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Resource Allocation Based on Imprecise Information

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Abstract

The main objective of this work is to develop a methodology for risk management in a distributed system. Security is a very important issue when different users have potential access to operations of various databases of a system. There are benefits and risks involved in allowing these accesses overtime. Assuming that the probability of a user being hostile may be crisp or fuzzy is partially known, we implement fuzzy linear programming to maximize the benefits while keeping the loss under a certain fuzzy limit within the time allocation for each user. Furthermore, we develop an approach using fuzzy cognitive map to help estimate the probability of the user being hostile. In the paper, we use a specific model for simplicity in illustrating our methodology but the model can be extended to general problems of allocation of resources in a highly sensitive information distributed system such as online banking.

1. INTRODUCTION

Recently, requirements in computer communications relative to the benefits and risks posed by a great variety of users have dramatically expanded. Distributed processing systems have brought in a very large population of users accessing multiple databases. The banking area [2] is just one example of the many areas involved.

Distributed systems provide potential benefits and risks. Security is of prime concern and is a much more complex issue than the one raised by traditional networks [13]. An attempt to address the issue of the potential risk was the main goal of [1]. In this work a set of users is considered. Each of these users has potential access to operations of various databases. There is fuzzy probability of hostility associated with each user, and a fuzzy tolerance for potential damage. The fuzzy expected loss is then computed and compared with the fuzzy tolerable damage using the criterion defined by Jain in [4]. No potential benefit is considered in [1]. To obtain a more realistic model we propose in the present work to maximize the potential benefit subject to not going over the tolerance for potential fuzzy losses. Another important element missing in [1] is how to begin estimating the fuzzy probability of hostility for a user. The problem considered in the present work is also different from the direction taken in [1]. The purpose here is to evaluate a "reasonable" amount of time to be allocated to a user for different operations on different databases. In section 2, we define formally the main goal of the present work and maximize the potential benefit subject to not going over fuzzy tolerable losses. For the necessary background in Fuzzy Logic we refer the reader to the work contained in [9]. For specific information in fuzzy linear programming we refer to [9, 11, 17].

The results of Section 2 do depend on the fuzzy probability of hostility of a user. In Section 3 we outline an approach to estimate that probability. We propose the use of a fuzzy cognitive map. For material on fuzzy cognitive maps we refer to [3, 16]. In this section, we use a specific model for simplicity in illustrating our methodology but the

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model can be extended to general problems of allocation of resources in a highly sensitive information distributed system such as online banking.

In Section 4 we assume that we have some information on a set of users (some of the information might be obtained by the methods outlined in the previous sections). Now a new user is considered. Some policies are applied to the new user by comparing that user to the set of users we have some information on. We achieve this by introducing masses in the sense of [15] and obtaining a body of evidence on the set of users. For information on the use of body of evidence we refer to the works of [10, 14].

Finally, in Section 5, a different approach is taken. There is a set of possible time slices for a user. A selection of the "right slice" must be made. To do this a fuzzy decision approach is taken where goals and constraints play a symmetrical role. For fuzzy decision making the works contained in [5, 7, 8] constitute a comprehensive source. It is worth noting that in this context the potential benefits and losses are fuzzy sets of type 2 which recently have become the subject of much interest. The works in [6, 12] are excellent introduction to fuzzy sets of type 2.

2. TIME SLICES, BENEFITS AND LOSSES

We begin by formally defining the problem. Let $X=\{x_1,x_2,\ldots,x_n\}$ be the set of n users. Each user may want to perform operations $\{O^k_{i,1},O^k_{i,2},\ldots,O^k_{i,n_k}\}$ on the data set d_k where $1 \le k \le N$.

We have some partial information regarding these users. In particular we have some estimate on the probability Ph_i of the user x_i being hostile. Denote by $t^k_{i,l}$ the time slice allocated to user x_i to perform operation $O^k_{i,j}$ on the data set d_k where $1 \le j \le n_k$, $1 \le k \le N$, and $1 \le i \le n$. Denote by $c^k_{i,j}$ the benefits/losses associated with $O^k_{i,j}$ per unit of time. We may express $c^k_{i,j}$ as

$$c^k_{i,j}=(1-Ph_i)b^k_{i,j}-Ph_i\sum_{l=1}^{L}a^k_{l,i,j}$$

Where l denotes the type of damage/loss and $1 \le l \le L$. $b^k_{i,j}$ denotes the benefit derived per unit of time from $O^k_{i,j}$ if no hostility was present, and $a^k_{l,i,j}$ denotes the damage of type l sustained per unit of time by operation $O^k_{i,j}$ if the user turns out to be hostile.

