Pak. j. eng. technol. sci.
Volume 4, No 1, 2014, 41-63
ISSN: 2222-9930 print
ISSN: 2224-2333 online

Analyzing Human Communities using Fuzzy Graphs

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Received on: May 27, 2013; Accepted on: July 2, 2013

ABSTRACT

Fuzzy Graphs are used for analyzing and modeling levels of information in real-time systems (simple or complex networks). A community (network) is formed when human eProfiles (nodes) have links (edges) and interactions with each other. Considering multiple medium of communications like email, chatting and short message service (SMS) in the network, it will make the graph more complex (dense graph or forest). To address this issue in this paper analyzes those human communities with the help of fuzzy graphs and highlights the status of individuals in a human community. Max-Min Composition (fuzzy relation) was applied along with statistical analysis on fuzzy graphs of human community. Interaction Index (II) is used to estimate the intensity of communication and Role Index (RI) determine the participation status of individual in a human community. All this analysis will be used in our research and development of Community Algorithm, which will be used as a tool that will help in identifying, analyzing, manipulating, monitoring, and transforming human communities based on human eProfiles.

Keywords: Fuzzy Graphs, Fuzzy Graph Analysis, Interaction Index, RoleIndex, Max-Min Composiion, Community Algorithm

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1. INTRODUCTION

Rosenfeld introduced Fuzzy Graphs [1] in 1975, which are used for modeling real time systems, where the level of information varies with different levels of precision. Fuzzy Models are equally used in Engineering and Sciences. Fields like sociology, social psychology, anthropology, linear algebra, (fuzzy) automata, group theory, graph theory, and mathematics are used intensively in social network analysis (SNA) [2] and emerged with formal models and methods.

SNA focus on relationships among actors (social entities) rather than the attributes of individual actors. Types and patterns of relationships are emerged from that individual connectivity. From mathematics, we can have finite sets of actors and in this relations are usually represented by matrices, which can be visualized as graphs. This research will use the capabilities of SNA and Fuzzy Graphs on human communities.

Community Algorithm [7, 8, 9, 10, 11, 12, 13] is a variant of Genetic Algorithm (GA) [6, 14, 15, 16, 17, 18, 19, 20] and will be another area on which this research will focus and will help in formalizing the concept of Human Community in Community Algorithm.

While studying graphs, which can be used in analyzing interactions between human eProfiles in a community, many interesting types of graphs were found. Random graphs and Fuzzy graphs have major influence in Social Network Analysis. Fuzzy graphs [21] deal with uncertain values of each connection. Some other graphs are Fuzzy node fuzzy graph [22], crisp node fuzzy graph [22], Fuzzy Cognitive Maps (FCM), [23] Fuzzy Weighted Graphs [24], Time-aggregated graph (TAG) [25] and Spatio-Temporal Sensor Graph [26]. In this study, we will be using Fuzzy Graphs in general.

The rest of the paper is organized as follows. The parameters of human eProfiles were discussed in section 2 in detail, which are used to generate human communities. In section 3, results based on analysis of human communities by fuzzy and statistical operations were shown. Finally, a conclusion is given in section 4.

2. GENERATING HUMAN COMMUNITIES

In this section, we firstly describe the characteristics of human eProfiles (which can be seen in Table 3 and Table 4). Secondly, the human communities will be analyzed by fuzzy and statistical operations in detail. In this research, fuzzy graph is considered for the analysis of human communities which are created on the basis of number of parameters of human eProfiles. We can define fuzzy graph as G **= <*V*, *F*>**, where, ***V***={v_i} is the set of human eProfiles and ***F***=(f_{ij}) is the value of communication link between ***V***. Email, chatting, and Short Message Service (SMS) are the medium of communication considered in this research and applied on human communities to observe interaction level between individuals. Earlier web communities [36, 37, 38] were discussed in the research.

