Big Data Analysis and Simulation for Performance Measurement of Hospitals in Emergency Situations

Mubarak Banisakher
Mubarak.banisakher@saintleo.edu

Van Nguyen
van.nguyen@saintleo.edu

Derek Mohammed
derek.mohammed@saintleo.edu

Saint Leo University
Saint Leo, USA

Abstract **- An effective distribution of emergency resources such as, hospital, storage and transportation in a reasonable and equitable manner is very important to achieve post-disaster damages and recovery. Additionally establishing an appropriate relationship between governments, private and academic sectors will lead to better utilization of their capabilities (e.g. national mapping agencies) which allow PDMS to acquire plenty of data from the post-disaster responders. This research has identified a need for new simulation modeling approaches that responds to the changing the information system for the emergency post-disaster management systems by integrating more data available from the huge pile that is conducted during and after disasters to enhance the emergency response time and save efforts. Simulation results demonstrate the effectiveness of the proposed methodology by evaluating data from hospitals using a multi-level index Data collection system.**

Keywords - Big data; Fuzziness; Simulation; Emergency; Disaster management; Performance.

I. INTRODUCTION

The simulation tools should be able to develop comprehensive models that are inexpensive, scalable, and able to accommodate the continuous and discrete modes of behavior, the stochastic and deterministic natures of the various post-disaster management information systems, and the detail complexity and dynamic complexity perspectives in decision making.

In this research we propose to develop a framework to combine and synchronize the big data paradigms to simulate the behavior of the information system that is designed to provide accurate and timely manner information to the first responders.

The new approach can respond to the identified requirements in simulating the modern post-disaster management systems of how they should behave in terms of response time and data accuracy. It is directed toward building comprehensive simulation models that can accommodate all management information systems levels while explicitly recognizing the differences between them in terms of scope and frequency of decision making as well as the levels of details preferred and used at each level.

Fuzzy Set Theory (FST) was utilized in conjunction with classical methods to enhance the reliability and utility of disaster efforts while we focus on various forms of natural or man-made disasters [1,2,5], also there are some Fuzzy Set methods applied in PDMS, such as, fuzzy quantities [3], fuzzy logic programming [4], and fuzzy relation concepts for risk management [4]. He and Chen, introduced a chaotic differential evolution algorithm to solve a fuzzy clustering iterative model for evaluating flood disaster [5,6,7], while [7] and [8] represented the diffused-interior-outer-set model (DIOSM) to obtain the possibility-probability distribution (PPD) for risk calculation.

Fuzzy evaluation model also was applied in supervised learning process for PDMS and compared with non-supervised process, supervised or semi-supervised process, it resulted in much more accurate results through evaluating the outputs and continue to adjust the inputs.

On the other hand, unsupervised learning is based on training samples of the category unknown (not marked) to solve various problems in pattern recognition, such as clustering analysis. Sometimes, the lack of prior knowledge is difficult to manually label the category while artificial category label is too costly. Naturally, we hope that the computer on our behalf (partially) will help us to complete these tasks. These works include selecting some representative samples of the classifier from a huge collection of data [9,10,11]. First of all, samples automatically are divided into different categories marked by humans. The most common unsupervised learning based automatic classification is calculated based on the similarity.

The similarity measure also can be defined based on human experience. By clustering objective function of the squared error, such as various types of samples to the class mean vector distance and minimum variance criteria, it can be divided into:

- K-means algorithm
- Fuzzy K-means algorithm (K-means variant 1)
- Iteration K-means algorithm (K-means variant 2)
- Consolidation Act (also known as clustering)
- Secession Law (also known as decomposition clustering)

Some fuzzy set model based algorithms for semi-supervised learning were developed and improved by previous scholars, such as, fuzzy Petri net [12], and active fuzzy constrained clustering (AFCC) [13],[14],[15],[16] proposed a new heuristic semi-supervised fuzzy co-clustering algorithm (SS-HFCR) for categorization of large web.

From the background review we found out that, fuzzy evaluation makes the knowledge presentation more exact, but the shortcomings of fuzzy evaluation are in the complexity of calculation. So a fuzzy inference system needs to be developed to reduce the complexity. Combining with SSL for PDMS is an innovative method that will make the PDMS provide more effective information for decision-making for individuals in post-disaster.

II. METHODOLOGY

The collection of dataset in this paper were processed by fuzzy factor analysis, which includes the following steps:

Steps of Evaluation:

Let the universe set be the P evaluation indices, and noted that $u = \{u_1, u_2, \cdots, u_p\}$

Let the evaluation level be $v = \{v_1, v_2, \cdots, v_p\}$

Each level relative to a fuzzy subset.

