Estimating Virtual Trust of Cognitive Social Heterogeneous and Homogeneous Networks empowered with Hierarchal Socio Fuzzy Inference System

Ayesha Tariq[1], Shahan Yamin Siddiqui1[2], Gulnaz Safdar[1], Syeda Fareeha Batool Nasir[1], Muhammad Rehan Saleem[3], Waqas Ali[3], Bilal Shoaib[1], Muhammad Adnan Khan[4*]

[1]School of Computer Science, Minhaj University Lahore, Lahore, Pakistan.
[2]Department of Computer Science, National College of Business Administration and Economics, Lahore, Pakistan.
[3]Department of Computer Science, University of Management and Technolgy, Lahore, Pakistan.
[4]Department of Computer Science, Lahore Garrison University, Lahore, Pakistan.
*Corresponding Author: Muhammad Adnan Khan: madnankhan@lgu.edu.pk

Abstract
These days, Mobile Ad-hoc Network categorizes (MANET) are increasingly defenseless against different kinds of assaults because of shaky correspondence medium and framework less condition. Societal network for multi Heterogeneous Networks (HetNet) and Homogeneous Networks (HomNet) can support practically and pragmatically grounded considerate of the activities as well as the network's role in the system. A node may share and store information of its own HomNet or HetNet to another network environment. To implement a secure network setup for communication, in harmony with demanded information is important to select a suitable receiver. In this type of situation cognitive sensations such as trust plays a dynamic part. This paper represents a trust-based hierarchal socio fuzzy inference by combining social association to examine cognitive nodes for their parts as being persuasive, dependable, and credible. The proposed model adopts the MATLAB simulation the inputs and optimizing results show concurrency to the calculated values according to the Mamdani fuzzy inference system.
Key Words:
HetNet, HomNet, Trust, Cognitive nodes, malicious activity, Socio FIS.

1. Introduction:

A considerable quantity of study has thus concentrated on the improvement of trust and repute models in P2P networks. The use of fuzzy methods in the strategy of repute methods built on accumulating and combining peers' estimations. Fuzzy techniques are used in the estimation and combination of all the estimations communicated by networks. The performance of the suggested method is defined by the evaluation of probabilistic methodologies [1].
A trust and status model is predictable as the main methodology to support huge circulated device networks in IoT besides malicious node occurrences, then trust formation devices can stimulate association between distributed computing and communication objects, enable the recognition of unreliable objects, and support decision-making method of many protocols. Based on in-depth considerate of trust founding procedure and computable evaluation between trust formation systems, a trust and repute model IoT to impose the support among things in a network of IoT established on their performances. The accurateness, strength, and grace of the suggested model is authenticated over an extensive set of models [2].
Portable specially appointed systems can be shaped with no fixed foundation. A MANET is a foundationless system since the hubs having a place with the system can without much of a stretch move in the earth. It is because of this versatility of nodes, the organize topology can't be anticipated. In this condition every hub can have been a handset and beneficiary, so every hub can likewise go about as a switch and the hubs speak with one another with no fixed foundation [3]. On the off chance that both the sender and the beneficiary hubs are inside their radio range, at that point they will impart legitimately generally correspondence needs at least one transitional hub. This is called multi jump correspondence. In this manner, there are ordinarily circumstances when every hub goes about as a host and switch simultaneously [4]. MANETs are progressively powerless against assaults as a result of the open correspondence Medium.it is stated that the Social network service (SNS) can be easily assumed as a big network of community relations between the public, which highlights the communication and influence between the separate networks. The public network links the real domain and the virtual domain and grows a new system of community message to support the more improvement of the Internet. The public network refuges almost all the systems of network amenities with the fundamental of the human community. Public linkage data are representative multi-basis heterogeneous data created [5]. Proposed one of the most significant features in human interface and communication is trust. Trust is also an exact significant piece for all independent multi-nodes network. The

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valuation of the risk associated with the network's assessments in a setting of insecurity about data worth delivered by other networks is one of the greatest significant complications and so stimulating research areas in multi-nodes networks. The section offerings an innovative idea of trust forming an exploration process for independent multi-nodes networks. The system is based on the hypothesis that multi-node networks institutes public network and so it is an instantiation of a multipart network [6].

2. Related Work

It is stated that today's gradually complicated networks involve further material, information, and autonomic preparation. The network is presently used in several parts and it needs a network to succeed it. Orientation administration is one of the efficient parts of network administration that observer network and procedure structure material so that the belongings on the network process of several objects like forms of hardware and software features and transmitting counters can be trailed and succeeded. In structure, topology managing problems are even extra imperative in the perspective of mobile ad hoc networks (MANETs) [7].

Discusses new theoretic simulations for sympathetic the heterogeneous cellular systems of tomorrow, and the applied limitations and experiments that operatives must challenge in instruction for these systems to influence their perspective. To report the volatile development in data loads focused by smartphones, tablets, and other media-hungry devices, network operatives will have to pointedly grow the capability of their systems as well as decrease the rate provided by possibly two instructions of the level. The increase of internet-linked mobile strategies will remain to initiative evolution in data circulation in an exponential way, imposing network operatives to intensely grow the capability of their systems [8]. Trust and status simulations for circulated, collective methods have been planned and practical in some areas, in instruction to motivate collaboration while avoiding selfish and spiteful performances. The purpose of this paper is to explain the demonstrating of schemes that use (i) trust and repute to administer the connections between nodes, and (ii) communication simulations described by a high level of flexibility [9]. Proposed public network exploration for multi-network established simulations can maintenance bottomless and empirically beached considerate of the actions as well as the node's roles in the networks.

