# AN AGENT-BASED ONTOLOGY FUZZY LOGIC CONCEPTUAL MODEL FOR FLOOD WARNING PREDICTION

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**Abstract—** In this paper, a flood prediction conceptual model that integrates software agent, ontology and fuzzy logic is proposed. The agent role is to provide information on flood based on river level and rainfall by giving notification to users. The ontology organizes flood knowledge in order to support agent communication. Fuzzy logic will be applied to predict uncertain whether situations.

**Keywords—** Agent, Ontology, Fuzzy, Flood, Prediction.

## I. INTRODUCTION

Flood is a current catastrophe in Malaysia. There has not been much research to predict the occurrence of flood. Previousresearches have utilized various techniques to produce flood disaster prediction models. Linear regression and multivariate analysisare among the techniques proposed to predict accuracy. CounterPropagation and Back-propagation algorithms are Neural Networktechnique that has produced good prediction accuracy. Additionally, CounterPropagation Neural Network technique is combined withagent technique to generate better prediction accuracy and provides alert through agents. There are also research that merged fuzzytechnique and genetic algorithm to analyse flood frequency. The fuzzy technique has been improved to derive flood risk vulnerabilityto handle uncertain climate change. These fuzzy models handle uncertainty efficiently. Besides the fuzzy technique, a nonparametricdata-based approach has been introduced for flood prediction to support uncertainty communication.

The mentionedmodels manage accuracy and uncertainty separately. In addition, they lack a mechanism to organize flood knowledge. We proposeda robust flood prediction model which incorporate three main techniques which are agents to give notification, ontology to organize floodknowledge in order to support agent communication and fuzzy to predict uncertain whether situations.

This paper is organized into four sections. Section two explains about the works that are related to our research. Section three presents the proposed model. Finally, section four is the conclusion and future works.

## II. RELATED RESEARCH

Early warning against various natural catastrophes like floods, volcanic eruptions, earthquakes, tsunamis and geologic processes isvery important to save life, property and decrease economic damage. Currently, flood is a major catastrophe issue in Malaysia.Although exist models that utilize various techniques to predict and support flood, however, more research should be done toimprove the models.

Agent is a popular technology that provides alert and notification with the autonomous, reactive, proactive and social ability features.Agents have been widely applied in various applications such as interactive tutoring (Yaskawa and Sakata, 2003), medical diagnosis(Iantovics, 2008) and image analysis (Bell et al, 2007). Agents have also been used to generate the semantics of Object-OrientedProgramming (OOP) (TehNoranis, 2011) and provide guidance (TehNoranis and ShahrinAzuan, 2013), (Maryam and TehNoranis, 2014), where agents act as knowledge representation. Furthermore, agents are used to model muscle myosin nanomotor in a bio-nanoroboticsystem (Khataee et al, 2012).

Neural Network (NN) is a powerful Artificial Intelligence (AI) technique that has the abilityto adapt to changes and been used for pattern recognition and prediction. The combination of CounterPropagation NN and intelligent agent algorithms is integrated in Taranis for early warning against flood which provides analysis and assessment of flood caused byrain (Lopez et al, 2012). The model predicts floods and provides information to manage hydroelectric reservoir managed by a secondlayer of the NN. The NN provides adaptation to new meteorological values caused by climate change proved that the NN classifierachieved a high level of accuracy. Kung et al (2012) proposed three disaster prediction models based on linear regression, multivariate analysis and back-propagation network, and among the models, they found out that back-propagation network producethe best prediction accuracy. They tested the models using data from watershed, channel length, channel slope, rocks in watershed, collapsed area in watershed precipitation, rainfall and vegetation index. These models have produced good accuracy rate

andprovides alert and notification through agents.Shu and Burn (2004) merged fuzzy technique and genetic algorithm to analyse flood frequency. The performance of the proposedmodel is improved by tuning the membership functions of the fuzzy sets using a genetic algorithm. The proposed model is applied toflood data from Great Britain. Furthermore, a fuzzy technique was introduced to quantify the weighing values and input data of proxyvariables to derive the flood risk vulnerability in South Korea, considering the impact of climate change (Jun et al, 2013). In theirresearch, they develop a six-step procedure to derive the flood risk vulnerability in South Korea consisting of determining all proxyvariables using Delphi process, derive the objective also using the Delphi process, collect and standardize all data using min-maxstandardization, compare all rankings using Multi-Criteria Decision Making (MCDM) techniques, quantify flood risk vulnerability usingfuzzy Technique for Order Preference by Similarity to Ideal Situation (TOPSIS) technique and fuzzify all weighing vales and inputdata using the Triangular Fuzzy Number (TFN) technique. Another research by Steenbergen et al (2012) introduced a non-parametric
data-based approach for probabilistic water level flood prediction to support uncertainty. The uncertainty is based on the statisticalanalysis of historical flood forecasting residuals results at river gauging stations using a non-parametric technique. The residuals arecorrelated with the value of simulated water level and time horizons. Percentile values of the residuals are calculated and stored in athree dimensional error matrix and confidence intervals on forecasted water levels are calculated and visualised. Then the results isconnected to the database of river flood forecasting system in Belgium where it is possible to update the error matrix in real time,based on the new proposed simulations. These models, which is based on fuzzy, genetic algorithm and non-parametric data-basedtechnique handles uncertainty efficiently.The models mentioned handles accuracy and uncertainty issues separately.