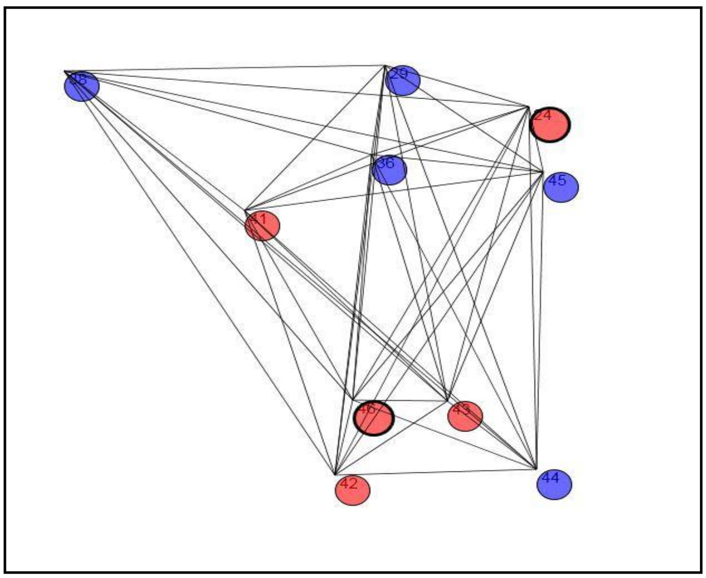

Fig. 1. A sample 10 nodes human community [Dark outlined nodes are the start and end nodes]

Table 3. Human eProfile parameters in different domains.

Reading Books	√	X	X	X	X	X	X	√	√	√
Listening Music	√	X	X	X	X	X	X	√	√	√
Watching Films	√	X	X	X	X	X	X	√	√	√
Photograph Name	X	√	X	X	X	√	√	√	√	√
# Emails Send	X	X	X	X	√	X	X	√	√	√
# Emails Received	X	X	X	X	√	X	X	√	√	√
# SMS Send	X	X	X	X	X	X	X	√	√	√
# SMS Received	X	X	X	X	X	X	X	√	√	√
Chat Duration	X	X	X	X	X	X	X	√	√	√

Table 4. Human eProfile selected parameters.

eProfile Parameters	Profile Type	Profile Ontology	Selected	GAHC
Username	Explicit	Identification Profile		
Firstname	Explicit	Identification Profile	*	√
Middlename	Explicit	Identification Profile	*	
Lastname	Explicit	Identification Profile	*	
Suffix	Explicit	Socio-Economic Profile		
Nick Name	Explicit	Socio-Economic Profile	*	
Gender	Explicit	Socio-Economic Profile	*	√
Birthday	Explicit	Identification Profile	*	
Place of Birth	Explicit	Identification Profile	*	
Address	Explicit	Identification Profile	*	
City	Explicit	Identification Profile	*	√
State	Explicit	Identification Profile	*	
Country	Explicit	Identification Profile	*	√

ZIP Code	Explicit	Identification Profile	*	
Email Address	Explicit	Identification Profile	*	
Alternate Email Address	Explicit	Identification Profile		
Home Phone	Explicit	Identification Profile	*	
Mobile Phone	Explicit	Identification Profile	*	
Religion	Explicit	Socio-Economic Profile	*	√
Language Speak	Explicit	Socio-Economic Profile	*	
Mate	Explicit	Socio-Economic Profile		
Father	Explicit	Identification Profile	*	
Mother	Explicit	Identification Profile	*	
Sibling	Explicit	Identification Profile		
Childless	Explicit	Socio-Economic Profile		
Relationship Status	Explicit	Socio-Economic Profile		
Degree Name	Explicit	Identification Profile		
Discipline	Explicit	Identification Profile	*	

Institution Name	Explicit	Identification Profile	*	
Year of Passing	Explicit	Identification Profile	*	
Study Type	Explicit	Identification Profile	*	
Education Summary	Explicit	Identification Profile	*	
Company Name	Explicit	Socio-Economic Profile	*	
Joining Date	Explicit	Socio-Economic Profile	*	
Work Type	Explicit	Socio-Economic Profile	*	
Designation	Explicit	Socio-Economic Profile	*	√
Industry Name	Explicit	Socio-Economic Profile	*	
Occupation History	Explicit	Socio-Economic Profile		
Smoking Status	Explicit	Preference Profile		
Passion	Explicit	Preference Profile	*	
Playing Sports	Explicit	Socio-Economic Profile	*	
Reading Books	Explicit	Socio-Economic Profile	*	
Listening Music	Explicit	Socio-Economic Profile		