A network may save and segment material of its setting with further networks of the system. Applying a protected communication system, in agreement with demanded material is important to select a suitable receiver. In such a state of matters, perceptive occurrences as trust show a dynamic part. Nodes when inverse established on trust found demonstrative links of variable strength in their public network. This paper defines a trust established fuzzy inference model in a multi network system by integrating public relations and gives it to explore for networks for their parts as creature effective, reliable, and exposed [10]. To discover the unruly node in a homogeneous as well as a heterogeneous setting. Mobile Ad-hoc networks (MANET) are more exposed to several types of occurrences due to apprehensive communication standards and structure fewer settings. In such networks, to display the performance of nodes over an extensive situation it is suggested to comprehend an interruption discovery system with only a particular display mode to be selected [11]. It is proposed a summed up clustering intention to discriminate intruders, which had high acknowledgment level and low conduct and commemoration expenses. The ad hoc networks are exposed to outbreaks due to disseminated nature and deficiency of structure. Interruption recognition schemes deliver review and observing proficiencies that proposal the limited safety to a node and support to recognize the exact trust level of further nodes. The assembling procedures can be occupied as a further benefit in these dispensation reserved networks to collaboratively identify interruptions with fewer control procedures and insignificant above [12]. There is an estimated collection established disruption setting network and it observes the suggestion of overhead in group-based disruption detection structures and explored a few techniques for reduction of attacks. In any case, this approach has not assumed any secure scheming as much as time consumption. Manets are the ad hoc networks that are constructed on request or directly when some mobile nodes come in the flexibility variety of each other and choose to collaborate for data transfer and communication. So there is no clear topology for Manets. They interconnect in active topology which constantly variations as nodes are not established [13]. It is suggested to identify the mischievous node in a homogeneous as well as heterogeneous setting. In such systems, to display the performance of nodes terminated an extensive situation it is offered to recognize an interference recognition system with only a solitary display node to be picked [14]. To present, a cost constructed relative training of homogeneous and heterogeneous assembled instrument links. Efforts on the situation where the improper position is slightly sited and the device nodes are not mobile. And relating to the whole network dimensioning problematic proceeds into description the developed rate of the hardware along with the battery vitality of the nodes. A homogeneous device network contains matching nodes, whereas a heterogeneous device network contains two or further types of nodes [15]. Introduced as different to homogeneous networks, wherever supply reclaim one (with minor changes) is a moral communication system. To more develop broadband user capability in a permeating and cost-effective manner [16]. There is a present a metrics methodology, the first node dies (FND), Half of the nodes alive (HNA) and last node dies (LND), to describe the period of WSN. Virtual reality outcomes using NS-2.27 indications that the offered Leach- heterogeneous and enduring vitality built Leach procedure meaningfully decreases energy incorporation and growth the entire period of the wireless sensor network associated with the homogeneous LEACH protocol [17].

3. Interpersonal organization Societies among Cognitive nodes

Interpersonal network examination rose as a lot of techniques for the examination of social structures strategies that uncommonly permit examination of the social parts of these networks [18]. The utilization of these strategies, in this way, relies upon the accessibility of social instead of trait information [19]. The more the communication of operators is there, the increasingly social information will be there consequently better interpersonal network investigation could be led. Since, all things considered, social information can be gathered by general sentiments, this strategy is unrealistic if there should arise an occurrence of psychological specialists. Also, in actuality, the examination is directed from outside the human culture, though in the model viable, this investigation is led as a major aspect of the trust model incorporated into every specialist. It shows that conditional upon network formation, considerable growth in network period can be proficient as related to probabilistically choosing the nodes as constellation-skulls using only confined material. Wireless Sensor Networks (WSNs) extant a new group of real-time inserted systems with restricted reckoning, liveliness, and memorial possessions that are presently used in an extensive variety of applications where traditional networking setup is almost infeasible [20]. LEACH protocol using Fuzzy Logic (LEACH-FL), which proceeds the series level, detachment, and node concentration into consideration. The suggested process has existed shown manufacture a recovered range by association simulations using Matlab [21].

4. Social Networks in Multi Nodes Systems

Various trust mechanisms and models have been introduced which may be the key elements to design multi-node networks. This section presents a brief review of the works related to trust in multi-node networks from this decade [22]. Proposed fuzzy logic as an actual resource of convention these experiments, as much as both information exemplification and control execution are apprehensive. The definitive design for cross-layer optimization in perceptive radio networks is categorized by experiments such as modularity, inaccuracy, scalability, and complication constrictions [23]. Clustering is an actual methodology for establishing a network into a linked grading, load corresponding, and extending the network time. Fuzzy logic is accomplished by intelligently unification different factors. In accumulation, fuzzy logic is working to estimate the fitness (cost) of a node [24]. A fuzzy-logic-based assembling method with a postponement to the vitality prediction has been suggested to extend the time of wireless sensor networks (WSNs) by consistently allocating the capability. The simulation results display that the suggested method is further effective than other distributed procedures. [25]. Presented a novel idea to model trust for multi-node networks and proposed the idea of analyzing autonomous multi-node networks. They used the approach to define two classes of complex networks. Multi-node networks can be used for both simulation and evolution of social networks and can provide technical support for the services for networks. They have defined how the use of multi-node network technologies for the support of social networks. It is presented with various algorithms for the coordination of multi-node networks through consensus and diffusion of innovation in social networks. They proposed a common reference frame on the bases of gossip between nodes. The social network analysis can assist in modeling multi-node networks [26].
Computational Intelligence approaches like Fuzzy System [27,28,29], Neural Network [30], Swarm Intelligence [31] & Evolutionary Computing [32] like Genetic Algorithm [33,34], DE, Island GA [35], Island DE [36,37], Classifier [38], SVM [38], Hybrid Algorithm [39,40] and DELM [41-46] are strong candidate solutions in the field of smart city [47], wireless communication [48] and smart health [49-53] etc.

5. Estimation Trust of cognitive Multi-networks analysis: HetNet and HomNet Communication set-up

A multi-networking system has been appropriate resources for the displaying and reproduction of composite networks. This paper reflects a position containing four collections of networking from altered networks of a particular setup, (i.e. HomNet1, HomNet2, HetNet1, and HetNet2) that summarize particular characters as existence dependable. In actuality, the usage of such a methodology can offer significant outcomes in learning community exchanges and their part by providing the performance of those or sets of those and their communications. The network-based archetypal contains on a specific network, executed as software. Networks fitting to any specific set are in communication to individually additional and are presenting shortest trust (presented by hard outlines).

Internetworks communication is existence passed available through assured networks and therefore evolving shortest trust (exposed by spotted links). A specific network from a collection must consume an equal of virtual trust when it is necessary to start communication through a network of additional networks for that dependence approximation has remained passed out in the agreement to its nearby networks. Successively of the network basically quantities to instantiating a network populace of performances and interrelating through an added network. The examination directed here is created on a request of period wherever truthful networks are interrelating over data conversation. The measurements that add to the improvement and growth of dependability are proficiency, compassion, and reliability. Information consideration is the controller of admittance to material that may provide to harm the level of safety while released to others.

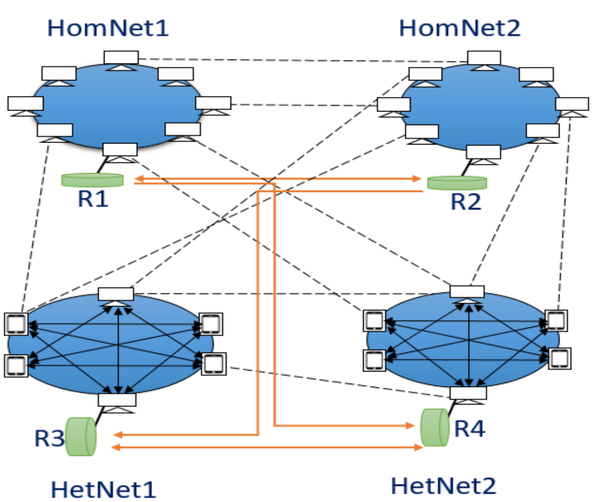


Fig. 1 Four different networks of Homogeneous and Heterogeneous Networks.

