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RESEARCH ARTICLE

INTELLIGENT COLLABORATIVE DECISION MODEL FOR SIMULATION OF DISASTER DATA IN CITIES AND URBANLIZATION.

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Abstract

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In recent years, scientists and researchers have been investigated conventional urban disaster and earthquake models for particular disaster mitigation categories, one of the basic solutions in single decision models in theory and practice.This paper presents a novel approach integrated by intelligent techniques and Self-Organizing Maps (SOM), called Intelligent Collaborative Decision Model for dynamic simulation of urban disaster and earthquake mitigations in real-time uncertain environments. This approach uses to aggregate multiple dimensional data series from networking sensors and tangible/intangible disaster events, together with spatial decisions made from disaster experts. In addition, this approach aimstooptimize appropriatedecisions at the right time and reduce risks of pre and post urban disasters and earthquake. To confirm the study performance this proposed model has validated by experiments usingdynamic simulation results. In simulation experiments, this model can be extended by incorporating Geographic Information Systems/Google API to demonstrate disaster and earthquake phenomenain complex geological environments.

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Introduction:-

Every year, thousands of human lives are lost, millions of people bear the destruction of their homes and an invaluable economic harm is made. Natural or environmental disasters have the disadvantages of including both natural and man-made dimensions, such as lithosphere disasters (landslide, subsidence, earthquake, tsunami)and hydrosphere disasters (flooding, typhoon), which cause substantial damage or injury to civilian property or cities in disaster areas (Naim, 2012). All major managing disaster activities are required for decision-making needs under uncertain disaster/earthquake environments (Atilla et al. 2010, Yusuf el al. 2018). In recent years (Damon, 2011), scientists and researchers have been investigated conventional urban disaster and earthquake models for particular disaster mitigation categories, one of the basic solutions in single decisions in theory and practice.

A large number of disasterand earthquake related singledecision models have been developed as part of managing disaster and earthquakeactivities involved with a decision making or spatial decision that can handle a single model of disaster and earthquake situations(John et al. 2012). The smart algorithm for disaster has been proposed by (Junaid el.all 2018).Limitations of these current approaches include that they are applied in specific disaster areas with only a basic solution. In addition, these approaches have not aggregated expert sensibilities and preferences, ecological consequences and environmental phenomena, together with real-time data sets from sensors.

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The purpose of this study is to solve the existing problems by encompassing all aspects of urban disaster and earthquake mitigation for responding to pre and post managing disaster activities, such as prevention, hazard preparedness assessment, disaster risks, mitigation urban plans, and recoveryurbanization in managing disaster and earthquake activities. The main contribution in the proposed model is to present a new model that uses toquantify multiple dimensional data series from sensors and tangible/intangible disaster events, together with spatial decisions made from disaster experts. In addition, the proposed modelaimstooptimize appropriate decisions at the right time and reducing risks of pre and post urban disasters and earthquake. The main features of this study are presented as follows: (1) In order to reduce risks in urban disasters and earthquake, the proposed model is to automatically select multi-dimension data series, adaptive with optimizing decisions in dynamic disaster environments; (2) In order to utilize with maps using Google API/ GIS, quantitative and qualitative factors with uncertainty in dynamic disaster conditions, consisting of historical data and real time data sets through the mapping locations of disaster scenarios considered by the system, based on multiple expert decisions; (3)All significant natural signals, intangible-disaster events and ecological-phenomena consequences are quantified by using fuzzy reasoning to classifygrouping phenomena and events based on warning locations, occurred by disaster environments and earthquake. To confirm the model's performance, this proposed model has validated by experiments insimulation results. In case studies of real-world problems, this model can be extended by incorporating Geographic Information Systems/Google API to demonstrate disaster and earthquake phenomena in complex geological environments.