Watching Films	Explicit	Socio-Economic Profile		
Custom Tags	Explicit	Preference Pro-file		
Photograph Name	Explicit	Socio-Economic Profile		
Number of Emails Send	Implicit	Transaction Profile	*	
Number of Emails Re-ceived	Implicit	Transaction Profile	*	
Number of SMS Send	Implicit	Transaction Profile	*	
Number of SMS Received	Implicit	Transaction Profile	*	
Chat Duration	Implicit	Transaction Profile	*	

In Table 4, there exists a pool of human eProfile parameters from which we can extract communities. Common features among human eProfiles will link one human with other to form a human community [11]. The parameters which were considered in this analysis are First Name, Gender, Religion, City, Country and Designation. The resultant (sample) human community of 10 nodes can be seen in Fig. 1. In Computer Science, only web communities [36, 37, 38] were discussed, which are also known as FLG Community [36].

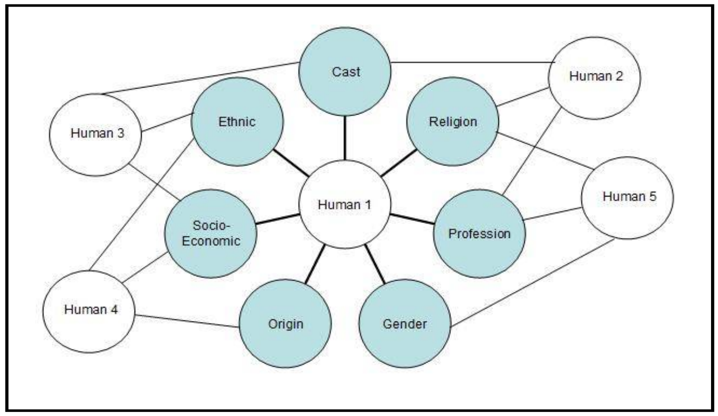

Fig. 2. Parameters used for human profiling [9, 10]

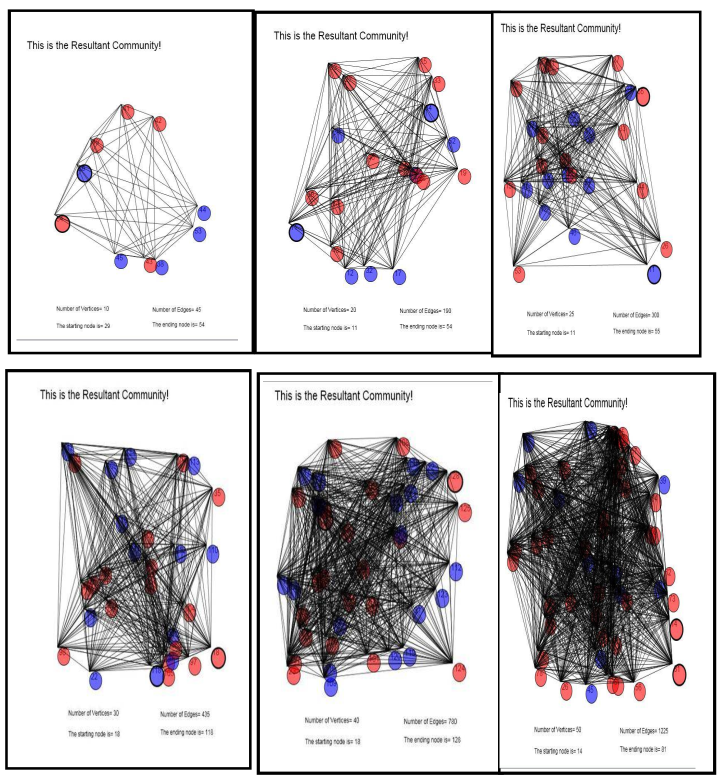

Fig. 3. GAHC [40] generated human communities with N=10, N=20, N=25, N=30, N=40 and N=50 [Dark outlined nodes are the start and end nodes of graph]

Fig. 2 shows human profiling [9, 10] i.e. how human beings are linked with each other based on their characteristics, like birth place, living place, caste, race, ethnic, gender, religion, education, habit, hobbies, etc. One human can be linked with other human on the basis of links l_1, l_2, l_3, and so on, which will help in forming human communities. As these links become complex as time passes, different roles will emerge. These roles can be r_1, r_2, r_3, and so on, which leads to role intensity, played by same human being in different communities.

