Influence of Air Quality towards the Extreme Rainfall Events: Rough Set Theory

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ABSTRACT

`This research focuses on the development of knowledge model for a prediction of the extreme rainfall events by using the air quality parameters. A knowledge model is a model containing a set of knowledge by rules that was obtained from mining certain amount of data. These rules will help in detection of extreme weather changes events and therefore is significant for safety action plans and mitigations measures, in terms of adaptation to the climate change. In this study, an intelligent approach in data mining called a rough set technique has been used based on its capability on handling uncertain database that often occurs in the real world problem. As a result, an association and sequential rules were produced and used for prediction of the extreme rainfall events in Petaling Jaya as a case study. Petaling Jaya is an urban and industrialized city in tropical climate of Malaysia which always experiencing flash floods and severe storms that might due to air pollution. A total of 2102 data were obtained from Malaysian Meteorological Department and Department of Environment Malaysia. There were 7 attributes used as input and one attribute as an output for the intelligent systems. Data has been through a pre-processing stage to facilitate the requirement of the modeling process. A total of ten experiments using ten sets of different data have been conducted. The best model was selected from the total models generated from the experiment. As for conclusion, the model has given a promising result with 100% accuracy and the rules obtained have contributing to knowledge for the extreme rainfall events.

Keywords – **Rough set, intelligent system approach, extreme rainfall events, air quality parameters**

I. INTRODUCTION

Petaling Jaya, Malaysia is an urban tropical climate that lies within non-arid climate in which all twelve-months have mean temperatures above 18°C. Unlike the extra-tropics, where there are strong variations in day length and temperatures, with season, but for tropical temperature remain relatively constant throughout the year and seasonal variations that are dominated by precipitation (Bardossy 1997). However, recently, this tropical climate region was struck by extreme rainfall events especially in Petaling Jaya area that were relatively frequent happened in this case study area. The implications of this sudden increase of rainfall and an extreme high volume and frequency of rainfall have caused for a major flooding events in this region. In November 2010 more than 20,000 hectares area were damaged and 2 people were killed due to extreme flash flooding in most part of Malaysia especially in Petaling Jaya area. The event has cost the country at least 1 billion Ringgit Malaysia in damages (Utusan Malaysia 2010). According to the IPCC (2007), the frequency of heavy precipitation events has increased over most land areas, which the heaviest types of rains that cause flooding have increased in recent years. It is believe that the impacts of this climate change events is due to the increase of greenhouse gases levels, such as ozone, nitrous oxide, carbon monoxide, sulfate particles in the atmosphere because of the human activity (Whitfield and Canon 2000). For example the research by Muzik (2002); Whetton *et al*. 1993 and Suppiah 1994, using the carbon dioxide (CO2, which is one of the green house gas), has done the scientific evidence that indicates under doubled concentrations of carbon dioxide (CO2) at the atmosphere have increased the flood frequencies and changes the rainfall intensity. Santer *et* al. (2007) used a climate model to study the relative contribution of natural and human-caused anthropogenic effects on increasing climate change and water vapor (increase in precipitation), and concluded that this increases was primarily due to human caused increases in greenhouse gases. This was also the conclusion of Willet *et* al. (2007). For Bell *et al*. (2008), summertime rainfall over the Southeast US is more intense on weekdays than on weekends, with Tuesdays having 1.8 times as much rain as Saturday during the period of 1998 – 2005 analyses. Air pollution the particulate matter also peaks on weekdays and has a weekend minimum, making it significantly proven that pollution is contributing the observed mid-week rainfall increase. Pollution particles act as nuclei around which raindrops condense and increase precipitation for some storms. For this study it involves 7 important parameters of air quality, which were PM10, CO, SO2, NO, NO2, ozone and surface temperature, and this is the first study ever to examine how extreme rainfall events would affected by this air quality parameters. Therefore, evidence for changes in the intensity of extreme daily rainfall events over Petaling Jaya, Malaysia during the last 5 years is assessed.