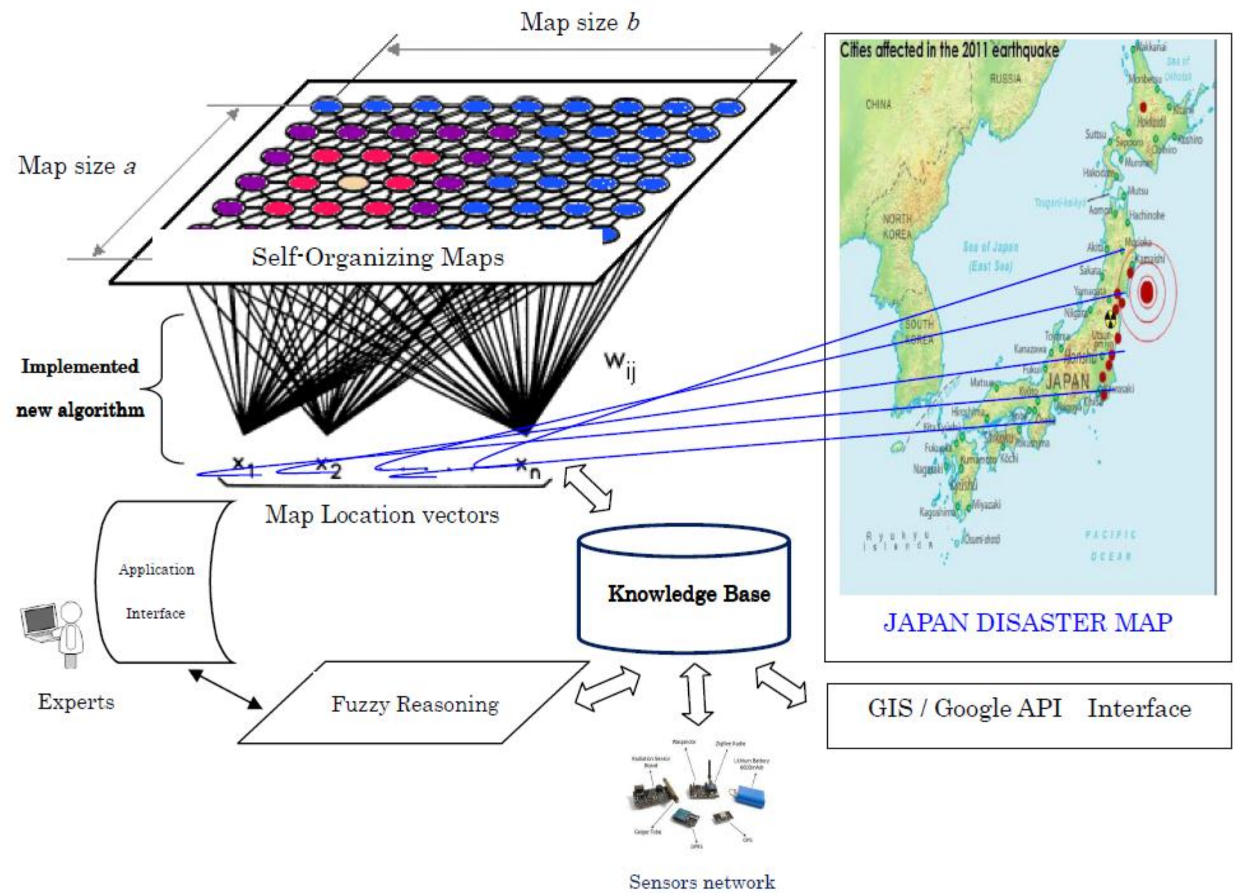


Figure 1:-Overview of the proposed system

Research Background:-

Self-Organizing Map (SOM) is an unsupervised learning algorithm which was invented by Kohonen as a computational method for the visualization of high-dimensional data (Kohonen,1988). Here is lack of SOM model in terms of scientific and research evaluation:

1. Difficult to determine what input weights to use
2. Mapping can result in divided clusters and specific results that is not identified

3. Requires that nearby points behave similarly
4. Uncertain conditions includingdimension-data sets can not be presented in the conventional model.

In this study, we propose a novel approach which developed a new algorithm based on a conventional model of Self-Organizing Map (SOM) integrated with fuzzy reasoning techniques. The proposed approach called Intelligent Collaborative Decision Model for optimizingdisaster decisions at the right time and reducing risks of pre and post urban disasters and earthquake. The proposed approach has been addressed all complex problems by dealing with multi-dimensional data series, together with an aggregation of expert preferences and sensibilities

Proposed Model:-

System Overview:-

The proposed model is tooptimize decisions at the right time and reduce risks for pre and post urban disasters and earthquake, as shown in Figure 1.