Each community will hold individuals (Human eProfiles) as h_1, h_2, h_3, and so on in the Community Space, which is used in our ongoing research of Community Algorithm [7, 8, 9, 10, 11, 12, 13].
We have developed two small projects, namely, **LiveIT** [39] and **GAHC** [40]. **LiveIT** [39] gathers data for email, chatting, and Short Message Service (SMS) from LAN users having human eProfiles, from a genealogical perspective of a social network. **GAHC** [40] is the application which generates community graphs based on selected parameters (First Name, Gender, Religion, City, Country and Designation) from the human eProfiles. Different human communities were produced by GAHC tool [40] on the basis of religion in Fig. 3. We have shown the complexity of the (community) graph by taking different size of human community, i.e. number of nodes from 10 to 50.

3. ANALYSIS AND RESULTS

After generating Human Communities, we analyzed the interaction frequency based on number of emails and SMS and chat session hours among different humans living within a community. Lets analyze a human community from University Environment with N=10 (nodes) and providing data for each users for different medium of communication i.e. email (E), chat (C) and SMS (S). Data for these communications will be modeled through Fuzzy Graph Matrices. We analyzed and verified the results on the basis of Fuzzy and Statistical Operations on the three Fuzzy Graph Matrices.

4.1 Case 1 – Uniform Communication

We consider uniform communication (distribution of values) for Chat (C) Matrix will have same values for user to user communication such that every row total is equal to 1. Similar matrices will be produced for Email (E) and SMS (S) interactions for chat.

After applying Max-Min Composition [35] on these three Fuzzy Graph Matrices of Email (E), Chat (C) and SMS (S) we get result as S.E.C matrix (considering uniform distribution of values). So it can be unambiguously seen that all of the values in the resultant matrix [Max-Min Composition Matrix] are same. Therefore, all users have same level of interaction and no distinction can be made among users in this case.

4.2. Case 2 – Full Communication

Similarly, we will have three matrices when we consider 100% (full) communication on each channel (user-user communication) in every medium of communication i.e. Email (E), Chat (C) and SMS (S).

After applying Max-Min Composition [35] on these three Fuzzy Graph Matrices of Email (E), Chat (C) and SMS (S), we get result as S.E.C matrix (considering 100% communication). Again it can be seen that all of the values in the resultant matrix [Max-Min Composition Matrix] are same and are at 100%. Therefore all users have same level of interaction and no distinction can be made among users in this case either.

4.3. Case 3 – University LAN Environment

Now considering the three Fuzzy Graph Matrices for each of the medium of communication i.e. email (E), chat (C) and SMS (S) for analyzing human interaction in a university community. The values in the matrices are taken from some arbitrary communication of 10 users in a LAN environment of a University.