II. METHODOLOGY

The main focus of the study is to produce a knowledge model based on rough set theory or a rough classifier. Rough set theory is a new mathematical approach to data analysis, for example statistic cluster analysis, fuzzy sets and evidence theory. A rough set contains a number of rules generated through mining certain amount of dataset. The process of obtaining a classifier is called learning. The system must be given knowledge on hoe information can be obtained in order to start learning. To compare the performance of classifiers to classify a set of previously unseen objects, commonly referred to test set. A rough set concept was inspired by Pawlak, 1980. It was a framework for discovering relationship in imprecise data (Pawlak 1991). The primary goal of the rough set is to derive rules from data represented in an information system. The results from a training set will usually be a set of propositional rules that may be have syntactic and semantic simplicity for a human. The rough set approach consists of several steps leading towards the final goal of generating rule from the information or decision systems as given below:

- The mapping of information from the original database into the decision system format
- Data pre-processing
- Computation of data and attribute reductions
- Generation of rules from reductions
- Classification of new unseen data

This study involves five major phases, namely (i) cleaning and integration of data collection, (ii) selection and transformation, (iii) data mining, (iv) testing and evaluation; and (v) knowledge discovery, as shown in the framework of this study (Fig. 1). Based on the framework, the stage of pre-processing and data preparation is done in two steps, which were during cleaning and integration of data collection and data selection and transformation. Pre-processing is done so that the generated rules at the end of the study will be the certainty and reliable rules as a knowledge based. In this stage, several phases have been carried out, which were the data integration, data cleaning, attribute selection and data reduction. Data cleaning is required when there are incomplete attributes or missing values in data. It involved filling the missing values, smoothing noisy data, identifying outliers and correcting the data inconsistency.

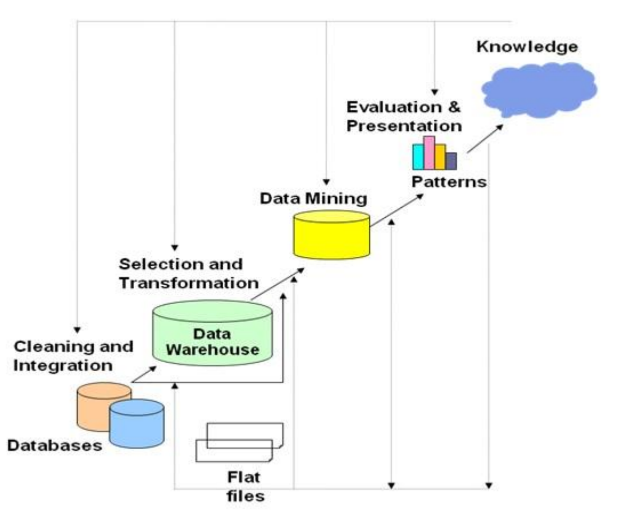

Figure 1. Methodolody framework

Data integration combines data from multiple sources to form a coherent data store. Metadata, correlation analysis, data conflict detection and resolution of semantic heterogeneity contribute towards smooth data integration. Data transformation converts the data into appropriate forms for data mining that depends on the mining technique. In the case of developing a knowledge based model, data are required to be discretized. This is because the rough classification algorithm only accepts categorical attributes. Discretization involves reducing the number of distinct vales for a given continuous attribute by dividing the range of the attribute into intervals. Interval labels can then be used to replace actual data values.

In rough set theory, the main task in generating rules is to calculate or to find the best set of attributes that can represent the whole decision system. These selected attributes are called reductions. These reductions are determined using several important steps namely, the formation of equivalence classes from a Decision System (DS), computation of discernibility matrix (dissimilarity), computation of discernibility functions and the identification of reducts for the DS. The objects in the DS are clustered into classes with similar attribute values. The process of forming the equivalence class is a process of looking for indicernibility relation (similarity) of objects. Next step is to compute the discernibility matrix from the equivalence class. Each element of the matrix is a list of attribute that discern in their attribute values. The key concept is for every pair of classes, the set of discerns attributes are listed. The attributes of each element in the matrix can be written as a conjunctive normal form (CNF) and the simplification of the CNF gives the discernibility functions of each class.

The final step in obtaining the rough classifier is to generate rules. Rules are generated through binding the attribute from the reducts into the values in its class. The membership degree is the measure of certainty of each rule. The value1 indicates the rules with definite decision and the values less than 1 indicates rules with uncertain decision. Further discussion of this method can be seen in Mollestad and Skowron 1996.

The main role of the rough classifier is to be able to predict or classify new unseen cases. The performance can be tested by presenting the rules to classify the new data. The accuracy of the classifier can be measured by calculating the number of data that are correctly classified over the number of test data. Next section will give the real world problem, for example the extreme rainfall events prediction problem in practice with the rough classifer.