The main goal of the present work is to get reasonable estimates for $t^k_{i,j}$ under a variety of conditions. As noted above, there are L types of potential losses. Let $\{\tau_1,\tau_2,\ldots,\tau_L\}$ denote the set of tolerances for each of those losses. In other words, one does not really want to exceed τ_l for losses of type l. A straight forward way to think about these losses could be in terms of dollar amounts.

Obviously we would like to maximize the potential gain while not exceeding our tolerance for loss of type l where $1 \le l \le L$. The problem then can be formulated as linear programming problem. The solution should yield reasonable values for $t^k_{i,j}$.

We need to

$$\text{Maximize } Z = \sum_{k,i,j} c_{i,j}^k t_{i,j}^k$$

$$\text{Subject to: } \sum_{k,i,j} a_{l,i,j}^k t_{i,j}^k \le \tau_l \quad 1 \le l \le L$$

The solution to the above problem represents maximizing the benefit subject to keeping the losses within the appropriate tolerance over the set of all n users. We make τ_l fuzzy. The membership functions of τ_l where $1 \le l \le L$ are of the type shown in Figure 1.

Thus we decide to totally tolerate loss up to T_l, then our willingness to tolerate goes down.

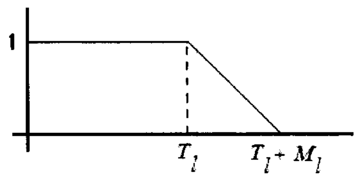


Figure 1: Membership Function of τ_l

Past a loss of T_l + M_l our willingness is null. The quantity M_l thus denotes the largest "extra tolerance", the willingness to go "the extra mile" for loss. Thus the membership function for τ_l is defined as

$$\tau_l(x) = \begin{cases} 1 & \text{if } x \le T_l \\ \dfrac{T_l + M_l - x}{M_l} & \text{if } T_l \le x \le T_l + M_l \\ 0 & \text{if } x \ge T_l + M_l \end{cases}$$

Thus the right hand sides of the constraints are fuzzy sets. We assume right now that the left-hand side consists of real quantities. We define the vector τ whose typical component is $t_{i,j}^k$. Let

$$D_l(\tau) = \tau_l\left(\sum_{k,i,j} a_{l,i,j}^k t_{i,j}^k\right)$$

Then $D_l(\tau)$ represents the degree to which the $t_{i,j}^k$ satisfy the l^{th} constraint. Indeed

$$\tau_l\left(\sum_{k,i,j} a_{l,i,j}^k t_{i,j}^k\right) = 1 \text{ if and only if } \sum_{k,i,j} a_{l,i,j}^k t_{i,j}^k \le T_l$$

and

$$\tau_l\left(\sum_{k,i,j} a_{l,i,j}^k t_{i,j}^k\right) = 0 \text{ if and only if } \sum_{k,i,j} a_{l,i,j}^k t_{i,j}^k \ge T_l + M_l$$

otherwise the constraints are partially satisfied. The feasible set is then defined as $\bigcap_{l=1}^{L} D_l(\tau)$ where $\bigcap$ denotes the minimum operator. The feasible set is then the minimum degree overall constraints satisfied by $t_{i,j}^k$. The lower bound of the optimal values is given by the solution to the standard linear programming problem.

$$\text{Maximize } Z = \sum_{k,i,j} c_{i,j}^k t_{i,j}^k$$
$$\text{Subject to: } \sum_{k,i,j} a_{l,i,j}^k t_{i,j}^k \le T_l \tag{P1}$$