$$
S = \begin{bmatrix}
0.00 & 0.02 & 0.03 & 0.03 & 0.05 & 0.14 & 0.02 & 0.11 & 0.05 & \mathbf{0.55} \\
0.17 & 0.00 & 0.17 & 0.00 & 0.02 & 0.01 & 0.05 & 0.14 & \mathbf{0.44} & 0.00 \\
0.00 & 0.06 & 0.00 & 0.05 & 0.06 & 0.07 & 0.13 & \mathbf{0.33} & 0.04 & 0.25 \\
0.01 & 0.04 & 0.09 & 0.00 & 0.07 & \mathbf{0.69} & 0.09 & 0.00 & 0.01 & 0.01 \\
0.01 & 0.16 & 0.00 & 0.00 & 0.00 & 0.06 & 0.17 & \mathbf{0.53} & 0.00 & 0.06 \\
0.05 & \mathbf{0.30} & 0.02 & 0.05 & 0.04 & 0.00 & 0.06 & 0.07 & 0.11 & \mathbf{0.30} \\
0.15 & 0.05 & 0.01 & 0.07 & \mathbf{0.27} & 0.00 & 0.00 & 0.05 & \mathbf{0.27} & 0.14 \\
0.17 & 0.10 & 0.02 & 0.03 & 0.05 & 0.01 & 0.05 & 0.00 & \mathbf{0.51} & 0.07 \\
0.00 & 0.06 & 0.06 & 0.06 & \mathbf{0.61} & 0.00 & 0.19 & 0.02 & 0.00 & 0.00 \\
0.02 & \mathbf{0.53} & 0.17 & 0.14 & 0.07 & 0.02 & 0.00 & 0.03 & 0.03 & 0.00
\end{bmatrix}
$$

$$
E = \begin{bmatrix}
0.00 & 0.15 & 0.02 & 0.11 & 0.06 & \mathbf{0.58} & 0.07 & 0.00 & 0.01 & 0.00 \\
0.05 & 0.00 & 0.05 & 0.14 & \mathbf{0.44} & 0.00 & 0.05 & 0.06 & 0.07 & 0.13 \\
0.06 & 0.02 & 0.00 & 0.14 & 0.02 & 0.10 & 0.05 & \mathbf{0.54} & 0.07 & 0.00 \\
\mathbf{0.31} & 0.18 & 0.04 & 0.00 & 0.02 & 0.01 & 0.04 & 0.10 & \mathbf{0.31} & 0.00 \\
0.00 & 0.12 & 0.13 & 0.12 & 0.00 & 0.05 & 0.06 & 0.07 & 0.12 & \mathbf{0.32} \\
0.01 & 0.32 & 0.10 & 0.08 & 0.04 & 0.00 & 0.01 & 0.06 & 0.03 & \mathbf{0.34} \\
0.11 & \mathbf{0.28} & 0.00 & 0.07 & 0.00 & 0.23 & 0.00 & \mathbf{0.28} & 0.00 & 0.04 \\
0.08 & 0.00 & 0.05 & 0.26 & 0.02 & \mathbf{0.45} & 0.07 & 0.00 & 0.01 & 0.05 \\
0.14 & 0.02 & 0.07 & 0.14 & 0.01 & 0.00 & 0.08 & \mathbf{0.38} & 0.00 & 0.15 \\
0.15 & 0.00 & 0.03 & \mathbf{0.58} & 0.02 & 0.02 & 0.06 & 0.02 & 0.11 & 0.00
\end{bmatrix}
$$

$$
C = \begin{bmatrix}
0.00 & 0.12 & 0.06 & \mathbf{0.63} & 0.08 & 0.00 & 0.01 & 0.01 & 0.03 & 0.07 \\
0.12 & 0.00 & 0.15 & \mathbf{0.45} & 0.06 & 0.02 & 0.03 & 0.04 & 0.12 & 0.05 \\
0.06 & 0.15 & 0.00 & 0.14 & 0.04 & \mathbf{0.42} & 0.05 & 0.02 & 0.04 & 0.11 \\
\mathbf{0.63} & \mathbf{0.45} & 0.14 & 0.00 & 0.01 & 0.04 & 0.07 & 0.20 & 0.21 & 0.01 \\
0.08 & 0.06 & 0.04 & 0.01 & 0.00 & 0.05 & 0.09 & \mathbf{0.23} & 0.09 & 0.18 \\
0.00 & 0.02 & \mathbf{0.42} & 0.04 & 0.05 & 0.00 & 0.06 & 0.02 & 0.08 & 0.03 \\
0.01 & 0.03 & 0.05 & 0.07 & 0.09 & 0.06 & 0.00 & 0.08 & \mathbf{0.22} & 0.10 \\
0.01 & 0.04 & 0.02 & 0.20 & \mathbf{0.23} & 0.02 & 0.08 & 0.00 & 0.10 & 0.05 \\
0.03 & 0.12 & 0.04 & 0.21 & 0.09 & 0.08 & \mathbf{0.22} & 0.10 & 0.00 & 0.17 \\
0.07 & 0.05 & 0.11 & 0.01 & \mathbf{0.18} & 0.03 & 0.10 & 0.05 & 0.17 & 0.00
\end{bmatrix}
$$

