the competitive layers so that it can automatically classify the given input vectors (Fujiki and Kazuko, 2009).

The process for determining a highly reliable oil fuel distribution system is further simulated on an agent. An agent can help determine a highly reliable oil fuel distribution system with by considering multiple attributes. An agent is a component or individual capable of responding to the environment by considering many attributes and of adaptation so that they can make independent decisions. Reliability is defined as the ability of a component or system to perform the functions required in a particular environment and operational condition for a predetermined period of time (Ahmad and Kamaruddin, 2012). Thus, reliability constitutes one of the aspects capable of affecting the success of production process. Reliability is of paramount importance since it will affect the cost of maintenance, which in turn will affect the profitability of the company.

Reliability of the distribution system is a measure of oil fuel availability or service level of oil fuel provision from the system to the end-users. The measure of reliability can be expressed as how often the distribution system experiences a delay, how long a delay occurs and how quickly is the distribution system to recover to its previous normal condition. A highly reliable system will be able to provide oil fuel any time when needed, while a poorly reliable system is frequently late to distribute oil fuel. The service continuity level of the means of distribution is structured on the basis of length of the efforts to re-establish the supply after a downtime due to interruptions (Dhillon, 2005; González *et. al*, 2009).

Oil fuel distribution is part of the Energy Supply Chain*,* since the quality levels of oil fuels distributed from the refinery to the consumer are determined by the distribution system, particularly the reliability of the oil fuel distribution system. Distribution of oil fuels is influenced by multiple aspects, including minimizing losses*,* minimizing cost, improving reliability of supply, and satisfying operational constraints (Dhillon, 2005). Attribute planning for determining the reliability of an oil fuel distribution system is based on the load point indeices consisting of λ, *r* and *U* and the system performance index consisting of SAIFI and SAIDI can be seen in Figure 1.
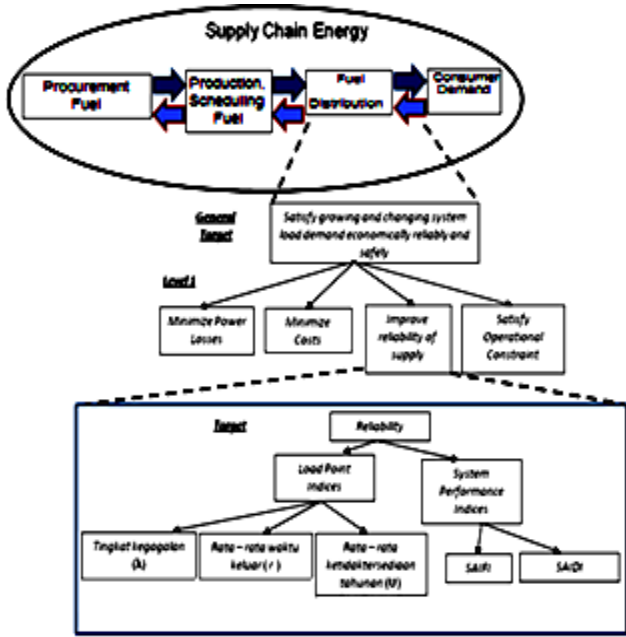
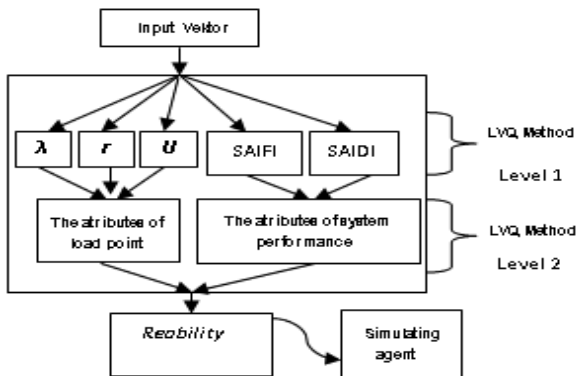**Figure-1.** Oil fuel distribution in the Energy Supply Chain

Figure-2. Flowchart of the study

performance index since the attributes of load point index has input vectors of λ, *r*, and *U* and the attributes of system performance index has input vectors of SAIFI and SAIDI. Classification flowchart such as figure 2.