Establish the fuzzy relation matrix R

Quantify $u_i(i = 1,2, \cdots, p)$, i.e. it is to calculate the fuzzy membership of each index for the evaluation object $(R|u_i)$ and to continue to get fuzzy relationship matrix:

$$R = \begin{bmatrix} R| & u_1 \\ R| & u_2 \\ \cdots & \cdots \\ R| & u_p \end{bmatrix} = \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1m} \\ r_{21} & r_{22} & \cdots & r_{2m} \\ \cdots & \cdots & \cdots & \cdots \\ r_{p1} & r_{p2} & \cdots & r_{pm} \end{bmatrix}_p \quad (1)$$

where the i-th row and j-col element, r_{ij} , in matrix R, denotes an object was evaluated by factor u_i of level v_j's membership and an object's aspect in u_i was calculated by fuzzy vector. $(R|u_i) = (r_{i1}, r_{i2}, \cdots, r_{im})$ In other algorithms, the evaluation was calculated by only one factor, so the fuzzy factors evaluation needs more information from the matrix.

Evaluation Factors are Weighted:

In fuzzy comprehensive evaluation process, the weight vector $A = (a_1, a_2, \cdots, a_{1p})$ is needed where the element a_i in A is the membership of factor u_i for evaluation objects. For a multi-level evaluation process, analytic hierarchy was used in order to sort the importance of factors and to decide the weights. Let the normal weights be

$$\sum_{i=1}^{p} a_i = 1 \quad , a_i \geq 0 \, , i = 1,2, \cdots, n,. \quad (2)$$

Result Vector by Fuzzy Synthetic Evaluation:

A and R of object were synthesized using given operator to get fuzzy synthetic evaluation B, i.e.

$$A \times R = (a_1, a_2, \cdots, a_{1p}) \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1m} \\ r_{21} & r_{22} & \vdots & r_{2m} \\ \cdots & \cdots & \vdots & \cdots \\ r_{p1} & r_{p2} & \cdots & r_{pm} \end{bmatrix} = \\ = (b_1, b_2, \cdots, b_m) = B \quad (3)$$

where b_l is calculated by A and the j-th Col of R which denotes the membership of the level set v_j on the evaluation object.

Analysis on Vector of Fuzzy Comprehensive Evaluation:

The maximum membership principle is the most common method in practice, however in certain cases it will not work effectively and will lose much of the information, potentially leading to inaccurate evaluation results. Due to this, the weighted average method was proposed for seeking membership level for many objects, followed by the evaluation according to their sorted levels.

The Weights by Analytic Hierarchy:

It is important to use a comprehensive evaluation to find the weights. Fuzzy analytic hierarchy method is a proven and effective method of determining the weight coefficients in practice. It is particularly suitable for difficult to obtain quantitative indicators to analyze complex problems. There are many interrelated and layered factors involved in considering principles based on the objective reality of the fuzzy judgment and the relative importance of each level while still maintaining a quantitative representation. Mathematical methods can be used to determine the weights of all elements in the relative order of importance. The steps were introduced as follows:

A) Let object's evaluation index be $u = \{u_1, u_2, \cdots, u_p\}$

B) Establish the judgment matrix: the element value of judgment matrix reflects the individuals' understanding of the relative importance of each element, generally as 1-9 and their reciprocal scaling method. But the importance of factors can be compared with each other with a meaningful description of the ratio, the value of the corresponding element of judgment matrix and then take the ratio .$S=(u_{ij})_{pxp}$

C) Calculate the judgment matrix: calculate the maximal eigenvalue λ_{max} of S and eigenvector A; actually, eigenvector A is the distribution of weights.

D) Consistency check: set consistency index $= \frac{\lambda_{max}-n}{n-1}$, and average consistency random index RI . This method is used to construct a random matrix by a plurality of samples;

the random structure and inverse scaling of the sample fills the upper triangular matrix. The value of the main diagonal is always one. In correspondence to the position of entry transpose, the random number uses the inverse of the corresponding position. Then in order for each random sample matrix to calculate the consistency index values obtained for these values, the average random consistency index values RI. While the random consistency ratio $CR = \frac{CI}{RI} < 0.10$, the sort that results in satisfactory consistency, namely the distribution of weights is reasonable; other else to adjust the value judgment matrix elements of redistribution of weight coefficient values.

III. DESIGN AND DATA COLLECTION

The data collected were designed for the emergency ability of hospitals in Central Florida Area, Volusia County and Flagler County. About ten hospitals were considered for involvement in this data collection and seven of them were selected for feedback through the data collection forms. A self-administered questionnaire was used to collect data. The Data collections included nine indexes and each index included eight questions that required every respondent to answer. Some questions must not be marked; the Data collection questionnaire was randomly distributed to people, and the questionnaire was independently completed, and each questionnaire was validated. From the 70 dispersed Data collections spectrum, 59 were returned, resulting in a return rate of 84%; 54 forms were validated; the validation rate was 91.5%. The respondents included doctors, nurses, patients and administrators of varying ages. The nine group indexes are listed in Table I.

TABLE I. NINE INDEXES FOR THE EMERGENCY ABILITY OF HOSPITALS IN POST-DISASTER

Group	Factors
GP-1	Decision-making system responsible for command and control
GP-2	Clear, accurate and timely communication of hospital in post-disaster
GP-3	Well-developed safety and security procedures
GP-4	The abilities for maintaining patient triage operations of hospital
GP-5	Surge capacity in post-disaster
GP-6	The ability of the continuity of essential services
GP-7	Human resources system
GP-8	Logistics and supply management for the hospital in post-disaster
GP-9	The ability for post-disaster recovery

The eight questions referred to as sublevel factors are listed in Table II. Table II only listed the first group factor GP-1.