Here in figure1 four features can be definite as:
Solid black line represents Direct Trust (DT) between nodes/ hops, a solid orange line represents Direct Trust (DT) between routers (R). Dash lines represent Virtual Trust (VT).

Proficiency – trusting in the network's capability in liability what it is predictable for.

Reliability – presence truthful and worthy good standards.

Compassion – the objective of supportive performance

Consideration – whether demanded info is to be united using alternative networks.

discarded. But when we talk about Proficiency, Reliability, Compassion, and Consideration they belong to our problem, based on these parameters we may calculate the trust. As

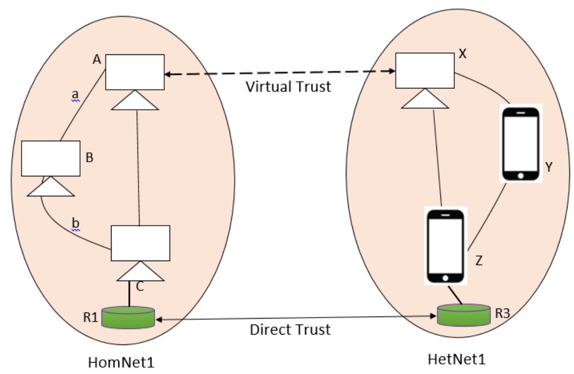


Fig. 2 Estimate trust level for Virtual Network

The above-stated divisions are constructing their consistent social networks over data conversation. Simply individual networks are measured that consume approximately the category of the message by as a minimum one network in the networking. Networking from one network can similarly connect with further networks through similar standards of existence reliability thus four different networks of homogeneous and heterogeneous as shown in Figure 1. We think through engaged diagram Figure 2 that displays the way of dependence level (e.g. "b" is faith that C has on B, "a" is belief level that B has on A, etc.). Supposing that C commencing network "HomNet1" here and now requests to connect with Y of networks "HetNet2", for an exact initial period. To construct the first trust ranks b, and a will be used and approximation of virtual network will be complete.

6. Proposed Hierarchal Socio Fuzzy Inference for estimating virtual trust to start communication between nodes

The three-element of honesty is built upon perception established trust, while information compassion and secrecy that is working to be communal essential also be detected. The intact four scopes are similarly significant while believing each other. From these magnitudes, current straight trust stages among the nodes are designed using the Fuzzy Implication Engine.

A proposed Fuzzy Inference System (FIS) methodology, which is used to calculate the Virtual Trust between Heterogeneous and Homogeneous Networks.

As in above figure3, let's consider 6 System factors like "Age, Beauty, Proficiency, Reliability, Compassion, and Consideration". Now take age and beauty there is no concern with the trust and with our problem, that why it

these factors are relevant to our problem that why we convert them to the fuzzy crisp input. After the fuzzy crisp input, Fuzzification will be applied.

Fuzzification includes three steps as shown in the above figure: (1) Fuzzifier (2) Fuzzy Inference Engine and (3) De-fuzzifier. Fuzzy Inference Engine depends on the Knowledgebase. The knowledgebase is further divided into (1) Membership Functions and (2) Fuzzy Rule Base. Based on these Direct Trust is calculated, there are multiple numbers of direct trust (minimum two) are calculated by different Direct Trust FIS Blocks. These multiple Direct Trust are going to Virtual Trust FIS Block to calculate Virtual Trust based on multiple Direct Trust.

A cascade fuzzy implication scheme with two layers from the perspective of beyond conversation is planned for the approximation of early dependence level among nodes to start communication.

In the meantime, the trust ranks have been considered through the fuzzy inference system, the inputs, and outputs are given in Tables 1 and 2.

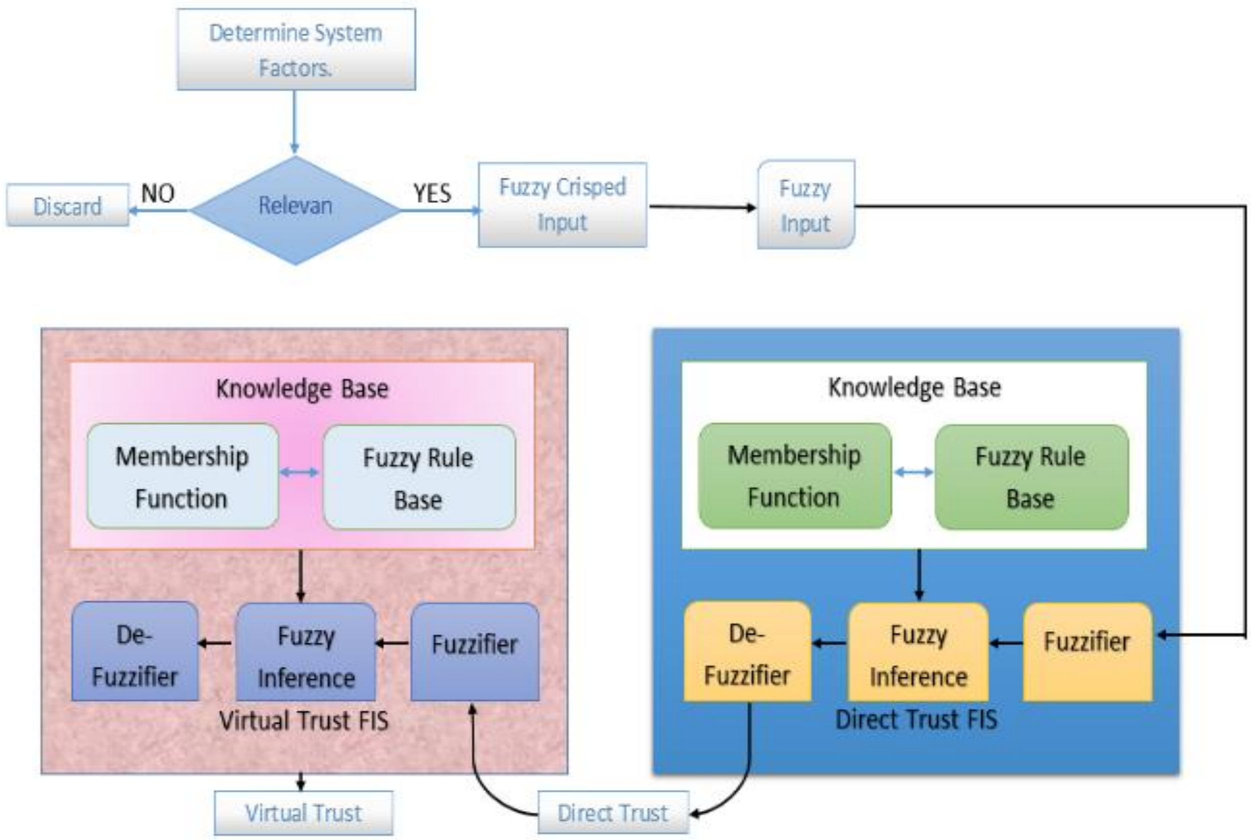


Fig. 3 Proposed Hierarchal Socio type-1 Fuzzy Inference System for estimating Virtual Trust to start communication between nodes.