Classification of multiple attributes to determine the reliability of the distribution system using LVQ can be seen in detail in Figures 3, 4 and 5. The classification steps of the attributes of load point index and system performance index until the shortest distance from the input vectors to the class is obtained.

Figure-3. Flowchart of study step for attribute level 1
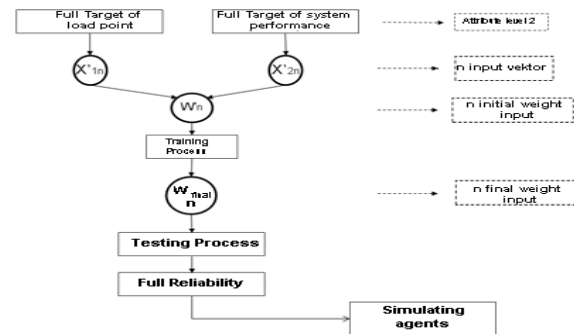
Figure-4. Flowchart of study step for attribute level

A classification process is required to determine the reliability of the distribution system by the use of the attributes of load points and system
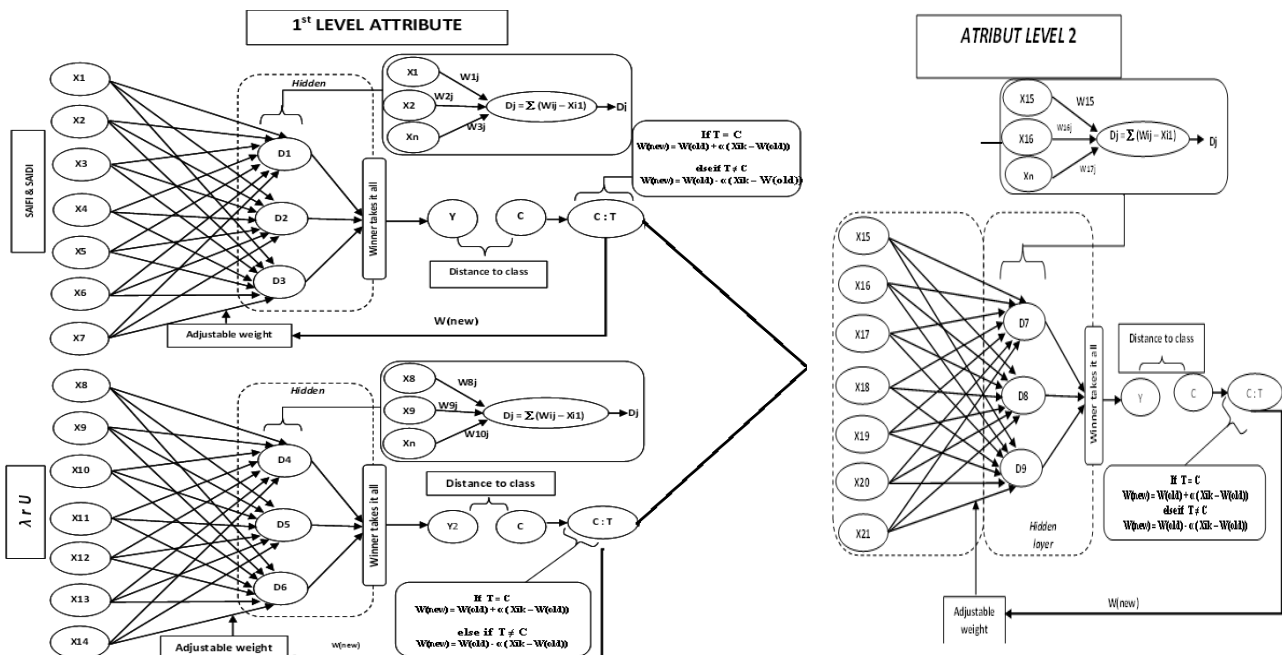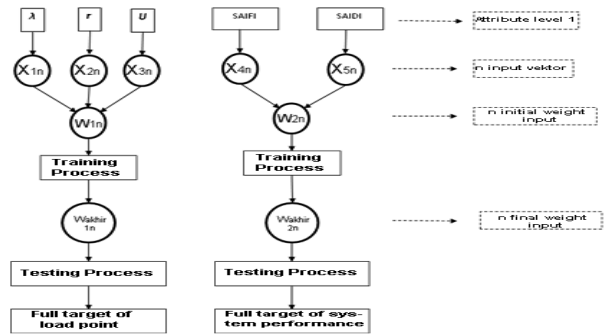