A time series datasets were obtained from Malaysian Meteorological Department and Department of Environment Malaysia consists of 2102 lines with 8 attributes of PM10, CO, SO2, NO, NO2, Temperature, Ozone and Rainfall. The first seven attribute is used as an input or predictor attribute, while the last attribute which is rainfall, as output or the target knowledge. Fig. 2 shows for each attribute and the classifiers. Based on these figures, the meteorological data obtained is continuous, derived from the collection center in Petaling Jaya and dated from April 2003 until December 2008, for a period of six years.

No	Atribute	Unit Measurement	Data Notation	Data Scale	Other Data Information
1	Site	Not Relevant	Collection Data	Petaling Jaya	-
2	Date	month/day/year	Date	April 2003 to December 2008	-
3	O3	ppm	Ozon	0 – 0.15	N/A, (Blanks)
4	PM10	µg/m3	Particulate Matter	18 – 482	N/A, (Blanks)
5	CO	ppm	Carbon Monoxide	0.192 – 6.773	N/A, (Blanks)
6	SO2	ppm	Sulphur Dioxide	0.001 – 0.024	N/A, (Blanks)
7	NO	ppm	Nitrogen Oxide	0.002 – 0.144	N/A, (Blanks)
8	NO2	ppm	Nitrogen Dioxide	0.008 – 0.062	N/A, (Blanks)
9	Temp	Celsius	Temperature	22.6 – 31.0	N/A, (Blanks)
10	Rainfall	mm	Rainfall	0 – 161.2	N/A, (Blanks)

Figure 2. Attributes on air quality parameter and rainfall

Site	Date	O3	PM10	CO	SO2	NO	NO2	Temp	Rainfall (mm)
Petaling Jaya	4/1/2003	N/A	74	N/A	0.011	0.049	0.034	29.2	0.0
Petaling Jaya	4/2/2003	N/A	73	N/A	0.009	0.056	0.030	28.0	10.2
Petaling Jaya	4/3/2003	N/A	77	N/A	0.009	0.060	0.033	28.7	0.0
Petaling Jaya	4/4/2003	N/A	58	N/A	0.006	0.033	0.025	29.5	0.9
Petaling Jaya	4/5/2003	N/A	71	N/A	0.007	0.030	0.033	28.2	18.5
Petaling Jaya	4/6/2003	N/A	66	N/A	0.005	0.042	0.034	28.3	0.7
Petaling Jaya	4/7/2003	N/A	65	N/A	0.006	0.042	0.038	28.0	36.9
Petaling Jaya	4/8/2003	N/A	71	N/A	0.007	0.060	0.034	27.7	37.7
Petaling Jaya	4/9/2003	N/A	73	N/A	0.007	0.064	0.044	28.7	0.7
Petaling Jaya	4/10/2003	N/A	78	N/A	0.006	0.075	0.046	28.4	3.6

Figure 3. First ten rows of the raw datasets that were provided

Fig. 3 shows the first ten rows of the data sets that were collected. All attributes in the dataset contain highly distinct values that required to be handled. The nature of rough classier is that the data to be modeled are in discrete form. Therefore, discretization is required to transfer the data in ranges of categories. Discretization data is sufficient especially for large number of datasets that involved and having a lot of incomplete attributes or missing value in the data. In this study discretization has been done by first performing several statistical analyses to investigate the distribution of values in each attributes. The equal frequency binning method was used to discretize the data (Han and Kamber 2001). Fig. 4 depicts the results of data discretization on each attribute.

MONTH	O3	PM10	CO	SO2	NO2	TEMP	RAINFALL
Aug	NORMAL	NORMAL	NORMAL	NORMAL	NORMAL	LOW	FLOOD
Sep	NORMAL	NORMAL	NORMAL	NORMAL	NORMAL	LOW	NORMAL
Feb	NORMAL	NORMAL	NORMAL	NORMAL	NORMAL	LOW	NORMAL
Sep	NORMAL	NORMAL	NORMAL	NORMAL	NORMAL	LOW	NORMAL
Sep	NORMAL	NORMAL	NORMAL	NORMAL	NORMAL	LOW	NORMAL
Jan	NORMAL	NORMAL	SENSITIVE	NORMAL	NORMAL	LOW	DRY
Feb	NORMAL	NORMAL	SENSITIVE	NORMAL	NORMAL	LOW	DRY
Jun	NORMAL	NORMAL	SENSITIVE	NORMAL	NORMAL	LOW	DRY
Jan	NORMAL	NORMAL	SENSITIVE	NORMAL	NORMAL	LOW	FLOOD
Jan	NORMAL	NORMAL	SENSITIVE	NORMAL	NORMAL	LOW	FLOOD