Table 1: Ranges for Fuzzy Inference System for calculating weights of virtual trust

Proficiency (P)	{"Incapable", "Capable", "Highly Capable"}	[0 - 35 30 - 65 60 - 100]
Reliability (R)	{"Dishonest", "Honest", "Highly Honest"}	[0 - 40 35 - 70 65 - 100]
Compassion(C)	{"Indifferent", "Compassionate", "Highly Compassionate"}	[0 - 0.4 0.33 - 0.7 0.63 - 1]
Consideration(ω)	{"Public", "Semiprivate", "Private"}	[0 - 0.4 0.35 - 0.7 0.65 - 1]
Direct Trust (Td)	{"Weak", "Reasonable", "Strong"}	[0 - 0.4 0.35 - 0.7 0.65 - 1]

Table 2: Ranges for Fuzzy Inference System for calculating weights of virtual trust.

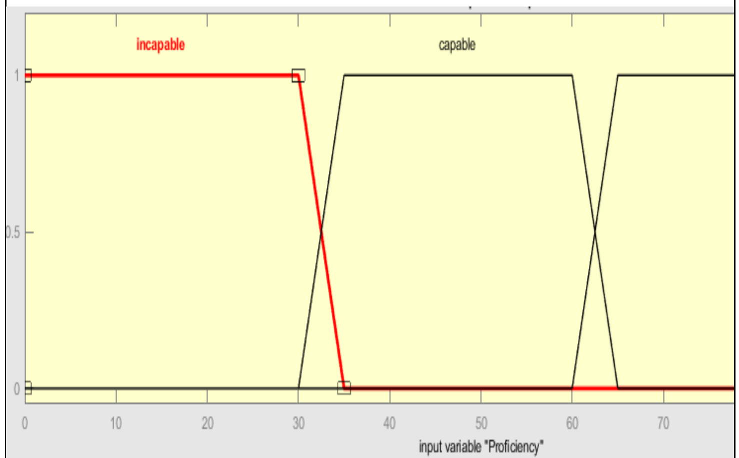
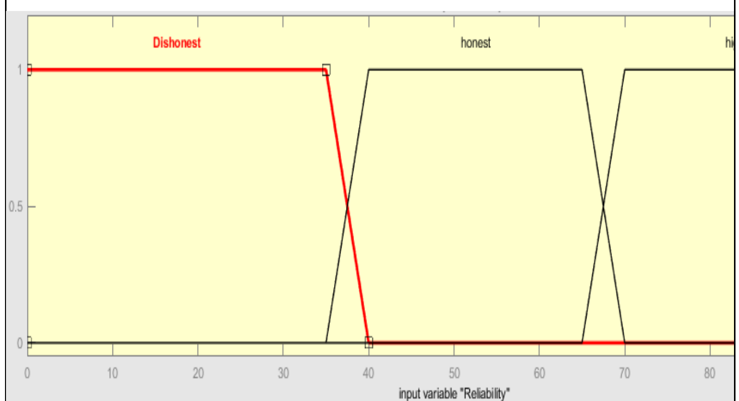
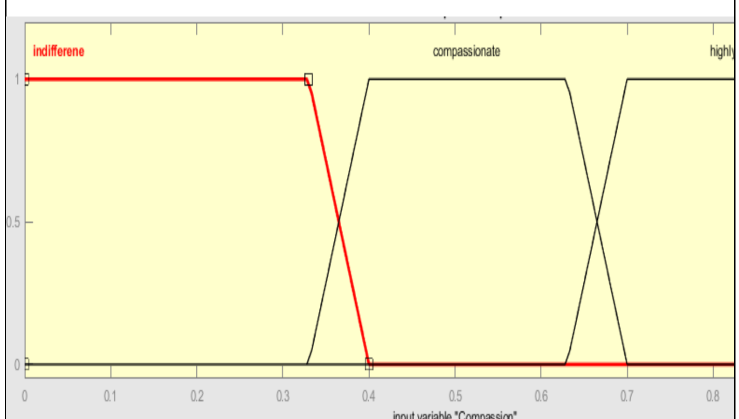
Direct Trust Td1	{" Weak", "Reasonable", "Strong"}	[0 - 40 35 - 70 65 - 100]
Direct Trust Td2	{" Weak", "Reasonable", "Strong"}	[0 - 40 35 - 70 65 - 100]
Direct Trust Td3	{" Weak", "Reasonable", "Strong"}	[0 - 40 35 - 70 65 - 100]
Virtual Trust VT	{" Weak", "Reasonable", "Strong"}	[0 - 0.4 0.35 - 0.7 0.65 - 1]

The above stated dimensions of trust given in Table-1 and Table-2 are arranged for all possible combination to build rules for the two levels of proposed fuzzy inference engine. The possible rules fed to the fuzzy system are covered later.

7. Membership Functions

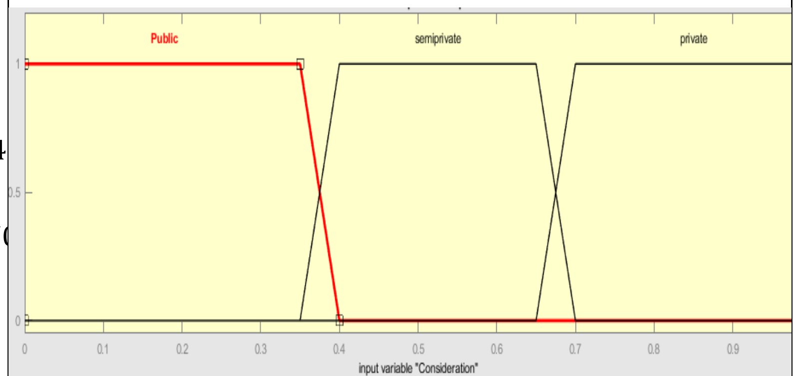
Membership functions for the proposed Socio fuzzy inference system are given in Tables 3 and 4.