Figure-5. Process for attributes level 1 and attributes level 2

METHODOLOGY
Reliability Index
Reliability index is an indicator of reliability expressed in a probability scale. Load point failure indices typically used include the frequency of failure λ (failure/month), the average duration of an outage r (h/failure) and the average annual outage time U (h/year). The average value of the three basic load point indices for load point j can be calculated from the (up-down) operation history of the load point by using the following equation (Díaz and Márquez, (2014).

$$\lambda = \frac{N_j}{\sum T_{uj}} \tag{1}$$

$$r_j = \frac{\sum T_{dj}}{N_j} \pi r^2 \tag{2}$$

$$U_j = \frac{\sum T_{dj}}{\sum T_{uj} + \sum T_{dj}} \tag{3}$$

$\sum T_{uj}$ = uptime for load point j
$\sum T_{dj}$ = downtime for load point j
N_j = number of failures during the simulation period for load point j

And based on Viktoria Neimane (Crespo and Benoit, 2007) to obtain the frequency of failure λ (failure/year), the average duration of outage r (h/failure) and the average annual outage time U (h/year) as follows:

$$\lambda_s = \lambda_1 + \lambda_2 + \cdots . \lambda_n \tag{4}$$

$$r_s = \frac{\lambda_1 . r_1 + \lambda_2 . r_2 + \cdots + \lambda_n . r_n}{\lambda_1 + \lambda_2 + \ldots + \lambda_n} \tag{5}$$

..
$$U_s = \lambda_s . r_s = \lambda_1 . r_1 + \lambda_2 . r_2 + \cdots + \lambda_n . r_n \tag{6}$$

System Average Interruption Frequency Index (SAIFI) is defined as the average number of failures per customer served by the system per unit of time (usually a year). (Fujiki and Kazuko, 2009).

$$\text{SAIFI} = \frac{\sum \lambda k . Mk}{\sum M} \tag{7}$$

λ_k = outage rate of the component
M_k = number of customers at load point k
M = total customers in the distribution system

System Average Interruption Duration Index (SAIDI) is defined as the average duration of failures for each consumer for one year. This index is determined by dividing the sum of continuous duration of failures for all customers during the specified period of time by the number of customers served during the year. The equation for SAIDI (average duration of interruption for each customer) can be seen in the following equation: (Fujiki and Kazuko, 2009).

$$SAIDI = \frac{\sum U_k . M_k}{\sum M} \tag{8}$$

U_k = component repair time
M_k = number of customers at load point k
M = total customers in the distribution system

The classification steps of the attributes of load point index and system performance index are described as follows: (Kate *et. al.,* 2001; Robi, 2001; Olden *et. al.,* 2004).
1. Determine the input vectors for each attribute;
2. Specify the initial weight randomly;
3. Determine the initial class as the target class in the training process of the input vectors.
4. During the learning process in the hidden layers, find the minimum distance to the input vectors of

predetermined initial classes by using the *Euclidean* distance formula. Dj = $\sum$ (Wij – Xi)   (9)
5. Once the minimum distance in the learning process has been obtained, the point is said to be the winner and the output, i.e., the minimum distance of the input vector to the target class is symbolized as the winner class.
6. Compare the winner class to the target class to find using the new weight by using the formula:
   if
   T = C
   W(new) = W(old) + α (Xik – W(old))   (10)
   else if
   T ≠ C
   W(new) = W(old) - α (Xik – W(old)   (11)

Results obtained, i.e., the new weight *W*, are then used for trials.