TABLE II. SUB-FACTORS OF GROUP 1 INCLUDING EIGHT FACTORS

Indexes	Sub-Factors
G11	Incident command team ability to respond
G12	Hospital command center ability
G13	The basic qualifications of disaster managers and employees
G14	Members of emergency response teams are sufficient trained
G15	Coincided with the World Health Organization (WHO) standards.
G16	Focal point continuity assurance capabilities.
G17	Strict compliance with the basic principles and accepted strategy
G18	Ensuring proper management and coordination of activities

For each question, the respondents needed to mark a score by 5- Likert Scale (1, 3, 5, 7, 9); A semantic for understanding using 4 levels can also be set: Good, median, normal and bad which is shown in Table III.

TABLE III. QUANTITATIVE EVALUATION OF GRADING STANDARDS

Score	Evaluation	Level
$x_i > 8.5$	Good	$E1$
$7.5 < x_i \leq 8.5$	Median	$E2$
$6.5 < x_i \leq 7.5$	Normal	$E3$
$x_i \leq 6.5$	Bad	$E4$

With the Data collection, fuzzy comprehensive evaluation was applied to calculate the performance of the emergency ability of hospitals in post-disaster. Evaluation of the object is to determine the factors of the evaluation set. But the GP-3, GP-4, and GP-7 received few responses throughout the Data collection process, leaving for consideration onlyGP-1, GP-2, GP-5, GP-6, GP-8, and GP-9.which are shown in Table VI where we averaged all the evaluation data set of 54 records.

TABLE VI THE FIRST LEVEL FACTORS FOR THE EMERGENCY ABILITY OF HOSPITALS IN POST-DISASTER

GP-1	GP-2	GP-5	GP-6	GP-8	GP-9
7.000	7.000	7.250	7.250	7.250	7.000
6.250	6.600	8.000	8.333	8.200	7.667
7.857	7.000	7.667	8.333	8.200	8.667
7.000	8.000	7.000	9.000	7.400	7.667
7.857	8.500	8.333	5.667	8.200	9.000
7.000	7.000	7.000	7.667	9.000	8.000
8.143	9.000	8.333	9.000	6.600	8.000
8.429	7.500	7.000	6.667	9.000	7.667
9.000	9.000	8.667	6.667	6.600	7.667
8.143	9.000	6.000	7.333	5.400	5.667
8.143	7.000	8.000	8.333	7.000	9.000
8.714	9.000	8.667	8.333	9.000	7.333
7.286	6.500	7.333	8.000	8.600	8.000
6.429	7.500	8.000	8.333	9.000	9.000
6.250	6.600	8.000	8.333	8.200	7.667
7.857	7.000	7.667	8.333	8.200	8.667
7.000	8.000	7.000	9.000	7.400	7.667
7.857	8.500	8.333	5.667	8.200	9.000
7.000	7.000	7.000	7.667	9.000	8.000
8.143	9.000	8.333	9.000	6.600	8.000
8.429	7.500	7.000	6.667	9.000	7.667
9.000	9.000	8.667	6.667	6.600	7.667
8.143	9.000	6.000	7.333	5.400	5.667
9.000	8.500	9.000	8.333	9.000	7.667
6.250	6.600	8.000	8.333	8.200	7.667
7.857	7.000	7.667	8.333	8.200	8.667
7.000	8.000	7.000	9.000	7.400	7.667
7.857	8.500	8.333	5.667	8.200	9.000
7.000	7.000	7.000	7.667	9.000	8.000
8.143	9.000	8.333	9.000	6.600	8.000
GP-1	GP-2	GP-5	GP-6	GP-8	GP-9
8.429	7.500	7.000	6.667	9.000	7.667
9.000	9.000	8.667	6.667	6.600	7.667
8.143	9.000	6.000	7.333	5.400	5.667
9.000	8.500	9.000	8.333	9.000	7.667
9.000	9.000	8.667	6.667	6.600	7.667
8.143	9.000	6.000	7.333	5.400	5.667
9.000	8.500	9.000	8.333	9.000	7.667
6.250	6.600	8.000	8.333	8.200	7.667
7.857	7.000	7.667	8.333	8.200	8.667
7.000	8.000	7.000	9.000	7.400	7.667
7.857	8.500	8.333	5.667	8.200	9.000
7.000	7.000	7.000	7.667	9.000	8.000
8.143	9.000	8.333	9.000	6.600	8.000
8.429	7.500	7.000	6.667	9.000	7.667
9.000	9.000	8.667	6.667	6.600	7.667
8.143	9.000	6.000	7.333	5.400	5.667
8.143	9.000	8.333	9.000	6.600	8.000
8.429	7.500	7.000	6.667	9.000	7.667
9.000	9.000	8.667	6.667	6.600	7.667
8.143	9.000	6.000	7.333	5.400	5.667
9.000	8.500	9.000	8.333	9.000	7.667
9.000	9.000	8.667	6.667	6.600	7.667
8.143	9.000	6.000	7.333	5.400	5.667
9.000	8.500	9.000	8.333	9.000	7.667

By expert and the confidence dataset from the Data collection form, we listed the weighted values on each second level factor and the first level factors' weights were calculated by the steps in Section 3.