Table 3: Mathematical & Graphical MF of Layer-1 Input/ Output variables

Input	Membership function	Sample MF Screenshot
Proficiency = P $\boldsymbol{\mu_P\ (p)}$	$\mu_{P,Incapble}\ (p) = \begin{cases} 1 & 0 \le p \le 30 \\ \frac{35-p}{5} & 30 \le p \le 35 \\ 0 & p \ge 35 \end{cases}$ $\mu_{P,Capble}\ (p) = \begin{cases} \frac{p-30}{5} & 30 \le p \le 35 \\ 1 & 35 \le p \le 60 \\ \frac{65-p}{5} & 60 \le p \le 65 \\ 0 & otherwise \end{cases}$ $\mu_{P,Highly\ capble}\ (p) = \begin{cases} 0 & p \le 60 \\ \frac{p-60}{5} & 60 \le p \le 65 \\ 1 & p \ge 65 \end{cases}$	
Reliability = R $\boldsymbol{\mu_R\ (r)}$	$\boldsymbol{\mu_{R,dishonest}\ (r)} = \begin{cases} 1 & 0 \le r \le 35 \\ \frac{r-35}{5} & 35 \le r \le 40 \\ 0 & r \ge 40 \end{cases}$ $\boldsymbol{\mu_{R,honest}\ (r)} = \begin{cases} \frac{r-35}{5} & 35 \le r \le 40 \\ 1 & 40 \le r \le 65 \\ \frac{70-r}{5} & 65 \le r \le 70 \\ 0 & otherwise \end{cases}$ $\boldsymbol{\mu_{R,highly\ honest}\ (r)} = \begin{cases} 0 & r \le 65 \\ \frac{r-65}{5} & 65 \le r \le 70 \\ 1 & r \ge 70 \end{cases}$	
Compassion = C $\boldsymbol{\mu_C\ (c)}$	$\boldsymbol{\mu_{C,indifference}\ (c)} = \begin{cases} 1 & 0 \le c \le 0.4 \\ \frac{0.4-c}{0.07} & 0.33 \le c \le 0.4 \\ 0 & c \ge 0.4 \end{cases}$ $\boldsymbol{\mu_{C,compassinate}\ (c)} = \begin{cases} \frac{c-0.33}{0.07} & 0.33 \le c \le 0.4 \\ 1 & 0.4 \le c \le 0.63 \\ \frac{0.7-c}{0.07} & 0.63 \le c \le 0.7 \\ 0 & otherwise \end{cases}$ $\boldsymbol{\mu_{C,highly\ compassinate}\ (c)} = \begin{cases} 0 & c \le 0.63 \\ \frac{c-0.63}{0.07} & 0.63 \le c \le 0.7 \\ 1 & c \ge 0.7 \end{cases}$	

<table>
<tr>
<td>Consideration = ω
$\mu_{\omega}\ (\omega)$</td>
<td>$\mu_{\omega,Public}\ (\omega)$ = $\begin{cases} 1 & 0 \le cn \le 0.35 \\ \frac{0.4-cn}{0.05} & 0.35 \le cn \le 0.4 \\ 0 & cn \ge 0.4 \end{cases}$

$\mu_{\omega,Semi\ private}\ (\omega)$ = $\begin{cases} \frac{cn-0.35}{0.05} & 0.35 \le cn \le 0.4 \\ 1 & 0.4 \le cn \le 0.65 \\ \frac{0.70-cn}{0.05} & 0.65 \le cn \le 0.70 \\ 0 & otherwise \end{cases}$

$\mu_{\omega,private}\ (\omega)$ = $\begin{cases} 0 & cn \le 0.65 \\ \frac{cn-0.65}{0.05} & 0.65 \le cn \le 0.70 \\ 1 & cn \ge 0.70 \end{cases}$</td>
<td></td>
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<tr>
<td>Direct trust = DT
$\mu_{DT}\ (dt)$</td>
<td>$\mu_{DT,week}\ (dt)$ = $\begin{cases} 1 & 0 \le dt \le 0.4 \\ \frac{0.4-dt}{0.05} & 0.3 \le dt \le 0.4 \\ 0 & dt \ge 0.4 \end{cases}$

$\mu_{DT,reasonalbe}\ (dt)$ = $\begin{cases} \frac{dt-0.3}{0.05} & 0.3 \le dt \le 0.4 \\ 1 & 0.4 \le dt \le 0.6 \\ \frac{0.7-dt}{0.05} & 0.6 \le dt \le 0.7 \\ 0 & otherwise \end{cases}$

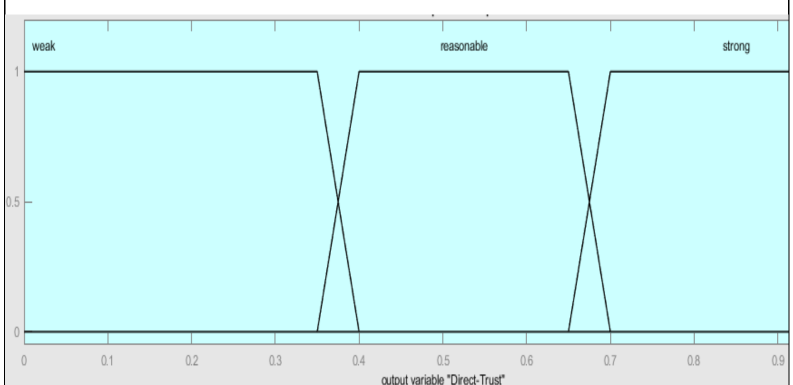
$\mu_{DT,strong}\ (dt)$ = $\begin{cases} 0 & dt \le 0.6 \\ \frac{dt-0.}{0.05} & 0.6 \le dt \le 0.7 \\ 1 & dt \ge 0.7 \end{cases}$</td>
<td></td>
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Table: 4 Mathematical & Graphical MF of Layer-2 Input/ Output variables

<table>
<tr><th>Input</th><th>Membership function</th><th>Sample MF Screenshot</th></tr>
<tr>
<td>Direct trust 1 = DT1

$\mu_{DT1}\ (dt1)$</td>
<td>

$$\mu_{DT1,week}\ (dt1) = \begin{cases} 1 & 0 \leq dt1 \leq 40 \\ \frac{40-dt1}{5} & 35 \leq dt1 \leq 40 \\ 0 & dt1 \geq 40 \end{cases}$$

$$\mu_{DT1,reasonalbe}\ (dt1) = \begin{cases} \frac{dt1-35}{5} & 35 \leq dt1 \leq 40 \\ 1 & 40 \leq dt1 \leq 65 \\ \frac{70-dt1}{5} & 65 \leq dt1 \leq 70 \\ 0 & otherwise \end{cases}$$

$$\mu_{DT1,strong}\ (dt1) = \begin{cases} 0 & dt1 \leq 65 \\ \frac{dt1-65}{5} & 65 \leq dt1 \leq 70 \\ 1 & dt1 \geq 70 \end{cases}$$

