Disaster management model based on Modified Fuzzy Cognitive Maps

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Abstract - This paper describes the use of a Fuzzy Cognitive Map (FCM) to model disaster reconstruction, based on data collected from the cities of BAM and Baravat. The extended fuzzy cognitive map augmented with an unsupervised learning algorithm has been used to transform the associated data into a graphical model. Further to which, a modular approach based on efficient clustering of correlated variables has been adopted to model the sparse data. Discussion and justification of the results is also presented.

I. INTRODUCTION

Significance of disaster management and analysis has grown rapidly over the last decade; especially due to the recent catastrophes. A typical disaster site is characterized by limited resources and urgent rehabilitation requirements; and such a situation calls for efficient use of these resources in order to extract maximum benefit. Efficient flow of information and apriori knowledge of such situations are of prime importance in disaster decision making. One way through which such knowledge may be obtained is by modeling prior disasters. In other words, effective disaster management warrants availability of accurate models and the ability to forecast the reconstruction requirements.

The work described in this article is an attempt to create a disaster management model. In particular, the data collected from the cities of BAM and Baravat has been used here. Fuzzy Cognitive Maps (FCM) have been used to encode the information into a graphical format and to use the same as a predictive model. An extension to classical graph theory, the fuzzy cognitive map represents domain knowledge through a graphical representation comprised of nodes and arcs joining various nodes. The objective of this work is to introduce the technique of a modified fuzzy cognitive map capable of learning from data and further, apply it to the problem of developing a disaster reconstruction model. The use of fuzzy cognitive maps has been determined to be appropriate for such a system since they provide an intuitive understanding about the problem domain.

This article is divided into six sections. Section 2 briefly introduces a fuzzy cognitive map followed by a description of some existing modifications provided in section 3. Section 4 describes the adopted methodology. Results along with a brief discussion are provided in section 5. Section 6 concludes the described work.

II. SIMPLE FUZZY COGNITIVE MAPS

A simple fuzzy cognitive map may be described as a graphical form of knowledge representation. A fuzzy cognitive map is network of nodes and directed arcs; wherein the nodes (referred to as concepts in this paper) represent various events, inputs, outputs or other domain specific parameters. The arcs connect the nodes to each other and carry a weight, representative of the causal relationship between the two connected concepts. In other words, a fuzzy cognitive map encodes the system knowledge into a set of interdependent concepts depicting the cause & effect between the concepts.

First proposed by Kosko [1986], fuzzy cognitive maps operate on the basis of a formal causal algebra, executed through simple matrix operations. Figure 1 depicts such a simple fuzzy cognitive map. Only a brief description about the fuzzy cognitive maps is provided in this section, but the reader may refer to Kosko [1988], Papageorgiou et al. [2004], Stylios-Groumpos [1998] for detailed descriptions.

A fuzzy cognitive map is usually constructed by an expert i.e. the expert chooses the concepts and the connecting arcs. Further, based on his knowledge about the concepts (or a heuristic) the expert assigns numeric weights to each of the arcs; the expert devices an appropriate weight matrix for the map. The weight matrix is square and is such that each element $w_{ij}$ represents the causalinity of the concept $i$ upon the concept $j$. The zero diagonal of the weight matrix is representative of the assumption that no concept affects itself. The concepts take values between [0 1] and the weights typically represent negative (-1 0), positive (0 1) or no causality [0]; it should be noted that both of these values are scaled but representative of the real world values.

Having the weight matrix, the value of each concept is computed as the weighted sum of the causalities of all other concepts connected to it. And similarly, the values for every concept in the map are computed in a cyclic fashion. For example (with reference to Figure 1): The value $A_3$ of the concept $C_3$ is computed as follows:

$$A_3 = f \left( C_2 \cdot w_{23} + C_6 \cdot w_{63} \right) \tag{1}$$

The fuzzy cognitive map is first activated; which refers to the act of initiating one (or more) concepts by assigning a number value to it. Typically a concept value of 1 resembles an active concept, but in practice, any number in the range [0 1] may be used. Once initiated the fuzzy cognitive map is allowed to iterate (cyclically computing the concept values)
until no further change in the concept values is observed; or simply, that the fuzzy cognitive map is allowed to equilibrate (a term commonly used in the literature [Taber 1991]). Through the iterations, the value of each of concept is computed using the following generalized equation:

\[ A_i^{(k)} = f \left( A_i^{(k-1)} + \sum_{j \neq i} A_j^{(k-1)} \right) \]

(2)

where \( A_i^{(k)} \) is the value of concept \( C_i \) at iteration \( k \); \( A_i^{(k-1)} \) is the value of the same concept at iteration \( k-1 \); \( A_j^{(k-1)} \) is the value of concept \( C_j \) at iteration \( k-1 \); \( C_j \) causes \( C_i \); \( w_{ji} \) is the weight on the arc connecting the concepts \( C_j \) to \( C_i \) and \( f \) is a thresholding operator.