TABLE V: TWO GRADES OF EVALUATION FACTORS OF HOSPITAL EMERGENCY ABILITY AND WEIGHTING

Factors	Evaluation factors	Weights	Factors	Evaluation factors	Weights
GP-1 0.212	G11 G12 G13 G14 G15 G16 G17 G18	0.143 0.121 0.178 0.221 0.130 0.121 0.178 0.213	GP-6 0.176	G61 G62 G63 G64 G65 G66 G67 G68	0.113 0.224 0.135 0.115 0.119 0.203 0.214 0.132
GP-2 0.204	G21 G22 G23 G24 G25 G26 G27 G28	0.213 0.123 0.132 0.225 0.210 0.211 0.303 0.129	GP-8 0.216	G81 G82 G83 G84 G85 G86 G87 G88	0.103 0.120 0.120 0.125 0.230 0.200 0.178 0.189
GP-5 0.178	G51 G52 G53 G54 G55 G56 G57 G58	0.121 0.213 0.222 0.122 0.121 0.204 0.233 0.121	GP-9 0.165	G91 G92 G93 G94 G95 G96 G97 G98	0.116 0.165 0.167 0.125 0.168 0.210 0.227 0.154

IV. INDEX WEIGHTS FUZZY ANALYSIS STEPS

The following steps are used to get each factor's weight:

1) Determine the evaluation object set *P*=Emergency Abilities of Hospitals
2) Structural evaluation factors set: $u = \{u_1, u_2, \cdots, u_6\}$ ={GP-1… GP-9}
3) Determine the domain level reviews: $v = \{v_1, v_2, \cdots, v_4\}$ ={Good, Median, Normal, Bad}
4) Weight calculation First level index

Construct judgment matrix of six factors:

$$S = (u_{ij})_{p\times p} = \begin{bmatrix} 1 & 4/3 & 5/4 & 1 & 9/5 & 6/5 \\ 3/4 & 1 & 9/10 & 8/9 & 7/5 & 8/9 \\ 4/5 & 10/9 & 1 & 4/5 & 3/2 & 1 \\ 1 & 9/8 & 5/4 & 1 & 2 & 5/4 \\ 5/9 & 5/7 & 2/3 & 1/2 & 1 & 4/6 \\ 5/6 & 9/8 & 1 & 4/5 & 6/4 & 1 \end{bmatrix} \quad (4)$$

The maximal eigenvalue of the judgment matrix is λ_{max}=6.00589 by Mathematica 9.0 and continue to calculate the $CI = \frac{\lambda_{max}-n}{n-1} = \frac{6.00589-6}{6-1} = 0.001178$ and *RI=1.24*。So the ratio is $CR = \frac{CI}{RI} = \frac{0.001178}{1.24} = 0.00095 < 0.10$, so it was regarded that the results of the weighted processing were reasonable. The relative eigenvector of λ_{max} is

A_0 = (1.21372, 0.935715, 0.9911, 1.21138, 0.634379, 1.0) (5)

Normalized and we have that,

A = (0.202, 0.156 0.165, 0.202, 0.109, 0.166) (6)

5) Calculate the weights of sub-level index.

Similarly, we still use the AHP method to find the index weights. Two indicators were constructed for each of their own judgment matrix, and then calculate the maximum eigenvalue of Mathematica and consistency test. Come to a reasonable weight coefficient. The GP-1 weighted vector is

{0.143, 0.121, 0.178, 0.221, 0.130, 0.121, 0.178, 0.213} (7)

Normalized and we have that,

{0.110, 0.093, 0.136, 0.169, 0.100, 0.093, 0.136, 163} (8)

and continue to calculate GP-2, GP-5, GP-6, GP-8, GP-9.

6) Multi-level fuzzy comprehensive evaluation

Synthesized using $M(o,\oplus)$ the weighted average fuzzy operator A and R will be synthesized and foot fuzzy comprehensive evaluation result vector. Commonly used fuzzy comprehensive evaluation is used to take large or small algorithm in many factors, each share of the weight factors is often very small. In the fuzzy synthetic operation, a lot of information is lost, the results are not easily distinguishable and often leads to irrational (i.e. model failure) situations. So, for the above mentioned problem, the weighted average type fuzzy synthesis operator is used. The formula is:

$$b_i = \sum_{i=1}^{p} \left(a_i \cdot r_{ij} \right) = \min\left(1, \sum_{i=1}^{p} a_i \cdot r_{ij} \right),\ j = 1, 2, \cdots, m \tag{9}$$

So we have that $A_1=a \circ R$=(0.130, 0.320, 0.307, 0.167) and by normalization we have that (0.141, 0.346, 0.332, 0.187), so we get the overall evaluation weight for GP-1 is:

$V_{GP-1}=4\times0.141+3\times0.346+2\times3.32+1\times1.81=2.12$, and continue to calculate the GP-2, GP-5, GP-6, GP-8 and GP-9 which were also listed in Table 5.