We proposed a robust flood prediction model to handlethe accuracy and uncertainty issues which incorporates three hybrid techniques consisting of agents to give notification,ontology to organize flood knowledge in order to support agent communication and fuzzy to predict uncertain situations as flood is anuncertain catastrophes beyond human expectations. To date, there has not been any research that combines the three techniquesto model flood. The type of data that will be used in our research consists of river level and rainfall (JabatanPengairandanSaliran Malaysia). The proposed model is presented in the next section.

## III. PROPOSED MODEL

Our proposed conceptual model is shown in Fig. 1. Generally, the model consists of an input module, processing module and output module. Three agents namely the river level agent,rain agent and decision agent are integrated inside this model.

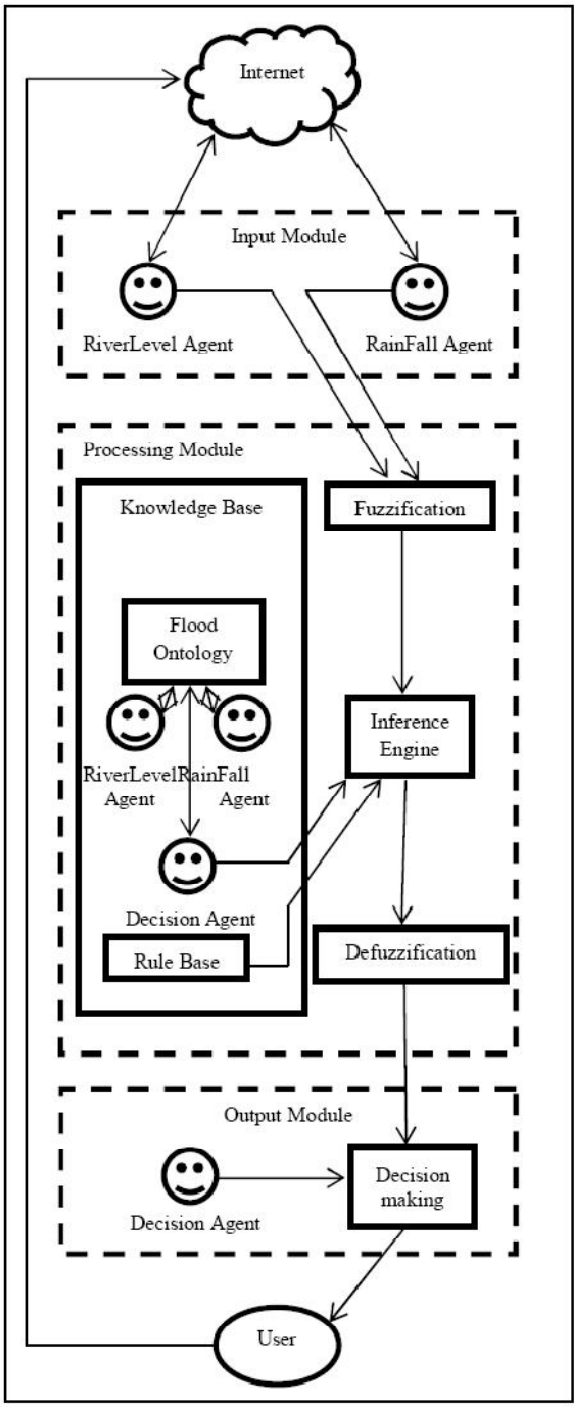


**Fig.1. Proposed conceptual model**

The Internet is the environment where the agents interact with. The RiverLevel Agent and RainFall Agent role is to sense the river and rain levels data from the Internet(JabatanPengairandanSaliran Malaysia website) which is the input to the processing module.The data are real time data which is frequently updated to and from the Flood Ontology by the RiverLevel and RainFall agents. The inputs will undergo the fuzzification process where crisp

inputs are fuzzified into linguistic values to be associated to the input linguistic variables. The combination of river and rain levels will be used as an indicator for the Decision Agent to provide notification to users on the action that needs to be taken. Through the use of membership functions defined for each fuzzy set for each linguistic variable, the degree of membership of a crisp value in each fuzzy set is determined. The numerical variable, river and rain levels is shown in the Table 1, were fuzzified using the gaussian membership functions defined for each fuzzy set for linguistic variables river and rain levels.