By iterating in such a cyclic fashion, the fuzzy cognitive map reaches a point where no further state changes are observed, then it is said to have a reached stable limit cycle or an equilibrium point. The significance of the fuzzy cognitive map rests in this equilibrium point; since such a point represents the final equilibrium state of the system for the given initial activation i.e. for the given initial state, the system will change and attain a new equilibrium, which is similar to this equilibrium point.

Why is such a point, of any significance? Consider a fuzzy cognitive map model for a furnace; the user would like to assess the effect of higher temperature on the metal entropy. Assuming that furnace temperature and metal entropy are two concepts in the map, the furnace temperature concept value would be increased and the fuzzy cognitive map would be allowed to iterate and eventually reach equilibrium. The equilibrium concept value for metal entropy is representative of the real world metal entropy that one should expect for the increased temperature. In other words, here the fuzzy cognitive map takes form of a system with temperature as input and entropy as an output.

One of the advantages that a fuzzy cognitive map provides is the fact that no particular output or input needs to be declared before the modeling process, rather the equilibrium state may be interpreted in numerous ways. This aspect also renders the fuzzy cognitive map the capability to perform inverse mapping. The fuzzy cognitive maps are easy to use; simple to execute but they are inherently unable to model complex systems due to the following reasons:

- Inability to model conditional causalities
- Inability to model time variant causalities
- Inability to appropriately encode non-linear relationships,
- Inability to learn from data and
- Inability to model self-causation (especially within time-series).

III. MODIFIED FUZZY COGNITIVE MAPS

Extended Fuzzy Cognitive Maps [Hagiwara 1992] address the disadvantages posed by simple fuzzy cognitive maps. The extended fuzzy cognitive map comprises of the following modifications to the original structure:

- simple numeric weights are substituted with non-linear functions wherever necessary
- causal arcs are established which activated based on a certain condition, specific to the arc
- weights incorporate a time-delay function wherever necessary;

The use of non-linear Hebbian unsupervised learning [Papageorgiou et. al. 2006] can help in learning the network structure directly from data instead of expert design. This work employs non-linear Hebbian unsupervised learning based on the following equation:

\[ w_{ji}(k) = \left( \frac{1}{\sum_{j=1}^{n} (1 - \gamma) A_j^{(k-1)} \cdot A_i^{(k-1)}} \right)^{1/2} \]

(3)

where \( A_j \) refers to the activated value of concept \( C_j \); \( k-1, k \) represent two consecutive iterations. \( \gamma \) is the weight decay coefficient and \( \eta \) is the learning rate parameter; both these parameters are positive scalars determined as follows:

\[ \eta^c = b_1 \cdot e^{-\lambda_1 \cdot c} \]

and

\[ \gamma^c = b_2 \cdot e^{-\lambda_2 \cdot c} \]

where \( b \) and \( \lambda \) are experimentally determined; but values: \( 0.01 < b < 0.09 \) and \( 0.1 < \lambda < 1 \) are usually recommended.

IV. ADOPTED METHODOLOGY

The work described in this article is based on the use of the extended fuzzy cognitive maps, but in order to efficiently
model the data, we have proposed further modifications. Considering that the value of a time series may also depend on its own value at the previous time frame; it can be said that a concept causes itself. In the given disaster management data, the value of a certain state or event would also depend upon its own value at the previous time frame; therefore a self-causal relationship has been implemented within the fuzzy cognitive map. Essentially, when put into perspective with the weight matrix, such self-causation transforms into a non-zero diagonal. And the diagonal weights herein represent the effect of a state on itself within consecutive time frames. Further to the above modifications, the following objective functions were also adopted:

Criterion 1. minimize \( J^1 = \mathbb{E} \text{(target - output)}^2 \)

Criterion 2. maximize \( J^2 = \sum \text{(output)}^2 \)

Criterion 3. \(| \text{output}^k - \text{output}^{k-1} | < \epsilon \) \hspace{1cm} (4)