There are five stages in this system as follows: (1) real-world data sets obtained from networkingsensors and experts' preferences and sensibilities; (2)disaster data sets in real-time are proceeded in automatically cleaning steps and data normalization (3) map location vectors represent by each location in a disaster map and each vector includes multi-dimension disaster data sets; (4) rules in uncertain disaster and earthquake environments represent by fuzzy reasoning; (5) taking appropriate decisions (warning urban levels, disaster levels, and earthquake level) as determined by expert preferences and spatial decision making.In experiments, all data sets including rules and vector attributes are updated in knowledge base. The experiments of this model have been tested through case studies in dynamic simulation for demonstration of this model. To appear results in a disaster map, the proposed model is possiblyimplementedwith GIS/ Google API interface.

Quantification of Uncertain Disaster/Earthquake Environments and Human Sense Reasoning:-

There are twosignificantuncertain disaster environments to consider in this system, as follows:

1. Human Sense Reasoning is part of human behavior in certain sensibilities that affect human final decisions. In collaborative expert decisions, human sense plays significant roles in human collaborative decisionmaking process, together with reasoning process. As collaborating decision making between humans and computer systems, experts may evaluate various alternatives under uncertainty in dynamic disaster environments.In human reasoning, linguistic expressions represent rules for expert decision situations. To quantify sense human reasoning of an expert in dynamic disaster/earthquake environments, we use the logical rules of the following:
2. **IF**<disaster/earthquake conditions>**AND**<other conditions>**THEN**<actions>
3. Map location vectors are included urban locations of main cities. When mapping with GIS/Google API, we can indentify disaster/earthquake status in terms of intelligent collaborative decision results. Each location vector contains a variety of data sets including historical data and series.
4. Disaster or earthquake warning levels are possibly to predict disasters and earthquakes. Researchers have been investigated the disaster and earthquakesymposiums with various phenomena such as seismicity patterns, crustal movements, ground water level, hydrogen gas emissions from the Earth, changes of seismic wave velocities,electromagnetic fields, ..etc (Newmark et al. 1971, Trifunac et al. 1975). However, conventional disaster and earthquake models can not be predicted exactly when or where locations are occurred. According the disaster or earthquake conventional models, disaster officers may give warning levels in disaster forecast. In a public media communication, they may inform disaster/earthquake levels coming but not responding for detail of locations in cities.

Mechanisms of the Proposed Model:-

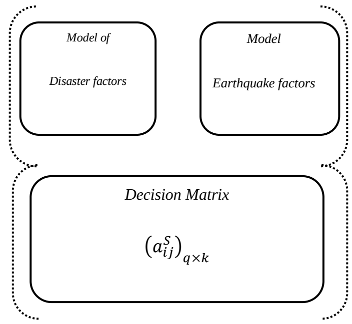
Mechanisms of the proposed model show how the method applies this model under uncertain disaster environments. To consider differences among attributes of location vectors, the attribute distance $d^R_{T_i \to C_j}$between two vectors $D^R_{T_i}$ and $D^R_{C_j}$ represents attributes of location vector$C^R_T$and C^R_jrespectively, as defined by Euclidean distance given by Eq.(1).

$$d^R_{C_i \to C_j} = \|D^R_{T_i} - D^R_{C_j}\| \quad (1)$$

Note that $D^R_{T_i}$ represents data sets for a standard disaster or earthquake level in disaster environment R, defined by a location vector.

The new algorithm is described in mechanisms of the proposed model as follows:

Step1:-Data sets are constructed in a matrix.
The data sets is constructed in a matrix in the Knowledge Base for SOM visualization, as follows:



1. Data series part (model of disaster and earthquake factors) includes initial data in a current disaster or earthquake environments.
2. A decision matrix is part of the whole data sets, which are used to apply an algorithm, together with the whole data sets in training.