So the overall performance of emergency ability of each hospital in post-disaster was presented by fuzzy set,

$$E = \frac{v(GP-1)}{W_1} + \frac{v(GP-2)}{W_2} + \frac{v(GP-5)}{W_5} + \frac{v(GP-6)}{W_6} + \frac{v(GP-8)}{W_8} + \frac{v(GP-9)}{W_9} \tag{10}$$

Or simply calculated as,

$$E = \sum_{i=1}^{9} W_i v(GP-i),\ W_3 = W_4 = W_7 = 0 \tag{11}$$

The most commonly used method in practice is the principle of maximum degree, but this method use is conditional as there are issues of validity and it may draw unreasonable evaluation results. According to the principle put forward, the weighted average method of seeking membership level, the principles for the use of a weighted average of these levels of evaluation to analyze the results of the evaluation. The results of this method with the principle of maximum degree the results obtained by the method is quite different, but the results were more in line with the actual situation.

Simulation on IF-THEN Rules Presented Graph Using Data collection Data-Set

We labeled seven hospitals to be {H1, H2, H3, H4, H5, H6, H7}; the value of each node (hospitals) is the performance data which was calculated in Section 3 and it was {7.35, 7.65, 6.88, 8.20, 8.54, 7.12, 8,82}, the distance of each hospital will be labeled on the available road on the graph. The IF-THEN will draw the relationship between each hospital, the processing was described in Section 2, and 3, and the fuzzy operation results were the value of emergency for a suitable resource such as "IF Hospital A is good THEN Hospital B is better, Cost is X" Figure 9. The best results are calculated by each node one by one and finally, the totally cost and the best node were located for individuals. Node A is the start node with the cost calculated by the value of the performance of each hospital and the distance as

$$Cost = v(GP-i)a + \frac{15}{d_{is}}(1-a) \tag{12}$$

We now let a=0.9, and calculated all the costs between two nodes whereas "-" is unknown or maximal, the cost matrix was

$$\begin{bmatrix} 0 & - & 6.5 & - & - & - & 15 \\ - & 0 & 8 & 7.5 & - & - & - \\ 6.5 & 8 & 0 & - & 7 & 4.5 & - \\ - & 7.5 & - & 0 & 4.5 & - & - \\ - & - & 7 & 4.5 & 0 & 4.5 & - \\ - & - & 4.5 & - & 4.5 & 0 & 2.5 \\ 15 & - & - & - & - & 2.5 & 0 \end{bmatrix} \tag{13}$$

And the rule set is:

IF H1 THEN H7, Cost is15
IF H2 THEN H3, Cost is 8
IF H3 THEN H5, Cost is 7
IF H4 THEN H5, Cost is 4.5
IF H5 THEN H6, Cost is 4.5
IF H1 THEN H3, Cost is 6.5
IF H3 THEN H6, Cost is 4.5
IF H4 THEN H2, Cost is 7.5
IF H6 THEN H7, Cost 2.5
IF P THEN H6, Cost is 12

We draw the non-vector graph by these rules. The node is the location of hospitals and the value on the edge was the cost shown in Fig 1 and 2.

Simulation Results

Simulation for Dataset of Fuzzy C-mean and Graph-Based Hospital Distribution

GIS is a directed graph, node value (multidimensional vector-based calculation), we can acquired the hospitals information in the pre-post stage from map based product. Figure 3 is a map for hospitals distribution. We can conduct a map and store them as a matrix shown as Figure 4. For such cases it is much more appropriate to use fuzzy clusters where each node can belong to multiple clusters, too. By fuzzy clusters, they are described by their cluster centers, we can print out the representative of each cluster. It shows the relationship of nodes in the graph-based system. We know that fuzzy c-mean method can be applied in the dataset processing of PDMS, and making it clear for decision-making in post-disaster systems. GPS dataset point (x) was collected from a GIS based hospitals location dataset, which is assigned by the clustering number, fuzziness, and accuracy; we simulated and ran the results in Figure 5. Suppose that we can identify the position as a net like Figure 6, so we can start the algorithm from a node; it represents the hospital which the individuals are looking for in post-disaster shown in Figure 7.

We can compare the Genetic Arithmetic based application from the Philippines; the researchers developed an android application based PDMS, based on its special geographical location and natural disasters. MyDisasterDroid's main function is to offer the optimal combination of routes, supplying the rescue team with the shortest and most efficient route to so they can aid as many victims as possible. The application calculates the route using the famous traveling salesman problem, in which given the limited number of travel destinations as well as the distance between each other, traveling salesman most choose the route to make the trip to meet a cost and time minimum (see Figure 8).

