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Fuzzy Logic Model for Flood Warning Expert System Integrating Multi-Agent and Ontology

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Abstract: An expert system is vital in flood warning to determine the decision making output in order for a proper control of the input consisting of river level and rainfall. The river level and rainfall input is naturally stochastic, uncertain and unpredictable. Therefore, a fuzzy logic model of the flood warning expert system has been designed for user to obtain information about flood. This fuzzy model integrates multi-agent and ontology and expected to handle both uncertainty and accuracy issues whereas previous researches focus on handling either uncertainty or accuracy issues only. Simulation of outcome based on river level and rainfall is presented in this study.

Key words: Fuzzy logic, flood, expert system, multi-agent, ontology

INTRODUCTION

Flood is one of nature's disasters worldwide. Design of flood warning expert systems has gained interest among researchers. Previous researchers have applied numerous techniques to produce flood warning models. Linear regression and multivariate analysis are among the techniques proposed. Counter-Propagation and Back propagation neural network techniques have also produced good recognition accuracy. Additionally, counter-propagation neural network technique is merged with multi-agent technique to generate better recognition accuracy and provides alert through multi-agent. These models handle the accuracy issues successfully.

There are also research that combined fuzzy technique and genetic algorithm to analyse flood frequency. Fuzzy technique has been improved to derive flood risk vulnerability to handle uncertain climate change. These fuzzy models handle uncertainty efficiently. Furthermore, current research utilized other Artificial Intelligence (AI) techniques for decision making consisting of Hidden Markov Model (HMM), decision trees, bagging, random forest, boosting and support vector machine which cater the uncertainty issues.

The mentioned models manage accuracy and uncertainty individually. Furthermore, they lack a mechanism to organize flood knowledge. Fuzzy logic is a popular technique to cater uncertainty conditions. We proposed a robust fuzzy logic model for flood warning expert system to handle uncertainty which incorporates multi-agent to give alert and notification and ontology to organize flood knowledge to support agent communication to handle the accuracy issues. Therefore, our model is expected to handle both uncertainty and accuracy issues.

Literature review: Early warning against various natural catastrophes like floods, volcanic eruptions, earthquakes, tsunamis and geologic processes is very important to save life, property and decrease economic damage. Flood is a major catastrophe issue worldwide. Although, exist models that utilize various techniques to support flood, however, more research should be carried out to improve the existing models.

Neural Network (NN) is a powerful Artificial Intelligence (AI) technique that has the ability to adapt to changes and been used utilized for recognition. The combination of counter-propagation NN and intelligent multi-agent algorithms is integrated in Taranis for early warning against flood (Lopez *et al*., 2012). The model provides flood information to manage hydroelectric reservoir managed by a second layer of the NN. The NN provides adaptation to new meteorological values caused by climate change proved that the NN classifier achieved a high level of accuracy. Shu and Burn (2004) merged fuzzy technique and genetic algorithm to analyse flood