Step 2:-Collaborative decision preferences using by SOM visualization**.**
These fuzzy rules represent by disaster environments of the *j-th* factor f_j^S affected by R_i^{fj} to evaluate a location,based on expert preferences. This represents by the form as follows:

IF $\boldsymbol{R_i^{f_j}}$THEN Update weights by the rule
An aggregation of a rule is expressed by using updated weights, as expresed byEq. (2).

$$m_{ij}^{t+1} = m_{ij}^{t} + \beta_j^S \left(\left\| \frac{1}{p} \sum_{j=1}^{m} w_{\lambda j}{}^{t} - v_{ij}{}^{t} \right\| \right) \qquad (2)$$

where (i = 1,.., q, j = 1,.., k) and p is the number of aggregation rules for collaborative decisions.
$m_{ij}^{t+1}$and m_{ij}^{t} represent by new updated weights and current weights, respectivly.

where β_j^S is aset of decision maker preferences as defined in a five-point scale (0: oppose, 0.25: almost oppose, 0.5: weak agree, 0.75: agree, 1: strong agree) $w_{\lambda j}^{t}$ and v_{ij}^{t} represents by updated weights and vector weights at integration t , respectively.

Step 3:-Clustering collaborative decisionsfor all rules of disaster and earthquake by SOM visualization.

IF $\boldsymbol{R_1^{f_j}}$**and**$\boldsymbol{R_2^{f_j}}$**and** ... **and** $\boldsymbol{R_m^{f_j}}$
THEN Update weights with aggregating rules
The weight of q_{ij}^{t} is expressed by Eq. (3).

$$q_{ij}^{t} = \left\| \frac{1}{T} \sum_{j=1}^{k} w_{\lambda j}{}^{t} - v_{ij}{}^{t} \right\| \qquad (3)$$

$$q_{ij}^{t+1} = m_{ij}^{t} + q_{ij}^{t} \quad (4)$$

where T is the number of total rules in uncertain disaster and earthquake environments.

Step 4:-Fuzzy reasoning matching with an aggregation of collaborative decisions based on conditional rules.
In the inference process, fuzzy rules represent by the disaster environments, affected by $R_i^{fj}(i = 1, \dots, m)$ to evaluate location vectorC_i^R based on expert preferences. The weight $w_{C_i}^{j}$ is expressed by Eq. (5).

$$w_{C_i}^{j} = \mu_{R_i}^{0} \otimes \mu_{R_i}^{f\,j} \tag{5}$$

where $\otimes$ is a t-*norm* operator, a$\otimes$b = a × b as an execution in the Knowledge Base.

The values R_i^0 representing an initial status and $R_i^{f\,j}$repsenting uncertain disaster/earthquake rules, are defined by $\mu_{R_i}^{0}$ and $\mu_{R_i}^{f\,i}$fuzzy membership values, respectively.

When trained by SOM together with the repeated Step 2 to 3, the closet vectors having similar their attribute weights are aggregated concurrently on a SOM map.

Step 5:-A warning disaster status forlocation vectors using Google/GIS map via its application interface.
In this step, Google API is linked to these data sets with warning earthquake or disaster alarms in the disaster map. Intelligent techniques include semantic web and intelligent tracking can be used to apply in the proposed model, in order to make system autonomous. The method provides dynamic views in terms of disaster or earthquake evaluation.

Case Studies With Simulation Results:-
The proposed system has been tested with data sets from a total of 100 locations of Earthquake Database and information disaster database,as major cities in Japan and Asia for demonstration of simulation experiments (Disaster 2012,Earthquake 2012).In this system, the proposed approach uses 30-35 disaster and earthquake indicators and factors for a Gaussian neighborhood function with an adaptive variance and learning rate. The parameters are set in this application (map sizes = 20 x 20, Sigma max = 10, Sigma min = 2, Iteration set = 40 and learning rates from 0.04 to 0.01).

Here is a case study of simulations result within four stages in this system:
1. Real-world data sets obtained from networking sensors and experts' preferences in order to construct a matrix including disaster and decision matrices;
2. The matricesare visualized by SOM training and screens out the disaster/earthquake locations from among hundreds of urbanizations in Japan;
3. The disaster/earthquake locations are matched with appropriate disaster levels at the right time for collaborative decisions;
4. Appropriate decisions are determined by expert preferences, based on simulation results. The experiments through case studies can be applied to real-world disaster data setsfrom using the single decision maker or Group Decision Support System (GDSS) for simulation.

Dynamic Simulation Results dealing with Multi-dimensionalData Series:-
All multi-dimensional data sets are visualized by SOM to find out pre and post disaster/earthquake phenomena, matched with selected locations in a map. After the training process from Step 1 to 3 of the algorithm mechanisms, an expert could look at a map results to find out the strongest clustering urban disaster and earthquake in terms of urban disaster and earthquake. For visualizing multiple-dimensional data series, an expert can see earthquake and disaster areas, as shown in Figure 2.