V. SUMMARY AND CONCLUDING REMARKS

This paper provides a relevant study of framework for Post-disaster management system which can recognize the data collected and the responses of users induced from different hospital. This paper collected the evaluation data from hospitals using a multi-level index Data collection system; the indexes were converted to factors which were evaluated by the Likert Scale nine point method. By using multi-level fuzzy factor analysis, the weights were determined; the weights decided the importance of the factor in the evaluation process for hospitals' performance in post-disaster. By implementing this framework in real information system environment, it will be able to estimate which hospital spot has the required needed resources in post-disaster. It answers the question that how we as scientific researchers will benefit from the huge data available to enhance the accuracy of the post-disaster management systems. While further verification of this method tests are needed to validate the robustness in real time environment. This framework generalizes the findings to different type of post-disaster management systems and try to improve predictions of the need of the affected individuals in the disaster area by accounting of the differences by hospitals responses.

The structure of the repository and the details of the data generation capability will be described in a future paper.

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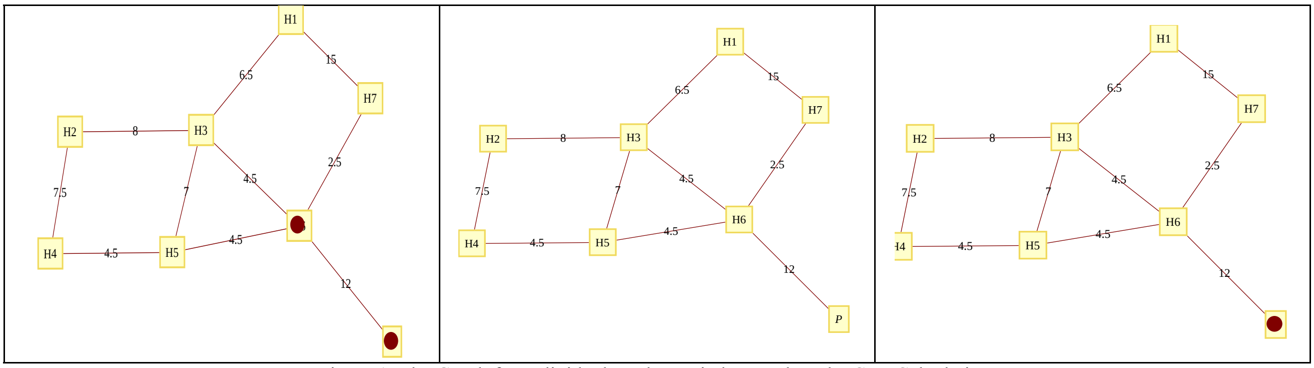


Figure 1. The Graph for Individuals and Hospitals Based on the Cost Calculation.
The process starts at node P to the resource location H2 in Fig 2.