Figure 4. First ten rows of the discretize datasets after binning

III. RESULTS & DISCUSSIONS

A series of experiment were carried out using 10-fold cross validation. Ten different sets of training and test data have been prepare to ensure efficiency of the modeling where all data have changes to be trained and tested. A rough set data analysis tool (ROSETTA) was used to generate the rules. The best model was obtained from the model which gave the highest accuracy. The accuracy is measured by the number of test data that are correctly classified upon the total number of test data. The ratio of training and test data also varied from 20% : 80% to 80% : 20% of train and test data respectively. Therefore in each fold 8experiments and total of 80 experiments were carried out throughout the modeling process. Fig. 5 presents the best model with highest accuracy from each set of data in all folds. The result showed that the accuracy increased as the number of training data increase. This is common in data mining where more training data indicates more knowledge obtained and the ability of classifying new unseen data should improved. This study has produced a very significant result where the model with 100% accuracy was obtained. It showed that the rules from the best model.

Model	Train (%)	Test (%)	ACC (%)
1	**20**	**80**	**85.05**
2	**30**	**70**	**97.86**
3	**40**	**60**	**98.12**
4	**50**	**50**	**100.00**
5	**50**	**50**	**100.00**
6	**60**	**40**	**100.00**
7	**70**	**30**	**100.00**
8	**80**	**20**	**100.00**

Figure 5. Accuracy results from 8 ratios set of data

IV. ANALYSIS OF THE KNOWLEDGE MODEL

The best model obtained from previous section has generated a total of 41 set of reductions with minimum and maximum length were 1 and 6 respectively. Fig. 6 and Fig.7 depict the ranking attributes frequency occurred in the reduction. The result indicated that the attribute CO was the most contributing factor that occurred in 100% of the reductions and the attribute SO2 has least occurrence 48.2%. The attribute ranking also reflected the importance of attributes in the data. The CO for extreme rainfall events has main influence compared to other factors where it gave 100% occurrence. Other factors that occurred more than 60% were Ozone, NO, PM10 and temperature. Overall, it was shown from this result that all the water quality attributes were highly related to the occurrence of extreme rainfall events, especially in Petaling Jaya area.

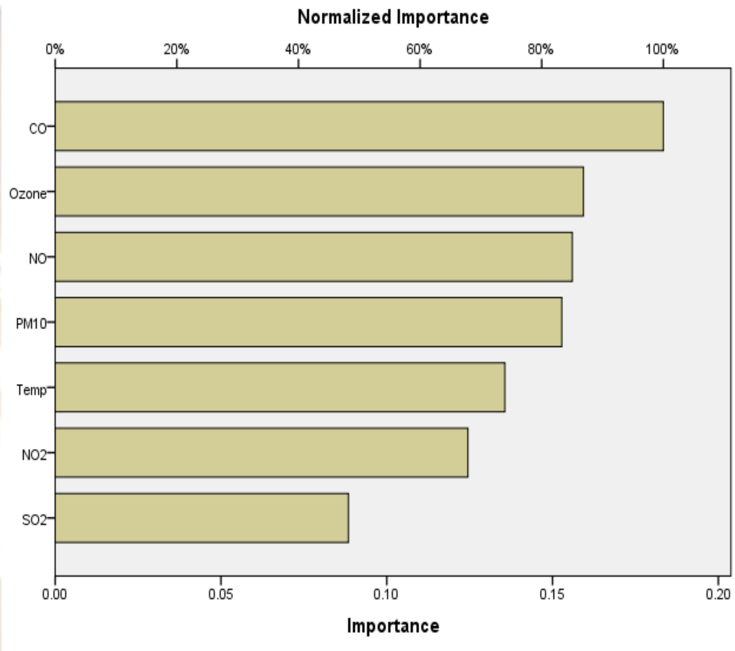

Figure 6. Attribute ranking

Independent Variable Importance

	Importance	Normalized Importance
Ozone	.159	86.8%
PM10	.153	83.3%
CO	.183	100.0%
SO2	.088	48.2%
NO	.156	85.0%
NO2	.124	67.9%
Temp	.136	73.9%