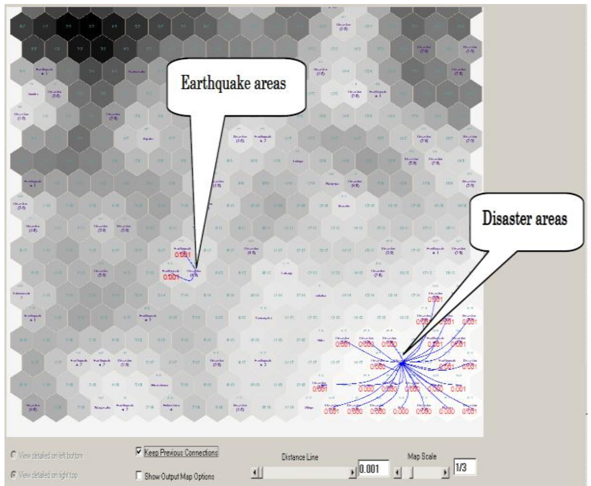


Figure 2:-Simulation results in a map

Simulation results by reducing distance of location vectors:-

After the training process, the final result showed the locations with their attributes in a group on the map. An expert selected the closest companies by reducing the maximum disaster distance of the locations and eliminating those that have a distance greater than the selected threshold. Figure 3 illustrates that the SOM map result showed the selected locations (Gifu and Shijo) for warning disaster.

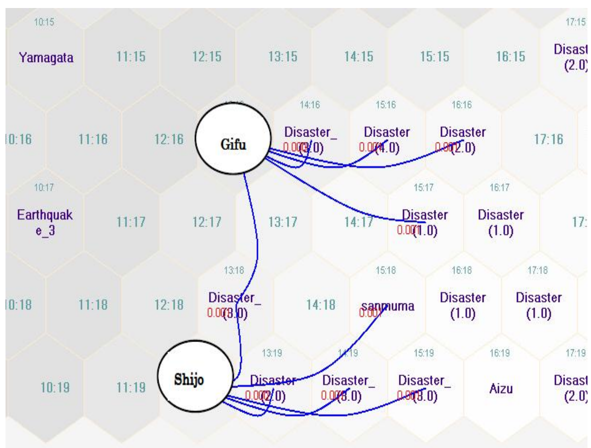


Figure 3:-Simulation locations based on disaster levels

Simulation results by mapping location vectors in a disaster map:-

In the SOM training, vector attributes were updated data sets to Knowledge Base. In addition, Google API was linked to these data sets with warning earthquake or disaster alarms in the disaster map. Figure 4 shows a sample of simulation results occurred by earthquake alarms in two locations (Sendai and Namie).These locations were appeared in SOM and disaster maps with dynamic views in term of pre/post disaster or earthquake phenomena evaluation.

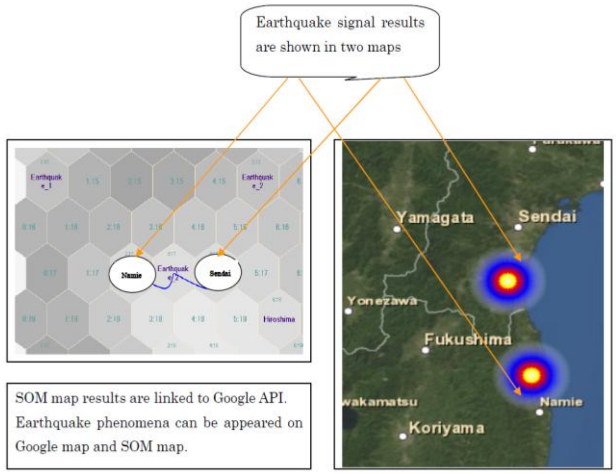


Figure 4:-Simulation locations based on Google API

Result and Discussions:-

In experiments, we have tested with sample data sets obtained from cities in Asia and Japan. In simulation results, the experimental results show that all disaster consequences and environmental phenomena are quantified in the system in the rand of uncertain fuzzy weight [0,1]. Based on these weights, the proposed system uses to visualize weathers and disasters dealing uncertain conditions. The emergency response simulation before disaster and earthquake is to predict its phenomena for urbanizations. To consider the right factor structure model we category multiple-dimension data sets which belongs to criteria, based on expert preferences.