Criterion 1 ensures that the output is conformal to the target as much as possible, therefore a cumulative deviation of the obtained output from the desired output for all concepts is considered here. Criterion 2 ensures maximized state values for the concepts. An equilibrium point that a fuzzy cognitive map attains after iterating over a period of time refers to a stable state that the entire system attains for a given activation vector. Considering that an output concept value in the training data may not necessarily be the equilibrium point, criterion 2 ensures that the system iterates until the true equilibrium point is reached; especially when the output concept value in the training data is an intermediate point between the initial state and the equilibrium state. A simple termination criteria based on the value of the output concept stops further iterations when the difference between squared sums of the outputs \((F)\) from two consecutive iterations falls below a certain threshold. Criterion 3 terminates the iterations when the error is below a certain threshold.

A. Procedure

Initial Conditions: Consider a subset consisting of \( p \) variables. Thereby we devise a weight matrix of size \( p \times p \). The elements of the weight matrix \( w_{ij} \) are initially set to positive, negative or no causality i.e. the element takes a value of +1 if increase in value of concept \( i \) causes an increase in the value of concept \( j \). On the contrary if an increase in the value of \( i \) causes a decrease in the value of concept \( j \), \( w_{ij} \) is set to -1. If no relation is perceived between the concepts \( i \) and \( j \), then \( w_{ij} \) is set to 0. Therefore the elements of the initial weight matrix are randomly set to either \([-1, +1, 0]\).

An activation [Taber 1991] vector may be defined as a row matrix containing the initial values assigned to each of the concepts present in a fuzzy cognitive map; assigning a positive value to a concept implies activating that particular concept. For example, an activation vector for a map consisting of 5 concepts may be given as \([1, 1, 0, 0, 1]\). This vector activates the concepts 1, 2 & 5 by assigning to them a positive value. In order to ensure consistency, all of the models discussed in this article have been initiated with the variable start values (time = 0) obtained from the data table; the real world values from the data set first need to be scaled down to the [0 1] range. In general, any one instance of input variable values from the training data may be used as an activation vector when the fuzzy cognitive map is being initialized. But when the fuzzy cognitive map is being evaluated, the vector of the input variable values, for which the output needs to be determined, is used for activation.

Learning / Training: After creating the initial weight matrix and the activation vector; the fuzzy cognitive map is allowed to iterate i.e. the concepts are computed in a cyclic manner using equation 2. One iteration comprises of computing the values of all of the concepts present in the map. After every such iteration, the weights of all of the arcs are updated using the equation 3. After updating the weights, the system proceeds to another iteration. This process continues until the three criterion mentioned in equation 4 are satisfied. Equation 4 may be regarded as termination criterion and once satisfied, the fuzzy cognitive map is said to have completed the training. The thus obtained weight matrix is stored and shall constitute the central part of the fuzzy cognitive map. The same procedure is repeated for the seven sub sets and the respective weight matrices stored. Sample trained weight matrix has been provided in the appendix (Table 3).

Validation: Checking, testing or validation all refer to the act of verifying that the generated model conforms to the real data under consideration i.e. the model obtained through the training phase is applied to the data and its reliability is established based on a performance index. Here, the average percent deviation of the obtained output from the desired target, referred to as percentage error, has been adopted as the performance index. The validation results and relevant discussions have been provided in the subsequent sections. The following text, briefly describes the validation methodology employed in this work.

As mentioned earlier, training a fuzzy cognitive map does not mandate the nomination of a concept as an input or an output; rather concepts can take on different roles most appropriate for a given situation. But for the testing process, it is necessary that an output be specified for every test trial. A two way testing approach has been adopted here. Firstly, concepts were randomly chosen to act as the output for each test trial and error was calculated by comparing the appropriate output and target. This was repeated for 500 trials and the results tabulated. In the second approach, trial error was calculated as the mean of the sum of errors for each concept in the map i.e. the absolute error would be calculated for each concept and the mean of the sum of all of these errors is regarded as the testing error for a given trial. This process is also repeated 500 times and the results tabulated. Opposed to the standard approach, the second method tends to produce generalized errors.

V. RESULTS & DISCUSSION

This section presents the results of modeling the disaster sites reconstruction data.

A. Data
The Baravat & BAM city disaster data consists of 74 variables recorded appropriately through 106 time frames (approx 7 day intervals). The data set comprises of various variables related particularly to the reconstruction phase of the cities. A list of variables has been provided in the Appendix. Conventional data mining methods are unsuited due to the number of involved variables, and their time-dependence; moreover the size of the available data set is not sufficient to indulge in conventional parameter estimation. The use of fuzzy cognitive maps has been justified in the following sections. A comparative analysis has also been provided.