The upper bound of the optimal values is given by replacing T_l in the above constraints by $T_l + M_l$. Let Z_l and Z_u denote the lower and upper bound values of Z, The extent to which $t_{i,j}^k$ meet the goal of maximizing Z is 1 if Z exceeds Z_u and is 0 if Z falls below Z_l and is defined linearly between Z_l and Z_u. Thus the extent to which the goal is met is given by

$$G(\tau) = \begin{cases} 1 & \text{if } Z_u \le \sum_{k,i,j} c_{i,j}^k t_{i,j}^k \\ \dfrac{\left(\sum_{k,i,j} c_{i,j}^k t_{i,j}^k - Z_l\right)}{(Z_u - Z_l)} & \text{if } Z_l \le \sum_{k,i,j} c_{i,j}^k t_{i,j}^k \le Z_u \\ 0 & \text{if } \sum_{k,i,j} c_{i,j}^k t_{i,j}^k \le Z_l \end{cases}$$

The problem is to maximize the joint condition of meeting the goal and satisfying the constraints, i.e. to obtain the τ maximizing $\bigcap_{l=1}^{L} D_l(\tau) \wedge G(\tau)$ i.e. we need to obtain the largest $\lambda \in [0\ 1]$ such that

$$\lambda \in \bigcap_{l=1}^{L} D_l(\tau) \wedge G(\tau)$$

This means

$$\begin{aligned} &\text{Maximize } \lambda \\ &\text{Subject to: } \lambda(Z_u - Z_l) - \sum_{k,i,j} c_{i,j}^k t_{i,j}^k \le -Z_l \\ &\lambda M_l + \sum_{k,i,j} c_{i,j}^k t_{i,j}^k \le T_l + M_l \\ &\lambda, t_{i,j}^k \ge 0 \end{aligned} \tag{P2}$$

The above is a standard linear programming problem. The first constraint comes from $\lambda \le G(\tau)$. The second constraint comes from $\lambda \le \bigcap_{l=1}^{L} D_l(\tau)$. To sum up the steps outlined are

1) Obtain Z_l by solving (P1).
2) Obtain Z_u by solving (P1) with T_l replaced by $T_l + M_l$.

3) Obtain $t_{i,j}^k$ by solving (P2) with $c_{i,j}^k$ replaced by

$$(1-Ph_i)b_{i,j}^k - Ph_i\sum_{l=1}^{L} a_{l,i,j}^k$$

More often that not Ph_i is not totally known and needs to be fuzzy, i.e.

$$Ph_i = \sum_{h=1}^{N_i} \alpha_{i,h}/p_{i,h}$$

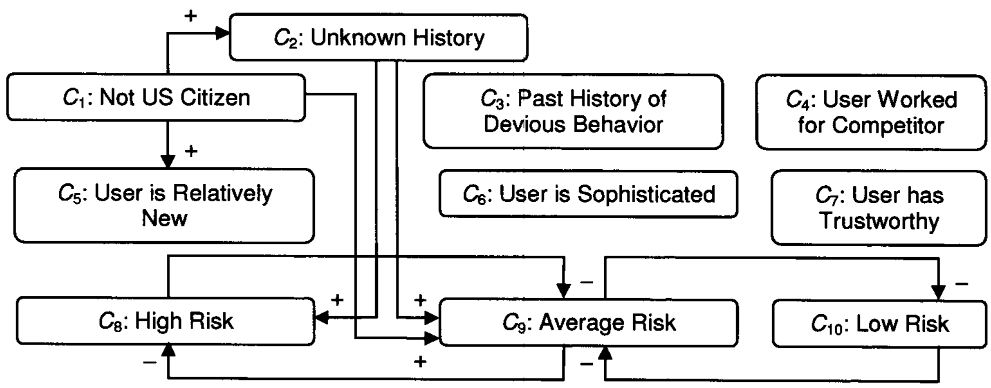
with $\alpha_{i,h}$ and $p_{i,h}$ in [0, 1]. Recall that this notation (see [9] for example) implies that the probability that Ph_i is $p_{i,h}$ is $\alpha_{i,h}$. The procedure then is to solve the linear programming problem as outlined in the 3 steps above for every index vector $h=(h_1,h_2,\ldots,h_n), 1\le h_i \le N_i$ with $Ph_i = p_{i,h_i}$ where i = 1, 2,..., n and obtain the corresponding time slices $t_{i,j}^k(h)$. The final solution is then given by the fuzzy time slices defined by

$$t_{i,j}^k = \sum_h (\min_i \alpha_{i,h_i}) \big/ t_{i,j}^k(h)$$

where the sum is overall index vectors h. A defuzzification process, see [9] would then yield a numerical value for $t_{i,j}^k$.