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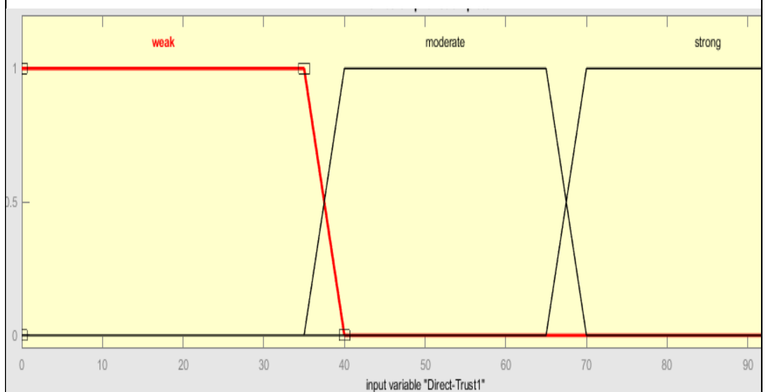

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<tr>
<td>Direct trust 2 = DT2
$\mu_{DT2}\ (dt2)$</td>
<td>

$$\mu_{DT2,week}\ (dt2) = \begin{cases} \mathbf{1} & \mathbf{0 \leq dt2 \leq 40} \\ \frac{\mathbf{40-dt2}}{\mathbf{5}} & \mathbf{35 \leq dt2 \leq 40} \\ \mathbf{0} & \mathbf{dt2 \geq 40} \end{cases}$$

$$\mu_{DT2,reasonalbe}\ (dt2) = \begin{cases} \frac{\mathbf{dt2-35}}{\mathbf{5}} & \mathbf{35 \leq dt2 \leq 40} \\ \mathbf{1} & \mathbf{40 \leq dt2 \leq 65} \\ \frac{\mathbf{70-dt2}}{\mathbf{5}} & \mathbf{65 \leq dt2 \leq 70} \\ \mathbf{0} & \mathbf{otherwise} \end{cases}$$

$$\mu_{DT2,strong}\ (dt2) = \begin{cases} \mathbf{0} & \mathbf{dt2 \leq 65} \\ \frac{\mathbf{dt2-65}}{\mathbf{5}} & \mathbf{65 \leq dt2 \leq 70} \\ \mathbf{1} & \mathbf{dt2 \geq 70} \end{cases}$$

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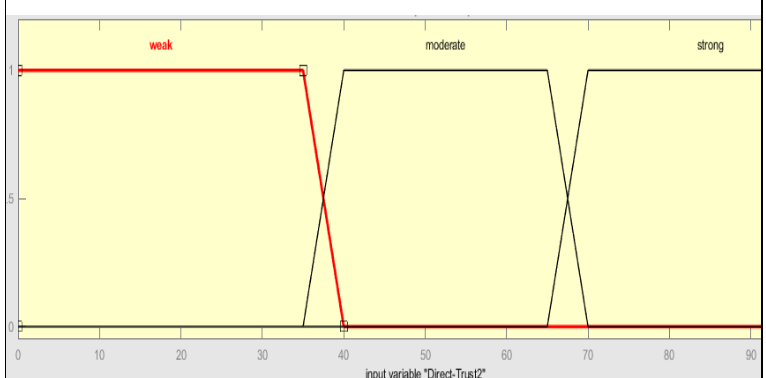

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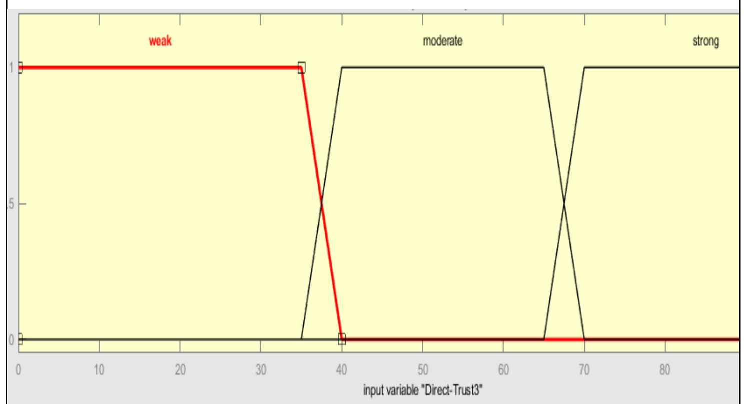
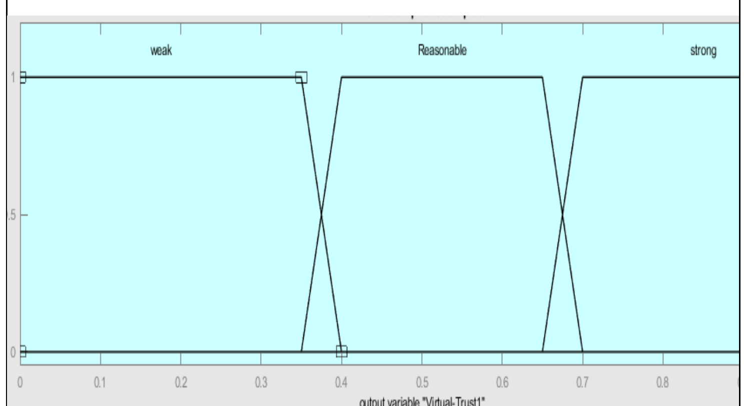
Direct trust 3 = DT3 $\mu_{DT3}\ (dt3)$	$\mu_{DT3,week}\ (dt3)$ = $\begin{cases} 1 & 0 \leq dt3 \leq 40 \\ \frac{40 - dt3}{5} & 35 \leq dt3 \leq 40 \\ 0 & dt3 \geq 40 \end{cases}$ $\mu_{DT3,reasonalbe}\ (dt3)$ = $\begin{cases} \frac{dt3-35}{5} & 35 \leq dt3 \leq 40 \\ 1 & 40 \leq dt3 \leq 65 \\ \frac{70-dt3}{5} & 65 \leq dt3 \leq 70 \\ 0 & otherwise \end{cases}$ $\mu_{DT3,strong}\ (dt3)$= $\begin{cases} 0 & dt3 \leq 65 \\ \frac{dt3 - 65}{5} & 65 \leq dt3 \leq 70 \\ 1 & dt3 \geq 70 \end{cases}$	
Virtual trust = VT $\mu_{VT}\ (vt)$	$\mu_{VT,week}\ (vt)$ = $\begin{cases} 1 & 0 \leq vt \leq 0.35 \\ \frac{0.4 - vt}{0.05} & 0.35 \leq vt \leq 0.4 \\ 0 & vt \geq 0.4 \end{cases}$ $\mu_{VT,moderate}\ (vt)$ = $\begin{cases} \frac{vt - 0.35}{0.05} & 0.35 \leq vt \leq 0.4 \\ 1 & 0.4 \leq vt \leq 0.65 \\ \frac{0.7 - vt}{0.05} & 0.65 \leq vt \leq 0.07 \\ 0 & otherwise \end{cases}$ $\mu_{VT,strong}\ (vt)$ = $\begin{cases} 0 & vt \leq 0.65 \\ \frac{vt - 0.65}{0.05} & 0.65 \leq vt \leq 0.7 \\ 1 & vt \geq 0.7 \end{cases}$	