Trials are continuously carried out with the term 'epoch' and will stop when the learning rate reaches a minimum value. The output of the process will be a minimum distance of the input vector to the class, in which the minimum distance data is simulated on the agent.

LVQ is a method that is based on an unsupervised learning algorithm. LVQ can also be used as a supervised vector quantizer since LVQ network has class points linked to the input vectors. (Kate *et. al.,* 2001).
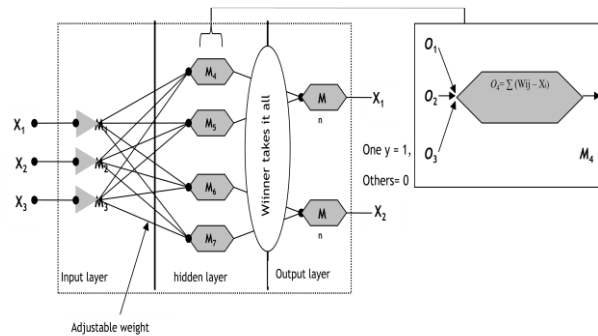

Figure-6. LVQ architecture: One hidden layer with kohonen neurons, adjustable weights between the input layer and the hidden layer (www.neural-forcasting.com)

The LVQ algorithm is as follows: (Sivanandam and Deepa, 2006)
1. Initialize weights and learning rate;
2. It will stop if it is incorrect, do steps 3−7;
3. For training input vector x, do steps 4−5
4. Calculate *j* using the Euclidean distance formula
   D(j)=$\sum$(wij – xi)^2
   find j when D (j) is at its minimum
5. Update *wj* by follow the following requirements
   If T=Cj, then
   wj(new) = wj(old) + α[x - wj(old)]
   If T ≠ Cj, then
   wj(new) = wj(old) - α[x - wj(old)]
6. Calculate the error of the weighting values
   e(t+1) = ||W(t+1) – W(t)||
7. Reduce the learning rate
8. Perform trials for stop condition; the condition will stop when the iteration rate or learning rate reaches the smallest value.

FSM AND AGENT SCENARIOS

FSM (Finite-State Machine) of the agent's simulated oil fuel distribution reliability is as figure 7. Agent scenarios based on the FSM in the simulation to determine the reliability of oil fuel distribution system is as follows:

1. Agents scan feeder (supply) 1 through feeder 7 to read the data of each feeder;
2. Subsequently, agents compare the data of the distance from the input vector to the class in all feeders;
3. Agents determine the shortest distance from the input vector to class 1 (class with the lowest possible interruption);
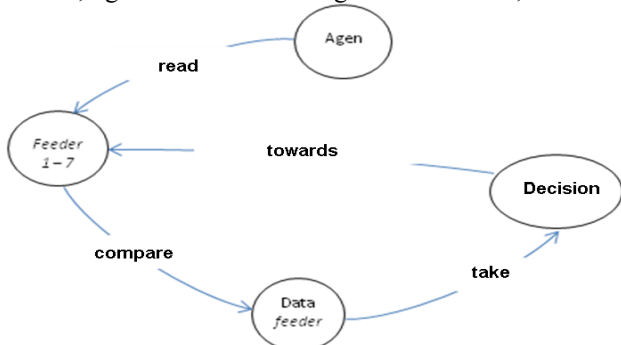4. Then, agents block or mark green the feeder;

Figure-7. FSM of the agent's oil fuel distribution reliability

TRIAL RESULTS

Trial 1

1. Indication values of load points are derived from the total LP (load point) of each feeder on BUS 4;
2. Values of SAIFI and SAIDI are calculated using equations 7 and 8 based on data;
3. Class inputs for load point indications and SAIFI SAIDI are determined randomly as in Tables 1-2;
4. Total data = 7
5. Number of the initial weight of each attribute = 3
6. Number of class of each attribute = 3
7. Max epoch = 10000000
8. Based on case (A): disconnect – fuses – alternative supply – repair transformer.