**B. Fuzzy cognitive map Advantage**

One of the very important advantages that the fuzzy cognitive maps posses is that of map-additivity i.e. two different maps built by different individuals even with a slightly different set of concepts can be merged to form one single fuzzy cognitive map; and while doing so no knowledge represented in either maps would be lost. Taking advantage of this aspect and also in order to gain better control over the process of modeling, a modular approach has been adopted to analyze the BAM data.

**C. Modular Approach:** As mentioned earlier, the data set consists of 74 variables and only 106 data points. In order to effectively model the data, the variables have been clustered into 7 groups i.e. the complete set of variables has been broken into smaller modules each containing a manageable number of variables. These smaller sets of variables have been made in such a way that all associated variables are placed within one (sub) set. Each of these (sub) sets has been modeled using one fuzzy cognitive map each. And using the map-additivity feature present in the fuzzy cognitive maps, all of these models can be brought together into one information model.

The data set consists of information about the reconstruction of urban residential units, and commercial units; the data also includes information about the usage of heavy equipment, manpower, and construction materials. The data about the reconstruction of the residential/commercial units also includes information about the status of the reconstruction at the recorded time frames. In order to sensibly divide the data, the sub sets were chosen based on a particular aspect; For example: a sub set containing all variables related to reconstruction of the commercial units or a sub set containing all variables only related to the usage of construction materials, equipment and any man power. As per this, a total of seven (7) sub sets have been created.

Following is a brief description of each of these sub sets (full list of included variables has been provided in the Appendix):

i. General sub set: This subset contains nine variables and essentially captures a wholesome view of the entire reconstruction process with reference to time.

ii. Manpower sub set: This subset models the manpower requirement in the overall reconstruction process. And in order to facilitate interpretation and interlinking, an additional concept of total manpower has been included. Total man power is a sum of the total number of workers/men at work at a given instant of time.

iii. Commercial units sub set: This subset models, the reconstruction process of the commercial units, with reference to time. It implicitly models the speed of reconstruction and the various intermittent stages.

iv. Residential units sub set: This subset models, the residential part of the reconstruction process with reference to time. It implicitly models the speed of reconstruction and the various intermittent stages.

v. Resources sub set: This subset details the resources that were consumed in the reconstruction process. It includes, human resource (consulting, etc.), equipment etc. Two super variables (construction materials and heavy equipment) have been used. These variables are in turn determined through two different models.

vi. Heavy Equipment sub set: This subset contains details about the different kinds of heavy equipment used at the sites.

vii. Construction Materials sub set: This subset contains all of the construction materials that were used up in the reconstruction process.

Table 1 lists the percent error of the seven fuzzy cognitive maps representing each of the seven sub sets (described in IV-B). The accuracy has been averaged over many trials wherein the input concepts and output concepts were randomly changed; for example: for one trial for model-2, number of engineers is the output concept and all other concepts are treated as inputs and for trial-2 the total manpower is the output with the other concepts acting as inputs. This was randomly done for 500 trials and the average deviation measured.

<table>
<thead>
<tr>
<th>Data sub set name</th>
<th>Number of variables</th>
<th>Percentage Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>General</td>
<td>9</td>
<td>5.1</td>
</tr>
<tr>
<td>Manpower</td>
<td>10</td>
<td>5.6</td>
</tr>
<tr>
<td>Commercial Units</td>
<td>11</td>
<td>5.0</td>
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<tr>
<td>Residential Units</td>
<td>10</td>
<td>7.3</td>
</tr>
<tr>
<td>Resources</td>
<td>17</td>
<td>7.7</td>
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<tr>
<td>Heavy Equipment</td>
<td>9</td>
<td>4.4</td>
</tr>
<tr>
<td>Construction Materials</td>
<td>11</td>
<td>6.4</td>
</tr>
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</table>

Table 1: Fuzzy cognitive map based error for various models. These results are based on random input/output allocation.

Table 2 also lists the averaged errors for the seven models, but the method of computing the mean deviation is the second approach to validation; i.e. here no concepts are set to be outputs or inputs, rather the deviation of all of the concept values is averaged over 500 trials and tabulated.

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And as it should be, one can see that the error does not change considerably.