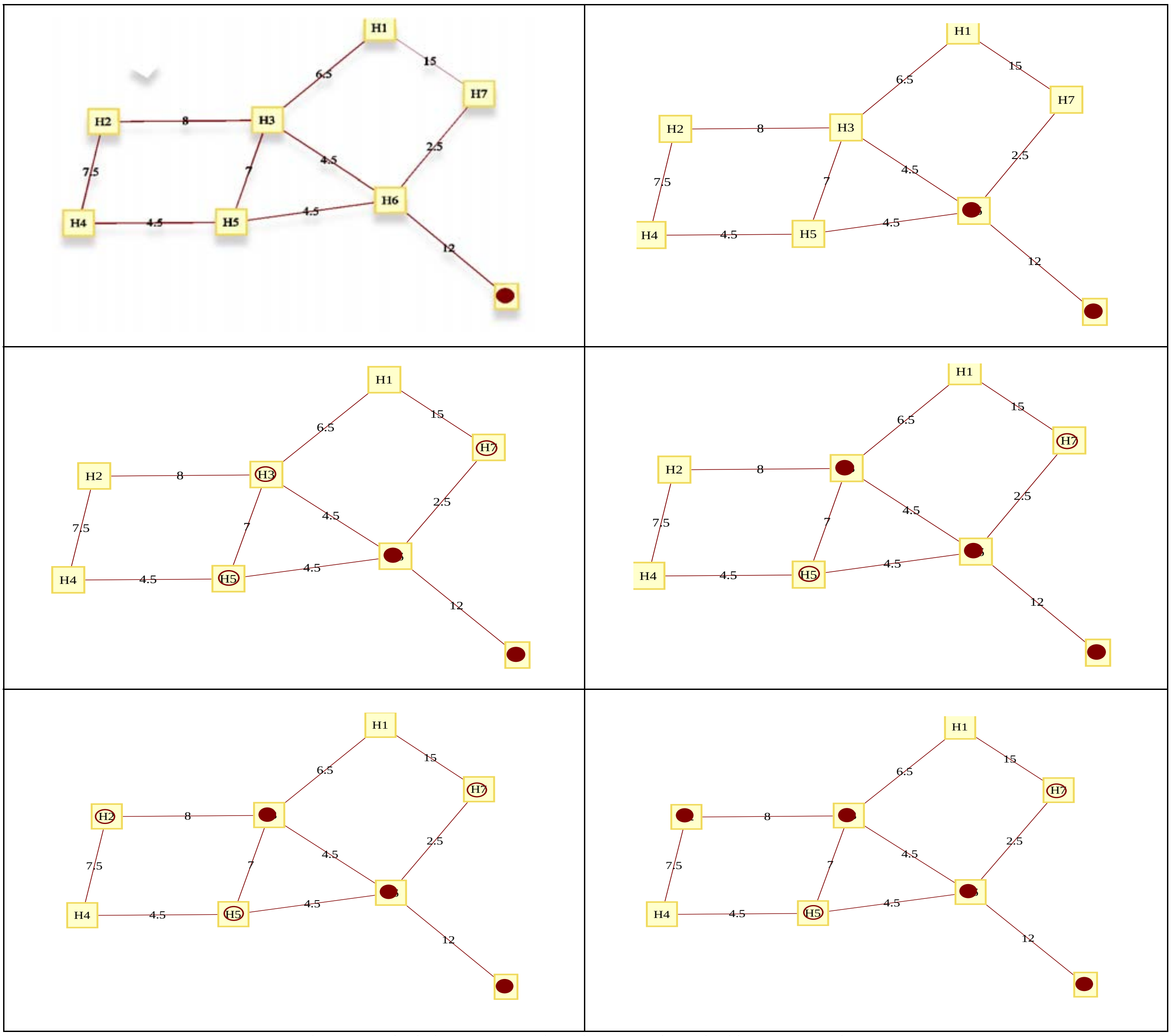


Figure 2. Calculation Process Using Shortest Path Method between P and H2
"○"is the template node in the path, and "●" is the confirmed node in the path.
The results showed that following the cost calculation, it was easier for the individual to locate the resource using shortest path method.

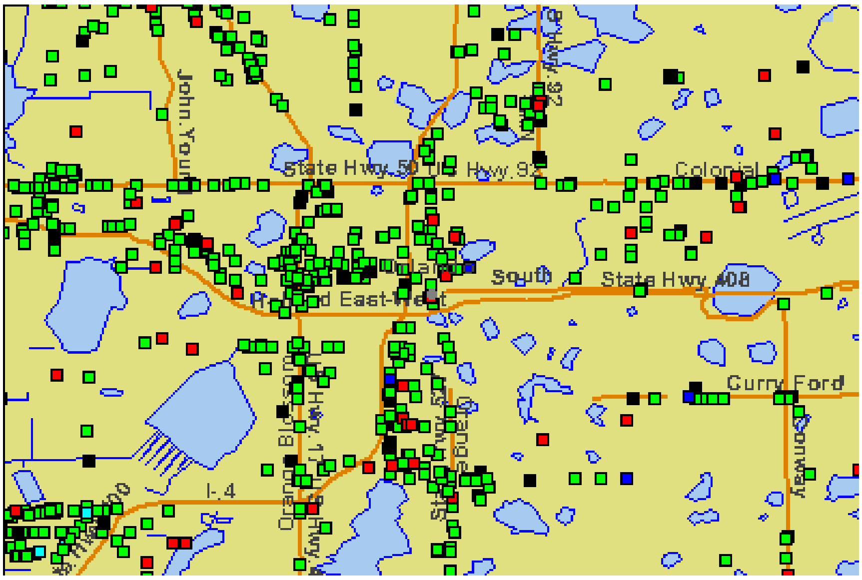


Figure 3 Hospitals Distribution Map Dataset.