Table-1. Data of load point and initial class indications

Feeder	Λ	*r*	U	Class
F1	1.343	157.25	30.14	1
F2	0.35	28.85	3.36	2
F3	1.299	161.55	30.01	3
F4	1.558	176.13	34.34	1
F5	0.344	29.19	3.36	2
F6	0.36	26.51	3.18	3
F7	1.313	160.07	30.01	1

Table-2. Data of system performance and initial class indications for the case A

Feeder	SAIFI	SAIDI	Kelas
F1	0.191	4.29	1
F2	0.117	1.12	2
F3	0.186	4.30	3
F4	0.195	4.30	1
F5	0.115	1.12	2
F6	0.120	1.06	3
F7	0.188	4.31	1

Results obtained from the attribute level 1 for SAIFI and SAIDI (chain 1) **;**
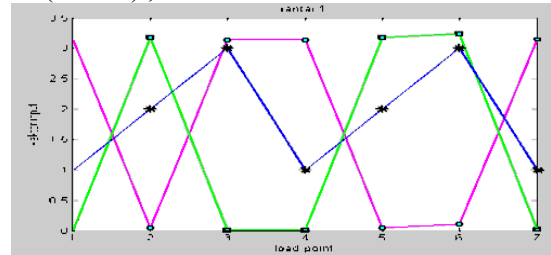

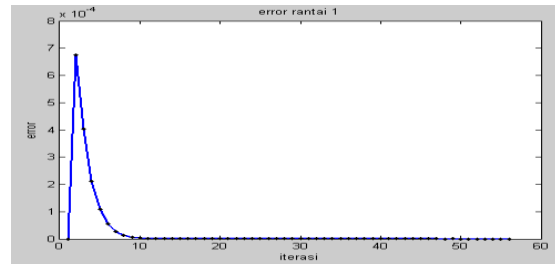**Figure-8.** SAIFI and SAIDI input vector chart (case A)

Figure-9. SAIFI and SAIDI input vector error chart (case A)

********** Chain 1 **********
Initial weight matrix
  0.1910   0.1170   0.1860
  4.2900   1.1200   4.3000
weight matrix after epochs to 56
  0.1925   0.1127   0.1762
  4.2985   1.1651   4.2940
Distance after epochs to 56
  0.0087   3.1258   0.0154
  3.1794   0.0453   3.1746
  0.0067   3.1357   0.0115
  0.0029   3.1359   0.0198
  3.1795   0.0452   3.1746
  3.2393   0.1054   3.2345
  0.0123   3.1458   0.0199
The initial class
  1   2   3   1   2   3   1
The bafter Training Class
  1   2   1   1   2   2   1

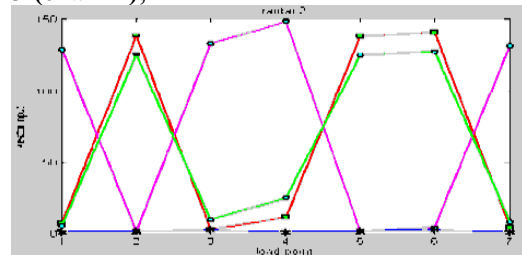**Results obtained from the attribute level 1 for λ, *r* and *U* (chain 2);**

Figure-10. Input vector chart for λ, *r* and *U* (case A)
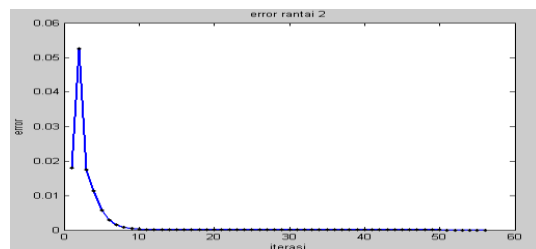

Figure-11. Error input vector chart for λ, *r* and *U* (case A)