In each of the fuzzy graph matrices, the values marked in bold are the maximum level of interaction between the users (i, j), where i is the row number and j is the column number. In other words, it is the level of communication between $user_i$ and $user_j$. When Max-Min Composition [34] is applied, we will have 6 matrices in result. Following equation (3) shows the average of all of them and we get AMM (Average Max-Min):

$$
AMM_{ij} = \frac{(C.E.S)_{ij} + (S.E.C)_{ij} + (E.S.C)_{ij} + (S.C.E)_{ij} + (C.S.E)_{ij} + (E.C.S)_{ij}}{6} \quad (3)
$$

Table 5. Summery of results of Max-Min Composition [35] on fuzzy graph matrices.

Users	C.S.E	C.E.S	E.C.S	S.C.E	S.E.C	E.S.C	AMM
1	1.49	1.82	*1.48*	*1.24*	**2.17**	1.61	1.63
2	1.59	1.85	1.58	1.78	*1.42*	1.45	1.61
3	1.65	1.85	1.52	1.50	1.84	1.35	1.62
4	**2.10**	**2.15**	1.79	1.27	*1.42*	1.69	**1.74**
5	1.47	1.43	1.45	1.52	2.02	1.57	1.58
6	*1.39*	*1.34*	1.55	1.72	1.83	**1.74**	1.60
7	1.44	1.41	1.57	**1.80**	1.54	1.65	*1.57*
8	1.59	1.76	1.91	1.67	1.44	1.57	1.66
9	1.60	1.80	1.56	1.39	1.48	1.60	*1.57*
10	1.45	1.48	**2.24**	1.73	1.53	*1.40*	1.64

Table 5 summarizes the results of Max-Min Composition [35] for 6 different combinations. Values in bold are the maximum ones and values in italic and underline are the minimum ones for each matrix. When Weighted Average is applied on the same fuzzy graph matrices, for each of the medium of communication i.e. email (E), chat (C) and SMS (S) for analyzing human interaction in a university community resulting in 6 combination matrices. The average of Weighted Average (AWA) can be seen in the following equation (4):

$$AWA_{ij} = \frac{(C.2E.3S)_{ij}+(S.2E.3C)_{ij}+(E.2S.3C)_{ij}+(S.2C.3E)_{ij}+(C.2S.3E)_{ij}+(E.2C.3S)_{ij}}{6} \quad (4)$$

Table 6. Summery of results of weighted average operation on fuzzy graph matrices.

Users	C.2S.3E	C.2E.3S	E.2C.3S	S.2C.3E	S.2E.3C	E.2S.3C	AWA
1	1.00	1.00	1.00	1.00	1.00	1.00	1.00
2	1.01	1.01	1.01	1.01	1.02	1.02	1.01
3	1.00	1.00	1.01	1.01	1.01	1.01	1.01
4	**1.13**	**1.13**	**1.25**	**1.25**	**1.38**	**1.38**	**1.25**
5	0.97	0.97	0.94	0.94	0.91	0.91	0.94
6	0.95	0.95	0.91	0.91	0.86	0.86	0.91
7	*<u>0.95</u>*	*<u>0.95</u>*	*<u>0.90</u>*	*<u>0.90</u>*	*<u>0.85</u>*	*<u>0.85</u>*	*<u>0.90</u>*
8	0.96	0.96	0.92	0.92	0.88	0.88	0.92
9	1.01	1.01	1.02	1.02	1.03	1.03	1.02
10	0.96	0.96	0.92	0.92	0.88	0.88	0.92

Table 6 summarizes the results of Weighted Average. Values in bold are the maximum ones and values in italic and underline are the minimum ones.