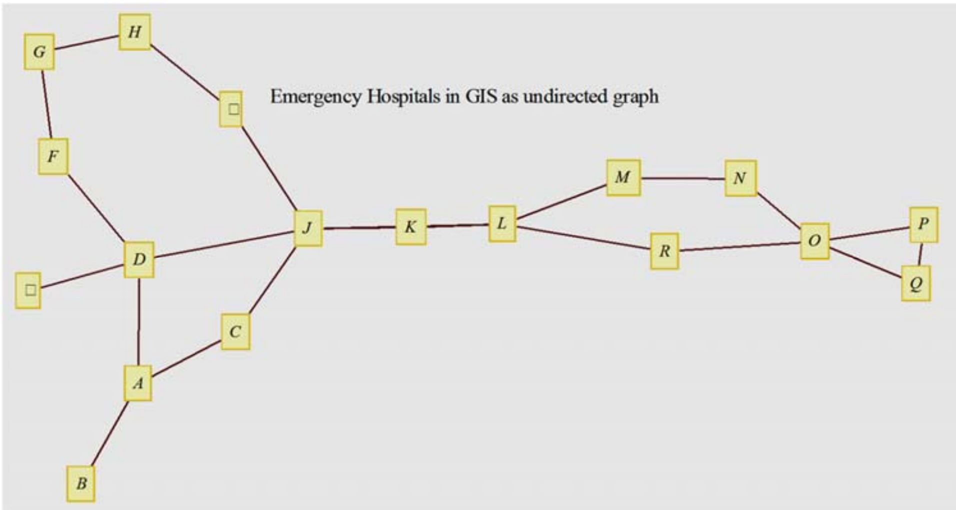


Figure 0 Graph Converted From Hospitals Distribution Map

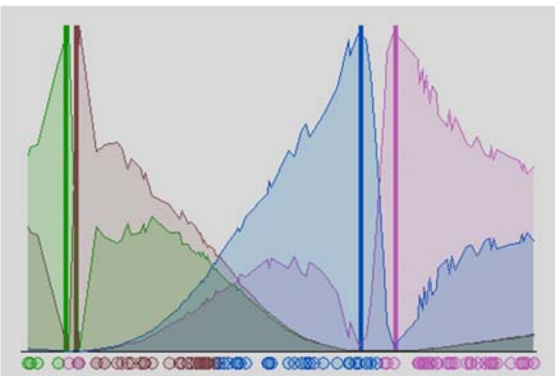


Figure 5: [DataN=100, ClusterN=3, Fuzziness=2, Accuracy=0.3].

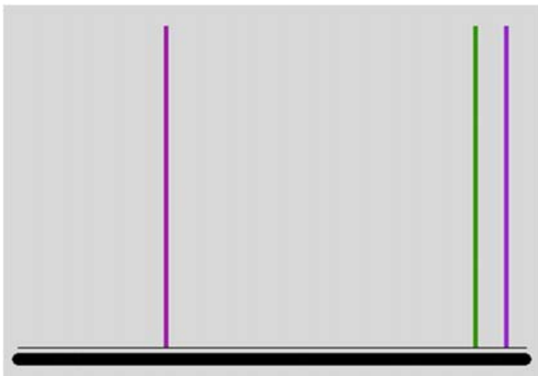
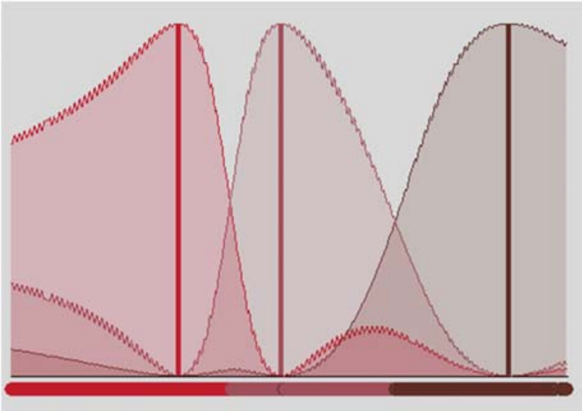


Figure 6: Initialed: [DataN=1000, ClusterN=3, Fuzziness=2, Accuracy=0.3]



Steps: [DataN=1000, ClusterN=3, Fuzziness=2, Accuracy=0.3]
Figure 7: Fuzzy C-mean Using GIS Based Hospitals Location Dataset.

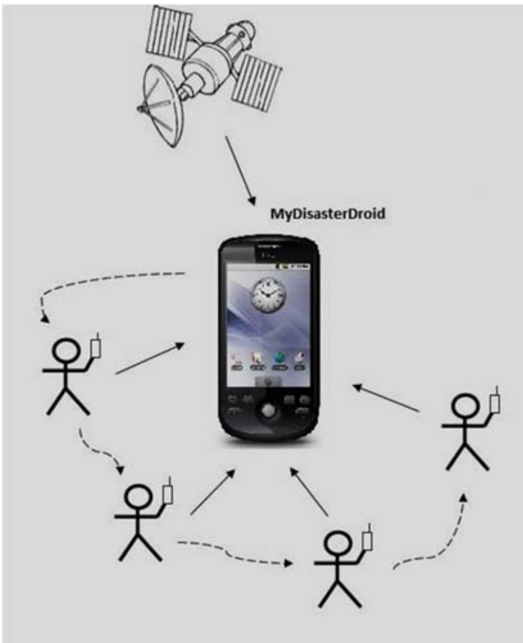


Figure 8 Frameworks of Shortest-Path Searching Based MyDisasterDriod Project.

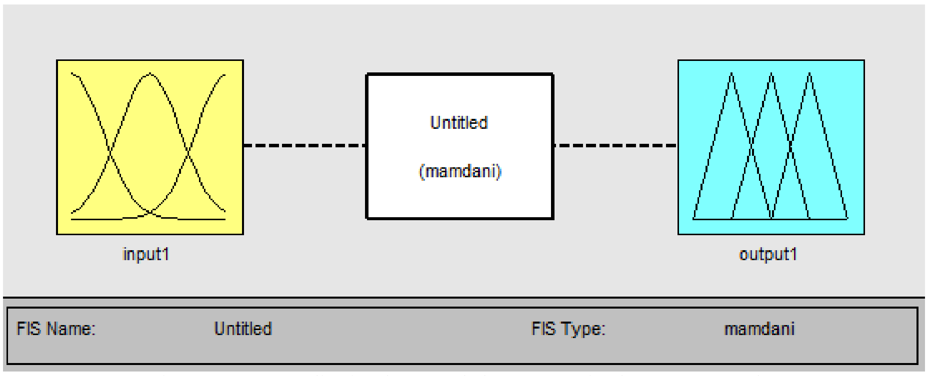


Figure 9 Fuzzy Implication for Knowledge Presentation by IF-THEN Rule.