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frequency. The performance of the proposed model is improved by tuning the membership functions of the fuzzy sets using a genetic algorithm. The proposed model is applied to flood data from Great Britain. Furthermore, a fuzzy technique was introduced to quantify the weighing values and input data of proxy variables to derive the flood risk vulnerability in South Korea, considering the impact of climate change (Jang and Sun, 1995; Jun *et al*., 2013). In their research, they develop a six-step procedure to derive the flood risk vulnerability in South Korea consisting of determining all proxy variables using Delphi process, derive the objective also using the Delphi process, collect and standardize all data using min-max standardization, compare all rankings using Multi-Criteria Decision Making (MCDM) techniques, quantify flood risk vulnerability using fuzzy Technique for Order Preference by Similarity to Ideal Situation (TOPSIS) technique and fuzzify all weighing vales and input data using the Triangular Fuzzy Number (TFN) technique. Another research by Van Steenbergen *et al*. (2012) introduced a non-parametric data based approach for probabilistic water level flood information to support uncertainty. The uncertainty is based on the statistical analysis of historical flood forecasting residuals results at river gauging stations using a non-parametric technique. The residuals are correlated with the value of simulated water level and time horizons. Percentile values of the residuals are calculated and stored in a three dimensional error matrix and confidence intervals on forecasted water levels are calculated and visualised. Then, the result is connected to the database of river flood expert system in Belgium where it is possible to update the error matrix in real time, based on the new proposed simulations. An early-warning of microcystin in water management systems utilizing Hidden Markov Model, Bayesian hierarchical modelling and Principal Component Analysis (PCA) have been proposed by Jiang *et al*. (2016). Their approach demonstrates an effective intelligent support tool for early-warning of risk-level grading. An expert system based on association rules and predicate logic for earthquake prediction has been presented by Ikram and Qamar (2015). Their expert system was able to predict all earth-quake that occurred within 12 h at-most. A comparative study of AI methods for project duration forecasting involving Monte Carlo simulation, PCA and cross-validation is proposed (Wauters and Vanhoucke, 2016). This method is compared with Earned Value Management/Earned Schedule (EVM/ES) methods. Results indicate that AI methods outperform EVM/ES methods if the training and test sets are at least similar to one another. These models which is based on fuzzy and AI technique handles uncertainty efficiently. Multi-agent is a popular technology that provides alert and notification. Multi-agent is widely utilized in interactive tutoring (Yaskawa and Sakata, 2003), medical diagnosis (Iantovics, 2012) and image analysis (Bell *et al*., 2007). Multi-agent have also been used to generate the semantics of Object-Oriented Programming (OOP) (Aris, 2011) and provide guidance (Noranis and Azuan, 2013; Rajabi *et al*., 2014) where multi-agent act as knowledge representation. Furthermore, multi-agent is applied to model muscle myosin nanomotor in a bio-nanorobotic system (Khataee *et al*., 2012). Multi-agents have been utilized with ontology to provide an effective communication between multi-agents (Lopez-Lorca *et al*., 2016; Rani *et al*., 2015; Yang and Chang, 2011).

The models mentioned handles accuracy and uncertainty issues separately. We proposed a robust flood warning model expected to handle the accuracy and uncertainty issues which incorporate three hybrid techniques consisting of fuzzy to predict uncertain situations as flood is an uncertain catastrophe beyond human expectations; agents to give alert and notification; ontology to organize flood knowledge in order to support agent communication. To date, there has not been any research that combines the three techniques to model flood. The type of data that will be used in our research consists of river level and rainfall from Jabatan Pengairan dan Saliran Malaysia (http://infobanjir.water.gov.my). The proposed model is presented in the next study.

MATERIALS AND METHODS

Proposed conceptual and fuzzy logic model: Our proposed conceptual and fuzzy logic model is shown in Fig. 1. Basically, the model consists of an input module, processing module and output module. Multi-agents integrated in this model consist of the river level agent, rain agent and decision agent.

These agents interact continuously with the internet. The riverlevel agent and rainfall agent sense the river and rain levels data from Jabatan Pengairan dan Saliran Malaysia website (http://infobanjir.water.gov.my) which is the input to the processing module. These are real time data which is frequently updated to and from the Flood Ontology by the RiverLevel and RainFall agents. The inputs will go through the fuzzification process where crisp inputs are fuzzified into linguistic values that are associated to the input linguistic variables. The combination of river and rain levels will be used as a marker for the decision agent to provide alert and notification to users on the action that needs to be taken.