3. USING FUZZY COGNITIVE MAPS TO ESTIMATE Ph_i

The results of the previous section depend on the values of Ph_i. The goal of this section is to indicate how using Fuzzy Cognitive Maps will help in the estimate of Ph_i. Fuzzy Cognitive Maps have been used in a variety of situations including plant control [3] and fuzzy knowledge processing [16]. The information compiled on a typical user x_i could look as outlined below.



For clarity sake only a few lines are represented. The lines labeled "+" from C_i to C_j represent the proposition C_i implies C_j. Lines label "–" represent the fact that C_i prevents C_j. Of course such a directed graph need to be binary and links can have values between

−1 and +1 for example. Again for simplicity sake we have assumed that a link can only have the value −1 or +1. Thus the completed graph above could be represented by matrix

$$M = \begin{array}{c|cccccccccc} & C_1 & C_2 & C_3 & C_4 & C_5 & C_6 & C_7 & C_8 & C_9 & C_{10} \\ \hline C_1 & 0 & 1 & 0 & 0 & 1 & 0 & 0 & 0 & 1 & 0 \\ C_2 & 0 & 0 & 0 & 0 & 0 & 0 & -1 & 1 & 1 & 0 \\ C_3 & 0 & 0 & 0 & 0 & 0 & 1 & -1 & 1 & 0 & 0 \\ C_4 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ C_5 & 0 & 1 & 0 & 0 & 0 & -1 & -1 & 0 & 0 & 1 \\ C_6 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 & 1 \\ C_7 & 0 & -1 & -1 & 0 & 0 & 1 & 0 & -1 & -1 & 1 \\ C_8 & 0 & 0 & 0 & 0 & -1 & 0 & -1 & 0 & -1 & -1 \\ C_9 & 0 & 0 & 0 & 0 & 0 & 0 & -1 & -1 & 0 & -1 \\ C_{10} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & -1 & -1 & 0 \end{array}$$

A zero entry in C_{ij} denotes the absence of any link from C_i to C_j. We input to the system the node C_1 i.e. the user is "not a US citizen. This system behaves similarly to temporal associative memories that is a dynamical system reaches equilibrium via forward evolving inferences. The system forms a recurrent net where links provide the means of "input" nodes to fire at "output" nodes and vice versa. In our example

$$[1\,0,\quad 0,0,0,0]M0,= [0\ \ 0,1,\,,1,0,0,0,00] \Rightarrow [1,\ \ ,0,1,1,0\,0,0,1,0]$$

The first component is changed from 0 to 1 since we continuously input 1 to C_1. Next

$$[1,\ 0,1,0,\quad 1,0]0,0,= [0\,2,\ ,0,1,0\,1,-3\,0,\ ,0] \Rightarrow [1\,1,0,0,1,\ ,0,0,1,0]$$

The −1 are changed to 0 on account of the threshold operation, where the threshold is say 0.5. Therefore $[\,,1\ \ ,0,1\ \ ,0,1,0,0]$ is a fixed point, meaning -- If the user is a non US citizen then there is unknown history, the user is relatively new, the risk is average. In this case we might consider Ph_i = 0.5 as a reasonable value. On the other hand if we assume the user has a trustworthy background, we turn off C_1 and turn on C_7 then

$$[0,\quad 1,0]M0,= [0,0,1,0,\ ,0,0,0,0\,0] \Rightarrow [0\,0,\ ,0,0,0\,1,0\,0,0]$$

C_7 is continuously on

$$[0\ \ 0,0,\quad 0,1,0]M0,= [0,\ ,0\ \ ,0,0,0,0,\ ,0] \Rightarrow [0\,0,\ ,0,0,0,1\,0,\ \ 0]0$$