Simulation results Chain 2 (case A)
********** Chain 2 **********
Initial weight matrix
1.3430   0.3500   1.2990
157.2500 28.8500 161.5500
30.1400   3.3600 30.0100
weight matrix after epochs to 56
1.4179   0.3364   1.1122
164.6319 30.9523 152.1007
31.6555   3.4954 26.9819
Distance after epochs to 56
7.5363   129.0816 6.0450
138.7030 2.1067   125.4963
3.4958 133.2656 9.9244
11.8081   148.4232 25.1346
138.3702   1.7675   125.1624
141.0307   4.4535   127.8285
 4.8508   131.8156 8.5276
The initial class
1   2   3   1   2   3   1
The bafter Training Class
3   2   1   1   2   2   1

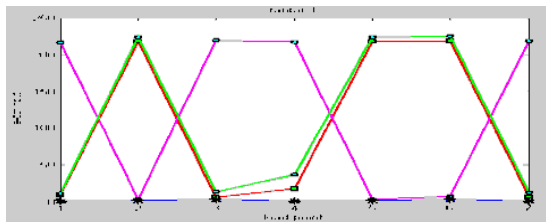**Results obtained from the attribute level 2 (chain 3);**

Figure-12. Input vector chart of the results of load

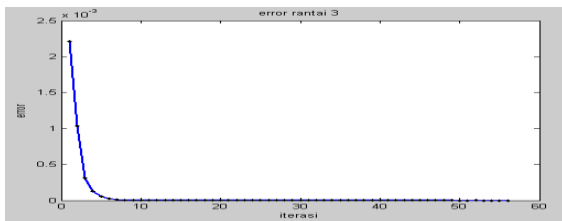point indications & system performance indications

(caseA)

Figure-13. Input vector error chart of the results of load
point indications & system performance indications
(case A)

Simulation results of all the input vectors (case A)
********** Chain 3 **********

Initial weight matrix
0.0087   3.1794   0.0067
3.1258   0.0453   3.1357
0.0154   3.1746   0.0115
7.5363   138.7030   3.4958
129.0816   2.1067   133.2656
6.0450   125.4963   9.9244
weight matrix after epochs ke 56
0.0093   3.1344   0.0089
3.1371   0.0000   3.1356
0.0203   3.1295   0.0066
8.6258   136.6172   -1.4916
135.7772   0.0001   124.1710
12.6068   123.4060   0.7983
Distance after epochs ke 56
 j class 1   j class 2   j class 2
 9.4379   217.0870   11.5389
218.0859   3.6281   223.9050
6.3104   219.9737   13.8156

18.0830   217.4703   36.8417
217.9233   3.0476   223.6963
219.2783   7.6748   225.4143
6.8253   219.0071   12.5861
The initial class
 1   2   3   1   2   3   1
The bafter Training Class
 1   2   1   1   2   2   1

Analysis of Trial 1

Trials for the attributes level 1 of chain 1 with SAIFI and SAIDI input vectors produced a feeder with the shortest distance from the input vector to class 1 or the class with high reliability. The feeder was feeder 4 which had a distance of the input vector to class 1 of 0.0029; in other words, feeder 4 had higher reliability as an oil fuel distribution system than other feeders. The next trials for the attributes level 1 of chain 2 for the input vectors λ, r and U produced feeder 3 as one that had high reliability as an oil fuel distribution system. It was due to the fact that feeder 3 had the shortest distance from the input vector to class 1 of 3.4958.

Trials for chain 1 (SAIFI and SAIDI) and chain 2 (λ, r and U) were followed by classification of the attributes level 2 of chain 3, or the attributes with the input vectors derived from classification of chains 1 and 2. Classification of the attributes level 2 of chain 3 was the last step of classification for case A, taking into account multiple attributes and using LVQ as the method of classification and obtained feeder 3 of 6.3104 as one with the shortest distance from the input vector to class 1.

Results of the Overall Trials

Trials 1 to 6 for case A to case F on feeder 1 to feeder 7 showed the Table 3. Input vector distance data from all the attributes of all the cases to class 1 of *each feeder*. Multi-attribute classification was conducted on three classes:

Class 1 = good, representing feeders with high system reliability

Class 2 = moderate, representing feeders with medium system reliability

Class 3 = poor, representing feeders with low system reliability

Determination of the distribution system reliability as high, medium, low is shown only for feeders with the input vector distance for all cases approaching class 1 (high system reliability) as shown in figure 13. Reliability was also determined for attribute data consisting of load point indices and system performance indices. Furthermore, the data were simulated on the agents.