In experimental results, the proposed system has been tested with amount of data series and hundred and thousand location vectors, dealing with uncertain disasters and earthquake conditions for the period of 2009-2011. In simulation results with various data sets of disaster, one of the primary tasks of the model forecasting is to perform a dynamic evaluation. A predicted performance of the proposed approach was estimated at 70-72% correctness when compared with disaster and earthquake of Asian and Japan in the past.

In further experiments, the experimental data consists of 500 locationsin three countries (Japan, Thailand, and Vietnam)for disaster tests from the period of June 2010 to May 2011. Whendoing the experiments, we carried out real-world data sets and showed the successful selected locations occurred by disasters,as shown in Figure 5. In terms of successful selected locations occurred by disasters, average percent of the proposed system has been estimated at about 65-75%, applied in a case study ofJapan.Furthermore, it reached 73-82% and 60-67%in a case study of Thailand and Vietnam, respectively. The experimental results consistently show that the proposed approach obtained successful selected locations in disaster and earthquake environments.

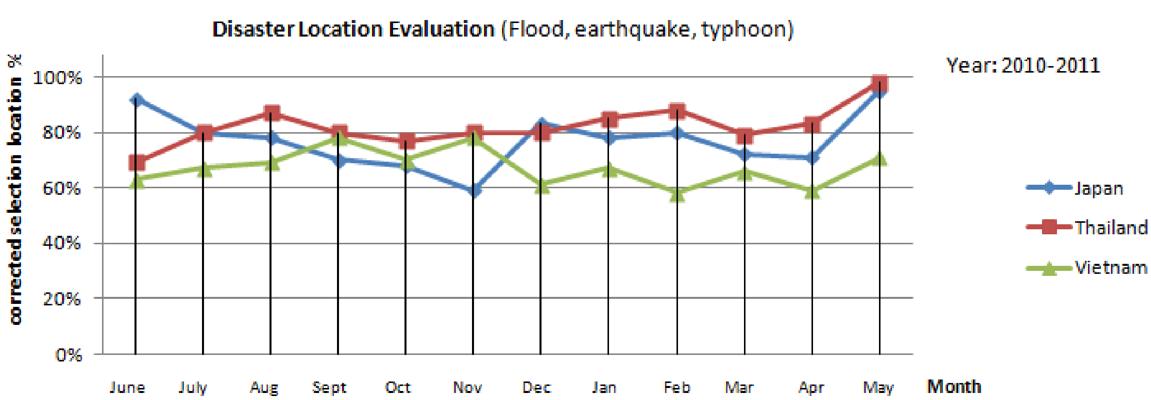


Figure 5:-Average % of Successful selected locations in simulations of disaster environments

To enhance a predicted performance the proposed approach deals with real-time embedded with remote network sensors. It involves tasks such produce effective decision making in urban disaster management that can also easily maintain addictiveness, special consideration is given to the modular approach for the development of intelligent collaborative decision model for disaster and weather forecast.In addition, rules under uncertain environments are updated in the Knowledge Base, adaptive with uncertain conditions in disaster environments.

This model attempts to support a collaborative decision making process in anurban disaster forecasting and earthquake migration by providing the ability to select modular subroutines to make a dynamic model. In addition, intangible and tangible information, ecological-phenomena on sequencesfrom disaster environments and animal behaviors can be considered together in this system. To dothis we will integrate with the emotional study with *Kansei* sensing and information. This model provides useful dynamic results in terms of multiple data sets evaluation.

Conclusions:-

In this paper we have presented a novel approachtooptimize appropriatedisaster decisions at the right time and reduce risks of pre and post urban disasters and earthquake. This methoduses to quantify expert preferences and sensibilities with intangible and tangible information in real-time. Furthermore, disaster and emergency in major cities are supported by quick decisions with autonomous response for urban disaster and earthquake mitigation.

In further work, the proposed model can be extended for solving all significant natural signals, intangible-disaster events and ecological-phenomena consequences are quantified by using fuzzy random variables in the proposed system, together with learning behavior data set sequences to forecast/plan response disaster emergencies.

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