Thus we have a fixed point and no inference shows up except that user has a trustworthy background. As the last example take the case of a non US citizen with highly sophisticated skills then taking the first fixed point, turning off non citizen and turning on C_6 we obtain

$$[0\,1,\ ,0,\ 1,1,0,0,0]M = [0\ \ ,1,\ ,0,0\,1,-3\ \ ,2,1]$$

After the threshold operation this changes to $[0,\ 0,1,0,0,0,\ ,1,1]$ and

$$[0\,1,\quad 0,0,0,\ ,1,1]M = [0,\quad ,0,0,0,0,0\,0,0] \Rightarrow [0,\ \ 0,0,0\ \ 0,1,0,0]0$$

$$[0 \quad ,0,0]M,0,0,[0,0,0 \quad ,0,0,0,0,1,1] \Rightarrow [0 \quad 0,0,0,1,0,1,1,1]$$
$$[0 \quad 0,0,0,0,1,0,1]M = [0, \ ,0 \quad ,0,0,0,0,0,1] \Rightarrow [0\ 0,0, \ ,0,1\ 0,1, \ ,1]$$

Now the risk is low, average, high. This indicates the fuzzy nature of Ph_i under such conditions. A reasonable fuzzy value for Ph_i might be

$$Ph_i = 0.6/0.2 + 0.7/0.5 + 0.6/0.8$$

4. COMPARING A NEW USER TO A POOL OF USERS

In this section we assume we have determined possible time slices $t_{i,j}^k$ for a set of users $X = \{x_1, x_2, \ldots, x_n\}$. A new user x^* is now under consideration and our goal is to determine the time slices $t_{*,j}^k$ for x^*. On a scale of 0 to 1 it might be difficult to assign a similarity score to the pair x^*, x_i. Instead we chose to partition [0, 1] into subintervals

$$I_{i,s} = (l_{i,s}, r_{i,s}], \quad 1 \le s \le N_i$$

Let $m_i(I_{i,s})$ denote the fraction of experts whose opinion is that similarity score of x^* and x_i is some number falling in $I_{i,s}$. Clearly

$$0 \le m_i(I_{i,s}) \le 1 \quad \text{and}$$
$$\sum_{s=1}^{N_i} m_i(I_{i,s}) = 1$$

We may view m_i as a mass with focal element in the sense of [15]. We now introduce a function that reflects on how falling in the interval $I_{i,t}$ implies similarity. Let

$$d_s(x^*, x_i) = (1 - M_{i,s}) + \frac{1-\alpha}{\alpha} | I_{i,s} |$$

Here $| I_{i,s} |$ denotes the length of $I_{i,s}$ that is $r_{i,s} - l_{i,s}$. $M_{i,s}$ denotes the midpoint of $I_{i,s}$ that is $\frac{r_{i,s} + l_{i,s}}{2}$ and α is a parameter where $0 \le \alpha \le 1$. The function d_s actually reflects the dissimilarity of x^* and x_i. If $M_{i,s}$ is close to 0, $1 - M_{i,s}$ is large, $d_s(x^*, x_i)$ is large and the similarity score being in $I_{i,s}$ is low. Conversely, if $M_{i,s}$ is close to 1, $| I_{i,s} |$ is small and the similarity score falling in $I_{i,s}$ is high while $d_s(x^*, x_i)$ is low. It is worth noting that a large $| I_{i,s} |$ leads to large dissimilarity because experts are then uncertain about the similarity score to assign.

If we pick $\alpha = 0\ 5.$ then

$$d_s(x^*, x_i) = (1 - M_{i,s}) + | I_{i,s} |$$

The distance of $M_{i,s}$ to 1 and $| I_{i,s} |$ play then an equal role in contribution to the dissimilarity of x^* and x_i. We would like to normalize the dissimilarity so we set

$$D_s(x^*, x_i) = \frac{d_s(x^*, x_i)}{\underset{s}{Max}\{d_s(x^*, x_i)\}}$$

Since we are interested in how similar x^* and x_i are we set

$$S_s(x^*, x_i) = 1 - D_s(x^*, x_i)$$

This comes from placing the score in $I_{i,s}$ so we define the average similarity of x^* and x_i as

$$AvgSim(x^*, x_i) = \sum_{s=1}^{N_i} m_i(I_{i,s}) S_s(x^*, x_i)$$

We then define the fuzzy time slices for x^* as

$$t^k_{*,j} = \sum_s AvgSim(x^*, x_i) / t^k_{i,j}$$

Then estimating $t^k_{i,j}$, for example, by methods previously outlined and applying some defuzzification to $t^k_{*,j}$ [9], we obtain an estimate for $t^k_{*,j}$. It is worth mentioning that the estimate $t^k_{*,j}$ was obtained by looking how similar x^* was on the average to the set of users $\{x_1, x_1, \ldots, x_n\}$. Applying the combination of masses rule for independent experts, one could work with a consensus mass instead of m_i, see [5]. Again, for simplicity sake we did not do this. The same comment could be applied to the previous section where a consensus fuzzy cognitive map could have been considered.