<table>
<thead>
<tr>
<th>Data sub set name</th>
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<th>Percentage Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>General</td>
<td>9</td>
<td>5.1</td>
</tr>
<tr>
<td>Manpower</td>
<td>10</td>
<td>6.1</td>
</tr>
<tr>
<td>Commercial Units</td>
<td>11</td>
<td>5.1</td>
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<tr>
<td>Residential Units</td>
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<td>7.3</td>
</tr>
<tr>
<td>Resources</td>
<td>17</td>
<td>7.5</td>
</tr>
<tr>
<td>Heavy Equipment</td>
<td>9</td>
<td>5.1</td>
</tr>
<tr>
<td>Construction Materials</td>
<td>11</td>
<td>6.2</td>
</tr>
</tbody>
</table>

Table 2: Fuzzy cognitive map based error for various models. Results based on random average deviation for all concepts values.

Another reason why the fuzzy cognitive map performs better than the other models is due to the human like inference mechanism that the fuzzy cognitive maps display. A careful thought would indicate that the modular approach taken with the large data set is how a human would wade through such a data set. In other words, the sub sets used in this work represent a granular information processing methodology. Though an automatic approach to clustering the input variables has not been investigated, the adopted granularity may typically be attributed for the better performance.

VI. CONCLUSION

This paper describes thoroughly the use of modified fuzzy cognitive maps for the purpose modeling BAM & Baravat city disaster management data. In particular the extended-fuzzy cognitive map augmented with unsupervised learning and self-causation has been adopted to model the data set. The larger data set was broken into manageable sub sets comprising only of associated variables. The results for the fuzzy cognitive map indicate an acceptable level of performance as opposed to the back propagation neural network and a neuro-fuzzy system. Though the fuzzy maps possess a much inferior mathematical framework, they perform better than the mathematical counter parts due to their inherent structure capable of accommodating inconsistencies in the data. In one way or the other, fuzzy cognitive maps are analogous to the way human’s inference.

REFERENCES


[Papageorgiou et. al. 2006] Papageorgious E. I., Stylios C., Groumpos P. P., Unsupervised learning techniques for fine-


APPENDIX

A: Sub set variables

Following is the list of variables included in the seven subsets:

1. General sub set;
   - time period, total number of damaged units that must be reconstructed, total number of damaged units that must be repaired, number of units received financing, number of prepared architectural plans, number of building permits (city of bam & city of baravat), number of residential units at framing stage, number of residential units ready for use, total manpower (addition of number of: engineers, technicians, office workers, service workers, other workers, staff in construction offices, loaders, graders).

2. Manpower sub set;
   - time period, number of: engineers, technicians, office workers, service workers, other workers, staff in construction offices, loaders, graders, total manpower.

3. Commercial units sub set;
   - time period, number of units filled for reconstruction, number of units filed for repaired, number of building permits commercial, number of commercial units at foundation stage, number of commercial units at framing stage, commercial units fencing, number of commercial units ready for use, completed urban commercial units.

4. Residential units sub set;
   - time period, total number of housing plans prepared, number of housing plans prepared for govt staff, number of residential units at foundations stage, number of residential units at framing stage, residential units fencing, number of residential units at roofin stage, number of residential units close to be used, number of residential units ready to be used, completed urban housing units.

5. Resources sub set;
   - total number of damaged units, total number of units to be reconstructed, total number of units to be repaired, number of reconstruction offices, number of construction material labs, number of workshops for material production, number of consultancy companies, number of heavy equipment, total number of plans prepared, total number of units in foundation stage, total number of units in framing stage, total number of units in roofing stage, total number of units in roofin stage, total number of units close to be used, total number of units ready to be used, construction materials, time period.

6. Heavy Equipment sub set;
   - time period, total number of heavy equipment, number of: large trucks, bulldozers, bill mechanical, cranes, water tanks, rollers, other heavy equipment.

7. Construction materials sub set;
   - time period, construction materials, cements bought, cements transported, bricks transported, roofing blocks distributed, cement blocks distributed, gravels and sands distributed, steel products bought, steel products transported, steel products distributed.

<table>
<thead>
<tr>
<th></th>
<th>C1</th>
<th>C2</th>
<th>C3</th>
<th>C4</th>
<th>C5</th>
<th>C6</th>
<th>C7</th>
<th>C8</th>
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<td>0.00</td>
<td>0.02</td>
<td>0.00</td>
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<td>0.59</td>
<td>0.77</td>
<td>0.81</td>
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Table 3: Trained Weight Matrix for the GENERAL sub set