Figure 7. Attribute importance by percentage

Demonstrated, the green house gases, especially carbon monoxide (CO) and ozone were the main contributor of the extreme rainfall events. Increased of these greenhouse gas such CO and ozone increases in extreme rainfall events. This can be explain primarily by the fact that when atmospheric greenhouse gas concentrations continue to rise, causing air temperatures to continue to warm and making the atmosphere more humid. Warmer atmospheric air means more water vapor, which is itself a greenhouse gas, exacerbating the problem. What goes up, must come down and more and more that water vapor is coming down in an extreme precipitation events (Allan and Soden 2008). Warmer temperature in air produce heat and thus accelerates the chemical reactions in the atmosphere (Stathopoulou *et al*. 2008).

The knowledge model obtained from the previous section was further investigated. The best Model 4 and Model 5 with 50:50 ratios of training and test data have been analyzed. The total of 175 rules was generated. Appendix I shows 50 of 175 rules from the best model. The occurrence of the attribute in every rule has been computed. The analysis involved statistical measures such as frequency (Freq) and percentage of occurrence of each attribute and value of percentage (%) occur. The detail is presented in Fig. 8 where the attributes, CO, ozone, NO, PM10, temperature, NO2 and SO2 showed a consistent in distribution. The attribute CO indicated the most frequent in the rules and the most important attribute occurred during extreme rainfall events, followed by ozone, NO and PM10. The attribute SO2 seems to be less important in the rules construction. For SO2, this is expected because it participates very little in the chemistry of urban warming (Goh 1995). It has been reported in previous studies that SO2 is the least reactive pollutant measured. It is transported in the atmosphere for long distances without reacting with other species (Maier and Dandy 2000).

Descriptor	Frequency	% Occur	Ranking
CO	31	19.87	1
Ozone	28	17.95	2
NO	26	16.67	3
PM10	21	13.46	4
Temperature	16	10.26	5
NO2	13	8.33	6
SO2	9	5.77	7

Figure 8. Attribute and class occurrences in the rule base

The significance of NO, PM10 and NO2 on extreme rainfall events was also highlighted. The results of Model 4 and Model 5 indicate the dependency of extreme rainfall on NO, PM10 and NO2. It should be noted that the importance of NO, PM10 and NO2 and its contribution in the variations on meteorological and climatic conditions, especially on extreme weather changes case, was expected because from previous studies (Zannetti 1994; Comrie 1997; Gardner 1996; Boznar et al. 1993; Poulid et al. 1991) showed that they were physically and chemically highly reactive air pollutants in the atmosphere. Looking at Fig.8, it can also be seen that the meteorological parameter which was temperature, with a high correlation to extreme rainfall events. The relationship between rainfall and temperature can be explained on theoretical ground by chemical reaction. Temperature plays an enhancing role in the propagation rate of the radical chain, and has an opposite effect on the termination rate of these chains (Ruiz-Suarez et al. 1995).

V. Conclusion

This study has given a promising and valuable contribution especially to the climate change management. It is the first attempt using the rough set theory in solving the environmental issue problems. The knowledge model obtained can be used as a decision support system to gain sets of knowledge that is useful in terms of adaption to the extreme weather changes on earth. From the rule base knowledge where can know what are the main contributors to the extreme rainfall events, so that more action plans can be done in resolving the problem, for example managing by restricting more on the greenhouse gasses emissions to the atmosphere. Rough classifier produces knowledge that is understandable by human. This is an advantage compare to other learning algorithm such as the conventional way, statistic analysis. Rules can be interpreted easily. This model should be further utilized by embedding it within a decision support system environment with good interface. From this study it indicated several most important attributes that have influence to the extreme rainfall events such as CO, Ozone, NO, PM10 and temperature. Rough set approach has many advantageous features like, identifies relationships that would not be found using statistical methods allows both qualitative and quantitative data to be analyzed and offers straightforward interpretation of obtained results.