Example: Assume a set of users is $X = \{x_1, x_2, x_3\}$ with the following subintervals and assigned masses.

User	Subinterval	Mass	Midpoint
x_1	$I_{1,1} = (0, 0.5]$	$m(I_{1,1}) = 0.5$	$M_{1,1} = 0.25$
	$I_{1,2} = (0.5, 1]$	$m(I_{1,2}) = 0.5$	$M_{1,2} = 0.75$
x_2	$I_{2,1} = (0, 1/3]$	$m(I_{2,1}) = 1/3$	$M_{2,1} = 1/6$
	$I_{2,2} = (1/3, 2/3]$	$m(I_{2,2}) = 1/3$	$M_{2,2} = 0.5$
	$I_{2,3} = (2/3, 1]$	$m(I_{2,3}) = 1/3$	$M_{2,3} = 5/6$
x_3	$I_{3,1} = (0, 1/4]$	$m(I_{3,1}) = 0.4$	$M_{3,1} = 1/8$
	$I_{3,2} = (1/4, 1]$	$m(I_{3,2}) = 0.6$	$M_{3,2} = 5/8$

Then, the dissimilarity for the new user x^* and x_1 can be computed as follows. First find the dissimilarity score, that is

$$d_1(x^*, x_1) = (1 - 0\ 25) + 0\ 5. = 1.25$$
$$d_2(x^*, x_1) = (1 - 0\ 75) + 0\ 5. = 0.75$$

Then normalize the score between 0 and 1, we obtain normalized dissimilarity as

$$D_1(x^*, x_1) = 1\ 25 /\ .25 = 1$$
$$D_2(x^*, x_1) = 0\ 75 /\ 25. = 0.6$$

Next the similarity can be determined as

$$S_1(x^*, x_1) = 1 - 1 = 0$$
$$S_2(x^*, x_1) = 0\ 75/1\ 25 = 1 - 0.6 = 0.4$$

Thus, the average similarity of x^* and x_1 is

$$AvgSim(x^*, x_1) = 0.5 \times 0 + 0\ 5 \times 0.4 = 0.2$$

Similarly, the average similarity of x^* and x_2, and x^* and x_2 can be obtained as follows

$$AvgSim(x^*, x_2) = 0.27 \text{ and } AvgSim(x^*, x_3) = 0.27$$

That means the fuzzy time slices for x^* is

$$t^k_{*,j} = 0\ \ /2t^k_{1,j} + 0\ 29/t^k_{2,j} + 0.27/t^k_{3,j}$$

By defuzzification, the numerical value of time slices for x^* can be determined.

5. SELECTING A TIME SLICE FROM A LIST

We assume in this section that for client x^*, there is a list of possible time slices $\{t^k_{*,j,p}, p = 1\ 2, \ldots, N^k_{*,j}\}$. Which of these slices should be allocated to x^*? A possible way to approach this is to view this as a decision problem, see [5, 7]. For a decision problem the following components are needed: A set of possible actions/alternatives, a set of goals and a set of constraints. Reasonable goals in the present case could be

(1) Potential benefit should be high
(2) Losses should be kept low

Constraints could be

(1) Assume that the time line is partitioned into subintervals $K^k_{j,v}$, where $1 \le v \le M$, we would like the solution $t^k_{*,j,p}$ to fall in an interval $K^k_{j,v}$ of high mass $m^k_{j,p}(K^k_{j,v})$
(2) For that $K^k_{j,v}$ of high mass we would like time slice of a user x_i, $t^k_{i,j}$ to fall not too far off $K^k_{j,v}$

Constraints (1) and (2) can be summed up as follows: The candidate $t^k_{*,j,p}$ is a good time slice for x^* if the belief is high that it falls in some interval such that some user has been allocated a time slice not falling too far from that interval.