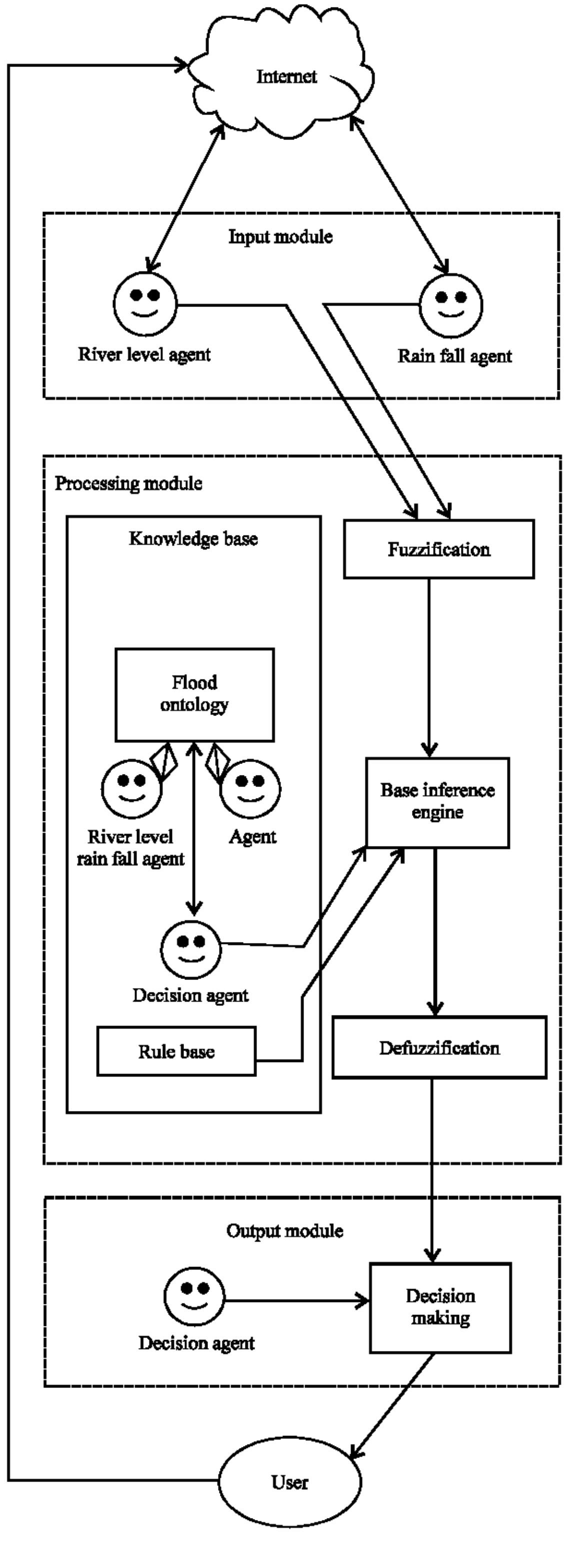

Fig. 1: Proposed conceptual model

The membership functions are defined for each fuzzy set for each linguistic variable and the degree of membership of a crisp value in each fuzzy set is also determined. The numerical variable, river and rain levels is shown in Table 1 were fuzzified using the gaussian membership functions defined for each fuzzy set for linguistic variables river and rain levels. The membership grades for each input implemented by the given fuzzy membership function utilizinggaussian curve membership function is given by:

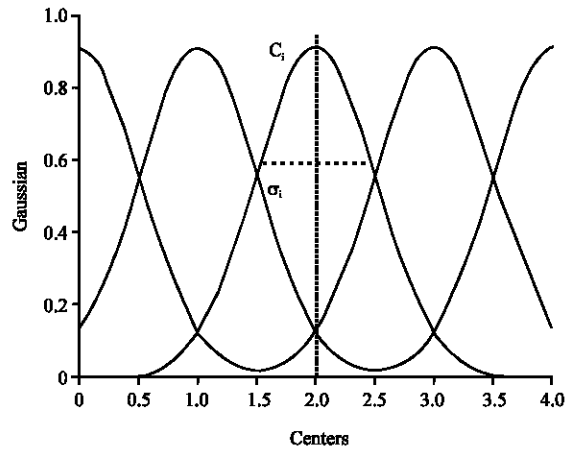

Fig. 2: Gaussian membership function

Table 1: Input-output values for flood data

Level/Range of level (mm)	Indicators	Reference
Rainfall		
1-10	Light	Fig. 1
11-30	Moderate	
31-60	Heavy	
>60	Very heavy	
River		
Depends on the river	Normal	Fig. 2
Different river have	Alert	
different level	Warning	
	Danger	

$$\mu A_t(x) = \exp\left\{-\left(\frac{x - c_i}{\alpha_i}\right)^2\right\}$$

where $\{a_i, c_i\}$ are the parameters of the membership function, the centre and width of the fuzzy set A_i, respectively the graph is represented as in Fig. 2.