7.1 Fuzzy Propositions

A compound fuzzy proposition is a composition of atomic fuzzy propositions using the connectives "and", "or", & "not" which represent fuzzy intersection, union, and complement respectively. Here, proficiency, reliability, compassion, and consideration are represented by p, r, c, and ω respectively. Here t-norm for layer-1 and layer-2 are defined as:

$$t: [0,1]\text{x } [0,1]\text{x}[0,1]\text{x}[0,1] \rightarrow [0,1] \quad (1)$$

$$t: [0,1]\text{x } [0,1]\text{x}[0,1] \rightarrow [0,1] \quad (2)$$

Eq. (1) transforms the membership functions of fuzzy sets of Proficiency, Reliability, Compassionate and Consideration for level 1 of proposed fuzzy inference system among membership function of the intersection of Proficiency, Reliability, Compassionate and Consideration that is: Above equation can also be write as follows:

$$t: [\mu_{\text{proficiency}}\,(p), \mu_{\text{reliability}}\,(r), \mu_{\text{compassionate}}\,(c), \mu_{\text{consideration}}\,(\omega) = \mu_{\text{directtrust}}\,(dt)] \quad (3)$$

$$t: [\mu_{\text{directtrust1}}\,(dt1), \mu_{\text{directtrust2}}\,(dt2), \mu_{\text{directtrust3}}\,(dt3) = \mu_{\text{virtual trust}}\,(vt)] \quad (4)$$

Whereas from eq. (2) membership functions of fuzzy sets of direct trust dt1, dt2 and dt3 among the membership function of the intersection of dt1, dt2 and dt3 for FIS level 2 as:

Eq. (3) can be written in terms of t-norm as:

$$\mu_{\text{proficiency}}\,(p) \cap \mu_{\text{reliability}}\,(r) \cap \mu_{\text{compassionate}}\,(c) \cap \mu_{\text{consideration}}\,(\omega) = \mu_{\text{directtrust}}\,(dt) \quad (5)$$

Similarly Eq. (4) can be interpreted as:

$$\mu_{\text{directtrust1}}\,(dt1) \cap \mu_{\text{directtrust2}}\,(dt2) \cap \mu_{\text{directtrust3}}\,(dt3) = \mu_{\text{virtual trust}}\,(vt) \quad (6)$$

7.2 Fuzzy IF-THEN Rules

To formulate the conditional statements that embrace fuzzy logic, if-then statements are used. These statements provide the core grounds to construct a fuzzy rule vase. In the current situation, few rules for layer 1 and layer 2 of the fuzzy inference system are provided as under:

IF (P is incapable and R is dishonest and C is indifference and ω is public) THEN (DT is a week)

IF (P is capable and R is honest and C is compassionate and ω is semi-private) THEN (DT is reasonable)

IF (P is *highly capable* and R is *Highly Honest* and C is *highly compassionate* and ω is *Private*) THEN (DT is *strong*)

Similarly, rules may be written for layer 2 of the proposed FIS as follows:

IF (DT1 is a *week* and DT2 is a *week* and DT3 is a *week*) THEN (VT is a *week*)

IF (DT1 is *reasonable* and DT2 is *reasonable* and DT3 is *reasonable*) THEN (VT is *moderate*)

IF (DT1 is *strong* and DT2 is *strong* and DT3 is *strong*) THEN (VT is *strong*)

7.3 Mamdani Implications

The fuzzy IF-THEN rule interpreted as a fuzzy relation Q81 with the membership function for the layer1 and Q27 with the membership function for the layer2 are as follows:

For Layer 1:

$$\mu_{81}(p, r, c, \omega) = min\,[\mu_{FP1}\,(p), \mu_{FP2}\,(r), \mu_{FP3}\,(c), \mu_{FP4}\,(\omega)] \quad (7)$$

For Layer 2:

$$\mu_{27}(dt1, dt2, dt3) = min\,[\mu_{FP1}\,(dt1), \mu_{FP2}\,(dt2), \mu_{FP3}\,(dt3)] \quad (8)$$

7.4 Fuzzy Rule Base (FRB)

Fuzzy IF-THEN rules are the constituents of the fuzzy rule base. FRB is the major component of the fuzzy system because all other components are used to implement these rules realistically and proficiently. FRB comprises the following fuzzy IF-THEN rules, where rules for layer 1 are denoted by Ru^m, where $1 \leq m \leq 81$:

Ru^1 = IF Proficiency is Incapable and Reliability is Dishonest and Compassion is Indifference and Consideration is PublicTHEN DirectTrust is Weak

Ru^2 = IF Proficiency is Capable and Reliability is Honest and Compassion is Compassionate and Consideration is SemiPrivate
THEN DirectTrust is Reasonable.

Ru^{81} = IF Proficiency is Highlycapable and Reliability is Highlyhonest and Compassion is Highlycompassionate and Consideration is Private
THEN DirectTrust is Strong.

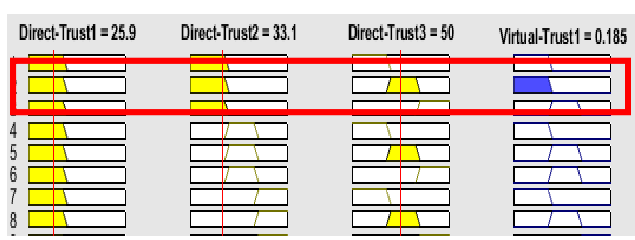


Fig. 4 Layer-1 rule viewer for proposed Socio Fuzzy Inference System

Now layer-2 is denoted by the ru^n, where $1 \leq n \leq 27$

ru^1 = IF DirectTrust1 is Weak and DirectTrust2 is Weak and DirectTrust3 is Weak
THEN VirtualTrust is Weak

ru^2 = IF DirectTrust1 is Reasonable and DirectTrust2 is Reasonable and DirectTrust3 is Reasonable THEN VirtualTrust is Reasonable
ru^{27} = IF DirectTrust1 is Strong and DirectTrust2 is Strong and DirectTrust3 is Strong
THEN VirtualTrust is Strong

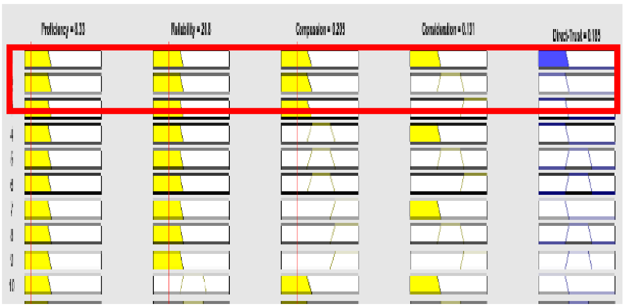


Fig. 5 Layer-2 rule viewer for proposed Socio type-1 Fuzzy Inference System

The above rules are in the form of canonical fuzzy IF-THEN rules as they comprise special cases of fuzzy prepositions and fuzzy rules; "Partial Rules" here.