The benefit coming from $t^k_{*,j,p}$ being allocated is

$$B(t^k_{*,j,p}) = (1 - Ph_*) b^k_{*,j} t^k_{*,j,p}$$

And the loss of type j for such an allocation is

$$L_l(t^k_{*,j,p}) = Ph_* a^k_{l,*,j} t^k_{*,j,p}$$

Note that B and L_l are fuzzy sets of type 2 on candidate time slices as Ph_*, $b^k_{*,j}$, $a^k_{l,*,j}$ are typically fuzzy. We now define three fuzzy sets whose membership functions are as shown in Figure 2.

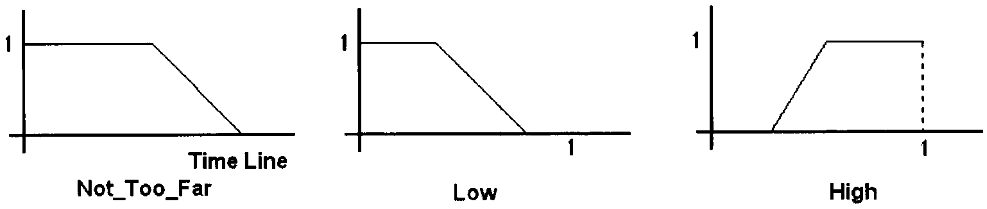


Figure 2: Not_Too_Far membership fumctions

Next we define

$$C^k_{j,v} = \min_s \text{Not\_Too\_Far}\left(d\left(t^k_{1,j}, K^k_{j,v}\right)\right)$$

where d denotes the distance function. Thus $C^k_{j,v}$ reflects how close $K^k_{j,v}$ comes to some allocated time slice. The fuzzy decision set on time slices can then be expressed as

$$E^k_j\left(t^k_{*,j,p}\right) = w_1 \text{Poss}\left\{B\left(t^k_{*,j,p}\right), \text{High}\right\} + \sum_l w_{2,l} \text{Poss}\left\{L_l\left(t^k_{*,j,p}\right), \text{Low}\right\} + w_3 m^k_{j,p}\left(K^k_{j,v}\right) + w_4 C^k_{j,v}$$

where $w_1 + \sum_l w_{2,l} + w_3 + w_4 = 1$ and Poss denotes the possibility function. Recall the possibility computed on a pair of fuzzy sets is the largest intersection of these sets [9]. To obtain the best solution $t^k_{*,j,p}$, we can maximize E^k_j over $\left\{t^k_{*,j,p}, p = 1,2,\dots,N^k_{*,j}\right\}$. The last two terms of the right hand side form a compromise between a high belief that $t^k_{*,j,p}$ will fall in $K^k_{j,v}$ and the proximity of some allocated time to $K^k_{j,v}$. The first two terms of the right proximity of the right hand side reflect the two goals mentioned earlier.

Note while it is often the case that $E(a) = \min\{\min_i G_i(a), \min_p C_p(a)\}$ where $E, G_i(a), C_p(a)$ and a are the decision, the goals, the constraints and the alternative, respectively, we have introduced possibility functions as benefits and losses are fuzzy sets of type 2. Such sets have recently generated much research, see [6,12,14].

6. CONCLUSION

In this work we have investigated the Time Slice Allocation. In Section 2 a set X of users is considered. One would like to allow these users certain operations on different date sets. There are benefits and risks involved in allowing access. One would like to maximize the benefits while keeping damages under a certain (fuzzy) limits. Important information in such a problem is the probability of the user being hostile. That probability may be crisp or fuzzy. The solution is obtained by considering a set of fuzzy linear programming problems. In Section3, we develop a possible methodology to help in the estimation of the user being hostile. The approach is to use a fuzzy cognitive map. In the paper, we use a specific model for simplicity in illustrating our methodology but the model can be extended to general problems of allocation of resources in a highly sensitive information distributed system such as online banking. In Section 4 a new user is compared to a largely known pool of users. The concept of average similarity of the new user to each user in the pool is introduced. This average similarity then yields a fuzzy time slice for the new user. A defuzzification process would then yield a possible time slice for the new user. In the last section there is a list of possible time slices for a new user. A selection from that list is then make by defining reasonable goals and constraints and treating this problem as a classic fuzzy decision making problem. The goals involve fuzzy sets of type 2 and for this reason possibility functions are introduced in the expression of the fuzzy decision.

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