RESULTS AND DISCUSSION

The result of fuzzification, linguistic variables river and rain are assigned linguistic values of “light to very heavy” and “normal to danger” with corresponding degree of membership (Fig. 3-4). The river level membership function in Fig. 4 is taken from one of the river in Kuala Lumpur, Malaysia (http://infobanjir.water.gov.my).

Once all crisp input have been fuzzified into their corresponding linguistic values, the inference engine will access the fuzzy rule base to derive linguistic values for the intermediate as well as the output linguistic variables. The two main steps in the inference process are aggregation and composition. Aggregation is the process of computing for the values of the IF part of the rules while composition is the process of computing for the values of the THEN part of the rules.

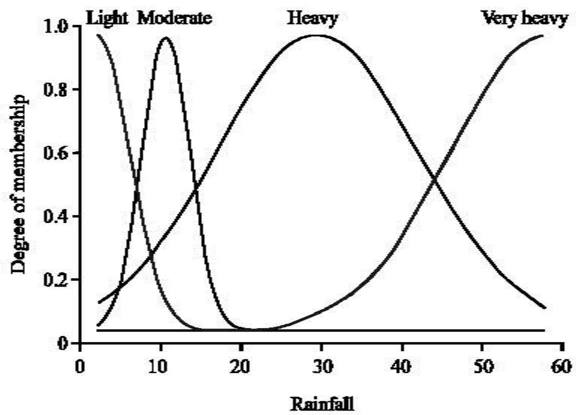

Fig. 3: Rainfall membership function

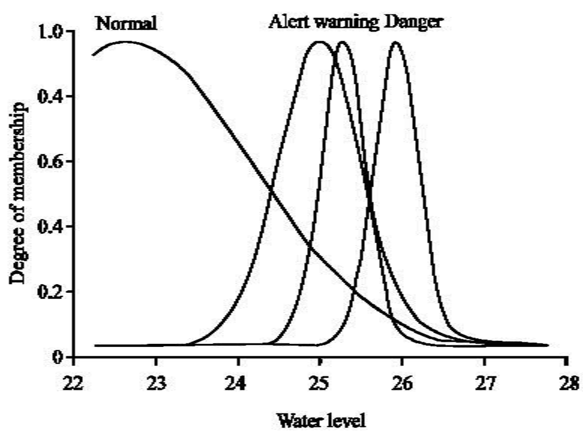

Fig. 4: River level membership function

Table 2: Expert system result based on river level and rainfall

River level	Normal level		Alert level		Warning level	Danger level
38.13	38.0		41.0		41.3	42.0
Data	26/10/16	27/10/16	28/10/16	29/10/16	30/10/16	31/10/16
Daily rainfall	1	3	25	53	3	1
Expert system result	0.500	0.500	0.650	0.7631	0.500	0.500
Notification	None	None	Alert	Warning	None	None

Station ID: 3214113; Station Name: Taman Cuepacs; River Name: Sg. Kelang; State: WP Kuala Lumpur; Date: 31/10/2016 (12:00)

The fuzzy rule base is characterized by construction of a set of linguistic rules based on expert's knowledge. The expert knowledge is usually in the form of IF-THEN rules which can be easily implemented by fuzzy conditional statements. We created sixteen fuzzy rules in our model are as shown in Fig. 5.

In the defuzzification process, the linguistic values of the output linguistic variables are converted into crisp values. The most typical value of each linguistic term is the maximum of the respective membership function. If the membership function has a maximizing interval, the median of that interval is taken. In the flood final decision making, the most typical values for the linguistic terms are "alert", "warning", "danger" or "none" as shown in Fig. 5. The crisp value is then computed as the best compromise for the given typical values and respective degrees of membership using weighted mean. The Decision Agent will notify the user based on the linguistic terms and user interacts with the environment which is the internet with the RiverLevel and RainFall agents continuously running in the environment and autonomously detecting the river level and rainfall data. The result of the simulation is obtained in the Sungai Kelang River in Kuala Lumpur, Malaysia. The results are illustrated in Fig. 6 and Table 2.