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Appendix I

Rules From the Best Model

First 50 rules from the best model

1. O3=NORMAL NO2=NORMAL Temp=NORMAL ==> Rainfall=DRY
2. O3=NORMAL SO2=SENSITIVE NO2=NORMAL Temp=NORMAL ==> Rainfall=DRY
3. NO2=NORMAL Temp=NORMAL ==> Rainfall=DRY
4. PM10=NORMAL NO2=NORMAL Temp=NORMAL ==> Rainfall=DRY
5. O3=NORMAL PM10=SENSITIVE CO=SENSITIVE SO2=SENSITIVE Temp=NORMAL==> Rainfall=DRY
6. SO2=SENSITIVE NO2=NORMAL Temp=NORMAL ==> Rainfall=DRY
7. O3=NORMAL PM10=SENSITIVE CO=SENSITIVE Temp=NORMAL ==> Rainfall=DRY
8. O3=NORMAL PM10=SENSITIVE SO2=SENSITIVE Temp=NORMAL ==> Rainfall=DRY
9. O3=NORMAL PM10=SENSITIVE CO=SENSITIVE SO2=SENSITIVE ==> Rainfall=DRY
10. O3=NORMAL CO=SENSITIVE NO2=NORMAL Temp=NORMAL ==> Rainfall=DRY
11. O3=NORMAL PM10=SENSITIVE Temp=NORMAL ==> Rainfall=DRY
12. O3=NORMAL Temp=NORMAL ==> Rainfall=DRY
13. CO=SENSITIVE SO2=SENSITIVE NO2=NORMAL Temp=NORMAL ==> Rainfall=DRY
14. O3=NORMAL PM10=SENSITIVE CO=SENSITIVE ==> Rainfall=DRY
15. O3=NORMAL PM10=SENSITIVE SO2=SENSITIVE ==> Rainfall=DRY
16. O3=NORMAL SO2=SENSITIVE Temp=NORMAL ==> Rainfall=DRY
17. O3=NORMAL PM10=NORMAL Temp=NORMAL ==> Rainfall=DRY
18. CO=SENSITIVE NO2=NORMAL Temp=NORMAL==> Rainfall=DRY
19. O3=NORMAL CO=SENSITIVE SO2=SENSITIVE Temp=NORMAL ==> Rainfall=DRY
20. O3=NORMAL PM10=SENSITIVE ==> Rainfall=DRY
21. O3=NORMAL CO=SENSITIVE Temp=NORMAL ==> Rainfall=DRY
22. O3=NORMAL SO2=SENSITIVE NO2=NORMAL==> Rainfall=DRY
23. O3=NORMAL NO2=NORMAL ==> Rainfall=DRY
24. O3=NORMAL PM10=SENSITIVE NO2=SENSITIVE Temp=NORMAL ==> Rainfall=DRY
25. O3=NORMAL CO=SENSITIVE SO2=SENSITIVE NO2=SENSITIVE Temp=NORMAL ==> Rainfall=DRY
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27. NO2=NORMAL ==> Rainfall=DRY
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32. PM10=SENSITIVE CO=SENSITIVE Temp=NORMAL ==> Rainfall=DRY
33. O3=NORMAL PM10=SENSITIVE NO2=SENSITIVE ==> Rainfall=DRY
34. PM10=SENSITIVE CO=SENSITIVE SO2=SENSITIVE ==> Rainfall=DRY
35. Temp=NORMAL ==> Rainfall=DRY
36. PM10=SENSITIVE SO2=SENSITIVE Temp=NORMAL ==> Rainfall=DRY
37. O3=NORMAL SO2=SENSITIVE ==> Rainfall=DRY
38. PM10=NORMAL Temp=NORMAL ==> Rainfall=DRY
39. CO=SENSITIVE SO2=SENSITIVE NO2=NORMAL ==> Rainfall=DRY
40. PM10=SENSITIVE Temp=NORMAL ==> Rainfall=DRY
41. SO2=SENSITIVE Temp=NORMAL ==> Rainfall=DRY
42. PM10=SENSITIVE CO=SENSITIVE ==> Rainfall=DRY
43. O3=NORMAL ==> Rainfall=DRY
44. CO=SENSITIVE SO2=SENSITIVE Temp=NORMAL ==> Rainfall=DRY
45. O3=NORMAL CO=SENSITIVE SO2=SENSITIVE ==> Rainfall=DRY
46. PM10=NORMAL NO2=NORMAL ==> Rainfall=DRY
47. PM10=SENSITIVE SO2=SENSITIVE ==> Rainfall=DRY
48. CO=SENSITIVE Temp=NORMAL ==> Rainfall=DRY
49. PM10=SENSITIVE ==> Rainfall=DRY
50. O3=NORMAL CO=SENSITIVE NO2=NORMAL ==> Rainfall=DRY