Similarly, we will have different results after applying different statistical operations on the same fuzzy graph matrices, for each of the medium of communication i.e. email (E), chat (C) and SMS (S) for analyzing human interaction in a university community. Following are the different equations from (5) to (9) for Average (AVG), Biased Weighted Averages for SMS (WAVS), Email (WAVE), and Chat (WAVC) and Average of all Biased Weighted Averages (WAVG) on the same fuzzy graph matrices, for each of the medium of communication i.e. email (E), chat (C) and SMS (S):

$$AVG_{ij} = \frac{E_{ij} + S_{ij} + C_{ij}}{3} \quad (5)$$

$$WAVE_{ij} = \frac{3 * E_{ij} + S_{ij} + C_{ij}}{5} \quad (6)$$

$$WAVS_{ij} = \frac{E_{ij} + 3 * S_{ij} + C_{ij}}{5} \quad (7)$$

$$WAVC_{ij} = \frac{E_{ij} + S_{ij} + 3 * C_{ij}}{5} \quad (8)$$

$$WAVG_{ij} = \frac{WAVE_{ij} + WAVS_{ij} + WAVC_{ij}}{3} \quad (9)$$

Table 7. Summary of all results of matrix operations on fuzzy graph matrices.

Users	AVG	WAVE	WAVS	WAVC	WAVG	AMM	AWA
1	1.00	1.00	1.00	1.00	1.00	1.63	1.00
2	1.01	1.01	1.01	1.02	1.01	1.61	1.01
3	1.01	1.00	1.01	1.02	1.01	1.62	1.01
4	**1.25**	**1.15**	**1.15**	**1.45**	**1.25**	**1.74**	**1.25**
5	0.94	0.97	0.97	0.90	0.94	1.58	0.94
6	0.91	0.95	0.95	0.84	0.91	1.60	0.91
7	*0.90*	*0.94*	*0.94*	*0.82*	*0.90*	*1.57*	*0.90*
8	0.92	0.95	0.95	0.86	0.92	1.66	0.92
9	1.02	1.01	1.01	1.04	1.02	*1.57*	1.02
10	0.92	0.95	0.95	0.85	0.92	1.64	0.92

The summery of all of the operations defined in equations from (5) to (9) applied on the three fuzzy graph matrices can be seen in Table 7. Values in bold are the maximum ones and values in italic and underline are the minimum ones. Therefore, it can be concluded statistically that eProfile 4 has the maximum level of communication in almost every medium of interaction and eProfile 7 has the minimum level of communication in every medium of interaction. This will lead us to define Indices for Interaction and Role.

Table 8 shows the summary results of the Matrix operations after applying Role Index and Interaction Index. User 4 has the most active role in the human community. Similarly, user 7 has the passive role and all other users have active role in the human community

Table 8. Applying Interaction Index and Role Index on the summary results.

Users	AVG	WAVE	WAVS	WAVC	WAVG	AMM	AWA	RI
1	M	M	M	M	M	M	M	A
2	M	M	M	M	M	M	M	A
3	M	M	M	M	M	M	M	A
4	**H**	**H**	**H**	**H**	**H**	**H**	**H**	**MA**
5	M	M	M	M	M	M	M	A
6	M	M	M	M	M	M	M	A
7	L	L	L	L	L	L	L	P
8	M	M	M	M	M	M	M	A
9	M	M	M	M	M	L	M	A
10	M	M	M	M	M	M	M	A

5. CONCLUSION AND FUTURE WORK

In this paper, Human Communities were analyzed successfully by using Fuzzy Graphs on the basis of human eProfile parameters. Interaction Index and Role Index emerged as two indices, which can classify or grade users, based on their interaction (in terms of Email, Chat and SMS) with other members of the human community [11]. Max-Min Composition [35] in Fuzzy Relation helps us in initiating the idea of combining three different medium of communication (i.e. Email, Chat and SMS) in one operation. All other statistical operations also upheld similar results and supplementing the analysis done in the desired direction. This analysis will lead us towards generating an algorithm which can help us in analysis of Human Communities and strengthen the ongoing research for Community Algorithm [7, 8, 9, 10, 11, 12, 13].

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