**Table1: Input-output values for flood data**

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

The selection of membership function type for fuzzy sets is usually determined by its suitability such as simplicity, convenience, speed, and efficiency. To determine the membership grades for each input implemented by the given fuzzy membership function, for example gaussian curve membership function is given by:

$$\mu_{A_i}(x) = \exp\{-(\frac{x - c_i}{a_i})^2\}$$

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.

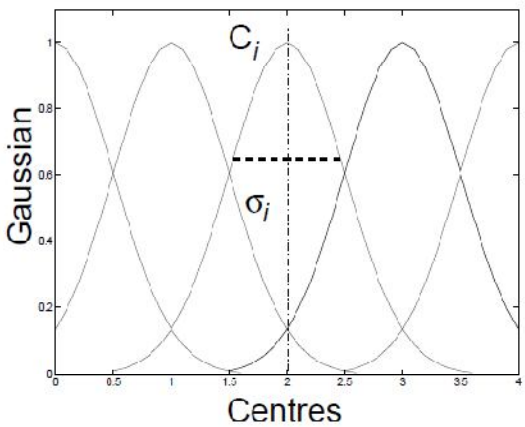


**Fig 2.Gaussian Membership Function.**

As a 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 (Figures 3-4). The river level membership function in Fig. 4 is taken from a river in Selangor, Malaysia, the Sungai Buluh at KampungBatuBertangkup

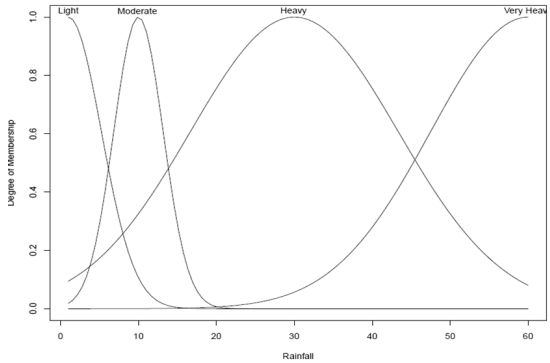


**Fig.3. Rainfall Membership Function.**

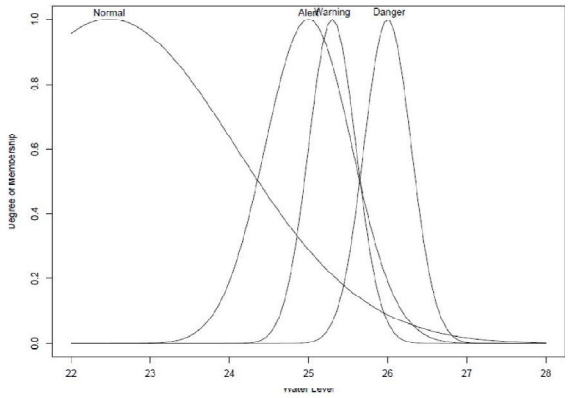


**Fig.4. River Level Membership Function.**

Once all crisp input have been fuzzified into their respective 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.

The fuzzy rule base is characterized by construction of a set of linguistic rules based on experts knowledge. The expert knowledge is usually in the form of IF-THEN rules, which can be easily implemented by fuzzy conditional statements. Some of the rules in our model are as follows:

<u>Rule 1:</u> IF (RainFall>=1) AND (RainFall<=10) AND (RiverLevel<=35.00) THEN (“light and normal”)

<u>Rule 2:</u> IF (RainFall>=11) AND (RainFall<=30) AND (RiverLevel<=38.00) THEN (“moderate and alert”)

<u>Rule 3:</u> IF (RainFall>=31) AND (RainFall<=60) AND (RiverLevel<=41.00) THEN (“heavy and warning”)

and so on.

In the defuzzification process, the linguistic values of the output linguistic variables are converted into crisp

values. The Center-of-Maximum (CoM) defuzzification technique is utilized because of simplicity and popularity. 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, pack your things”, “warning, beprepared to move out” and “danger, move out immediately”. 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.

## CONCLUSIONS

A conceptual model that integrates agent technology, ontology and fuzzy logic is proposed for flood warning prediction. Three agents namely the RiverLevel, Rainfall and Decision agents 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. 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.

For future works, the detailed designwill be produced based on the proposed conceptual model.

It is expected that our proposed model is beneficial as early warning of flood is vital in order to save life and property.

## ACKNOWLEDGMENTS

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