Table-3. Input vector distance of all feeders to class 1

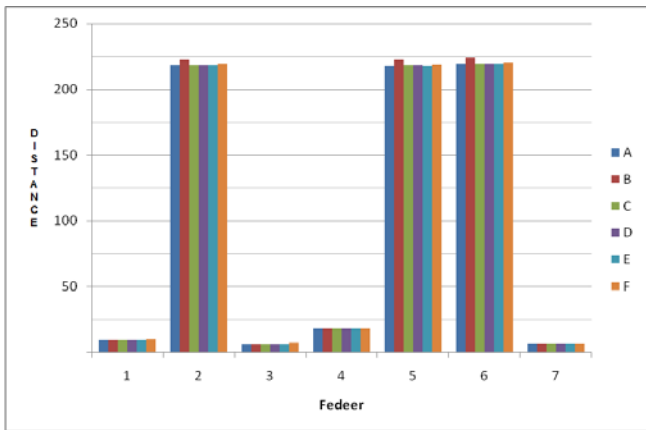| Feeders	Case					
	A	B	C	D	E	F
1	9.4379	9.6142	9.4381	9.4736	9.4379	10.0074
2	218.0859	222.6989	218.1668	218.2161	218.0188	219.0970
3	6.3104	6.6961	6.3168	6.3643	6.3104	7.3195
4	18.0830	18.4926	18.0834	18.0994	18.0830	18.0878
5	217.9233	222.5497	218.0080	218.0537	217.8560	218.9338
6	219.2783	223.8759	219.3514	219.4085	219.2107	220.2855
7	6.8253	7.1523	6.8277	6.8319	6.8253	6.8354

Figure-14. Chart of input vector distance of all cases to class 1
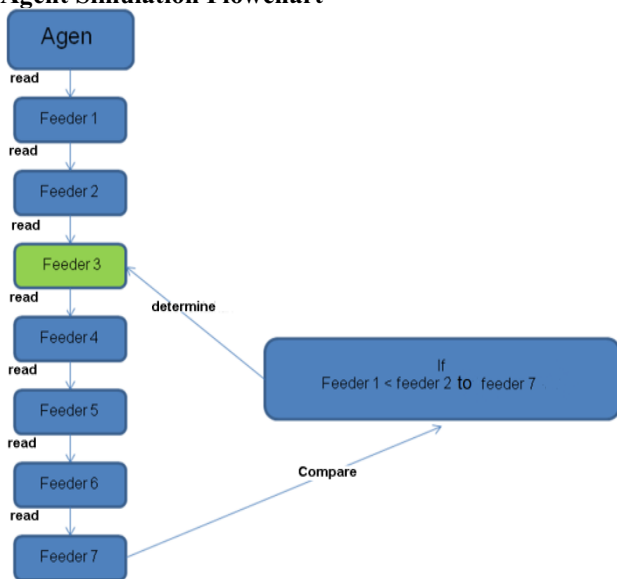
Agent Simulation Flowchart

Figure-15. Agent simulation flowchart

CONCLUSION

Trials performed to determine the reliability of the oil fuel distribution system using LVQ (Learning Vector Quantization) showed that an oil fuel distribution system can be considered reliable when the interruption value was low. Utilization of more detailed attributes would be able to determine the reliability of the distribution system more accurately. This was due to the fact that oil fuel distribution system reliability is influenced by multiple aspects that can be used as attributes. The use of simulation in some problems is of paramount importance since it helps understand them visually. In particular, agent-based simulations for oil fuel distribution system reliability can visually help determine a reliable oil fuel distribution system. Future research should emphasize the determination of the initial weights of input vectors from LVQ method since initial weighting is essential to achieve classification accuracy. Future research should consider the use of Multi-Layer LVQ on each hidden layer capable of affecting the degree of accuracy in order to obtain better classification results.

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