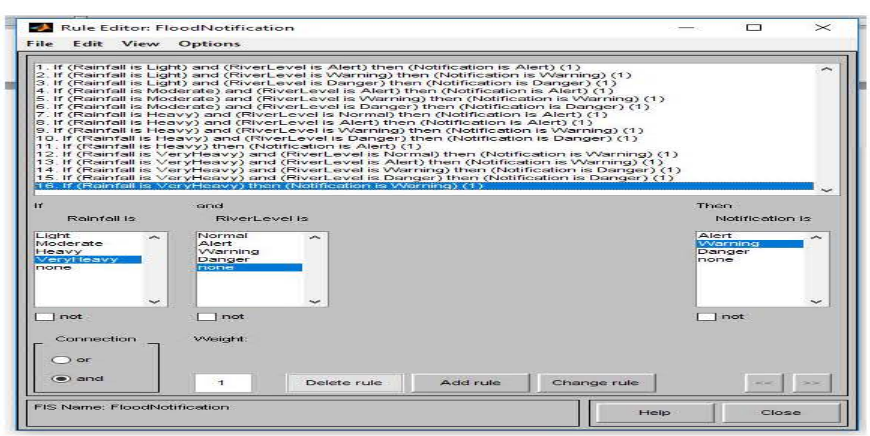

Fig. 5: Fuzzy rules

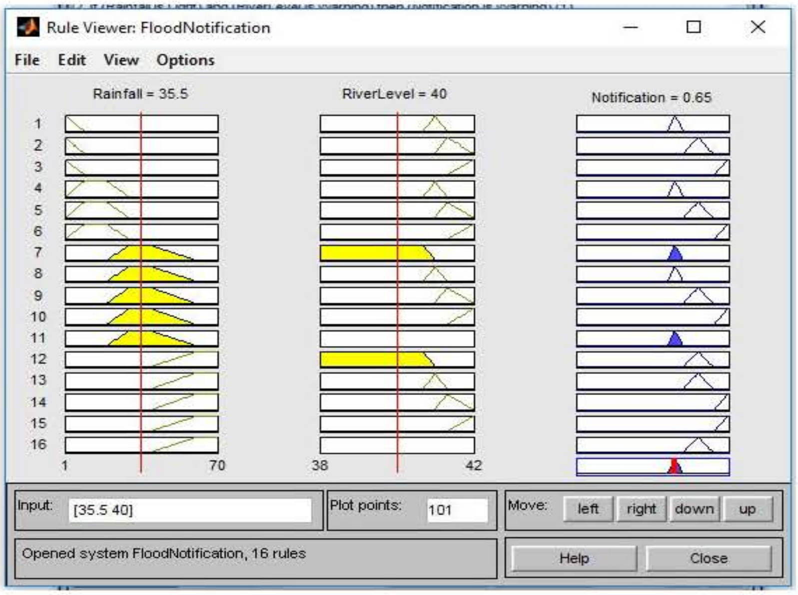

Fig. 6: Simulation result

CONCLUSION

A conceptual and fuzzy logic model that integrates agent technology and ontology is proposed for flood warning expert system. RiverLevel, Rainfall and Decision multi-agent were proposed. The internet is the environment for the RiverLevel and Rainfall agents that provide input for the fuzzification process. RiverLevel and RainFall agents update the river level and rainfall real time data in the flood ontology. The agents communicate with Decision agents to update the flood ontology. Fuzzy rules are constructed based on the range of river and rainfall levels. The flood ontology, agents and rules are associated with the inference engine that leads to the decision making by the decision agent. Input-Output values for flood are obtained from Jabatan Saliran dan Pengairan website (http://infobanjir.water.gov.my). The data are utilized using Gaussian curve membership function. Fuzzification result assigned linguistic values of “light to very heavy” and “normal to danger” with the corresponding degree of membership function. Defuzzification converts linguistic values output to crisp values. The expert system possible decision making may consist of “alert”, “warning”, “danger” or “none”. Simulation results are presented based on river level and rainfall from Sungai Kelang river in Kuala Lumpur, Malaysia.

SUGGESTIONS

For future works, the model will be extended to provide learning process in order to perform flood warning prediction. With our extended model, we expect that it will cater both uncertainty and accuracy issues as early warning of flood is vital to humans in order to save life and property.

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