7.5 Fuzzy Inference Engine (FIE)

In a fuzzy inference engine, fuzzy logic principles are used to combine the fuzzy IF-THEN rules in the fuzzy rule base into a mapping from an input fuzzy set to an output fuzzy set. A fuzzy IF-THEN rule is interpreted as a fuzzy relation in the input-output product space. Any practical fuzzy rule base constitutes more than one rules, the key question here is how to infer with a set of rules: There are two ways to infer with a set of rules: composition based inference and individual rule-based inference.
In FIE, fuzzy logic principals are used to combining the fuzzy IF-THEN rules.
Let Rum and run be fuzzy relation that represents any fuzzy IF-THEN rule.

$$Ru^m = P^m \times R^m \times C^m \times Cn^m \longrightarrow DT \quad (9)$$

$$ru^n = Dt1^n \times Dt2^n \times Dt3^n \longrightarrow VT \quad (10)$$

Accepting the first view of a set of rules, then the rules in the form are interpreted as a single fuzzy relation Q81 and Q27respectivly, are defined by:

$$Q_{81} = \cup_{m=1}^{81} R_u^m \quad (11)$$

$$Q_{27} = \cup_{n=1}^{27} R_u^n \quad (12)$$

The combination in eq. (11) and (12) are called Mamdani combination.

7.6 Product Inference Engine (PIE)

Let K, χ, and ϰ be random fuzzy set and remain the input and output of fuzzy Inference Engine (FIE) respectively. Then by inspecting Q81 and Q27 as a single fuzzy IF-THEN rule, we obtained the output of the FIS layer1 and layer2 as:

$$\mu_{weak \cap reasonable \cap strong}(\chi) = sup_{K \in (P,R,C,\omega)}\, t[\mu_K(p,r,rc,\omega), \mu_{81}(p,r,c,\omega,dt)] \quad (13)$$

$$\mu_{weak \cap moderate \cap strong}(\varkappa) = sup_{\chi \in (DT1,DT2,DT3)}\, t[\mu_\chi(dt1,dt2,dt3), \mu_{27}(dt1,dt2,dt3,vt)] \quad (14)$$

Mamdani composition based inference is used here. In product inference engine, we use:

1. Algebraic product for all t-norm operators.
2. Individual rule-based inference with union combination.
3. Mamdani's product implication.

We get PIE as:

$$\mu_{\chi(DirectTrust)} = \max_{1 \le e \le 81} \left[sup_{K \in (P,R,C,\omega)} \left(\prod_{r=1}^{81} \left(\begin{matrix} \mu_{P_r,R_r,C_r,\omega_r}(p,r,c,\omega) \\ \mu_{A_{1e},A_{2e},A_{3e}}\,(a1,a2,a3) \end{matrix} \right) \right) \right] \quad (15)$$

$$\mu_{\varkappa(VirtualTrust)} = \max_{1 \le f \le 27} \left[sup_{\chi \in (A1,A2,A3)} \left(\prod_{s=1}^{27} \left(\begin{matrix} \mu_{A_{1s},A_{2s},A_{3s}}\,(a1,a2,a3) \\ \mu_z\,(z) \end{matrix} \right) \right) \right] \quad (16)$$

Here, z is the output universe of discourse. Given a fuzzy set K, the product inference engine (PIE) χ acts as the output of layer1 and input of layer2 to calculate ϰ.

7.6 Defuzzifier

The defuzzifier is defined as a mapping from fuzzy set χ which is the output of FIE to crisp point Ό for layer1 and Ӫ for layer2. The task of the defuzzifier is to specify a point in output universe of discourse that best represents the fuzzy set χ.this is similar to the mean value of a random variable. A small change in χ should not change in Ό. The center gravity defuzzifier specifies the Ό as the center of the area covered by the membership function of χ, that is,

$$Ό = \frac{\int \chi \mu_\chi(\chi)\, d\chi}{\int \mu_\chi(\chi)\, d\chi}$$

And for layer2:

$$Ӫ = \frac{\int \varkappa \mu_\varkappa(\varkappa) d\varkappa}{\int \mu_\varkappa(\varkappa) d\varkappa}$$

Here ∫ is the conventional integral. The above equations calculated the output crisp values for direct trust between nodes of heterogeneous and homogeneous networks and virtual trust between nodes of different heterogeneous and homogeneous networks.

8. Fuzzy Logic Simulation and Results

Fuzzy logic has Boolean logic and that works partially true or false values. Fuzzy systems deal with the Boolean values in fuzzy logic or membership values in fuzzy sets that are indicated by a value on the range [0, 1], with 0 representing absolute Falseness and 1 representing absolute Truth. The proposed Socio Fuzzy inference system has been simulated on MATLAB and the simulated graphs have been presented in Figure (5-7) for direct trust and Figure (8, 9) for virtual trust estimation. For an effective communication setup, a node needs to possess a particular level of reliability and compassion. Graph simulation for these factors affecting the direct trust level among nodes is depicted in Figure 5. Although being integral is significant, whereas in the absence of reliable communication is not effective and hence trust level will be low. On the other hand with the rise of these dimensions, direct trust rises accordingly. These variations can easily be seen in Figure 6.

The proposed Hierarchal Socio type-1 Fuzzy Inference system has been simulated on MATLAB and simulated graphs have been presented in the following figures.

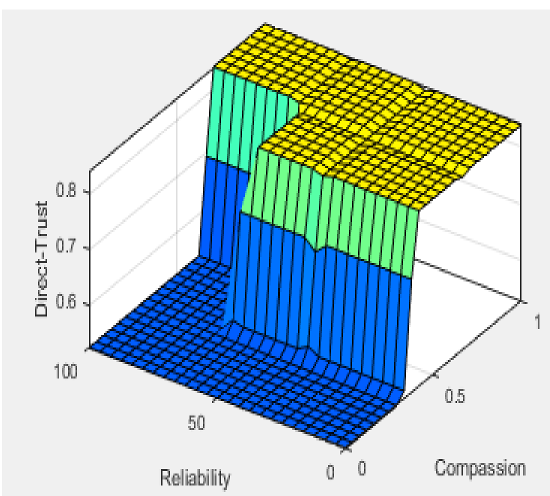


Fig. 5 Direct Trust level Dependency on Reliability and Compassion.

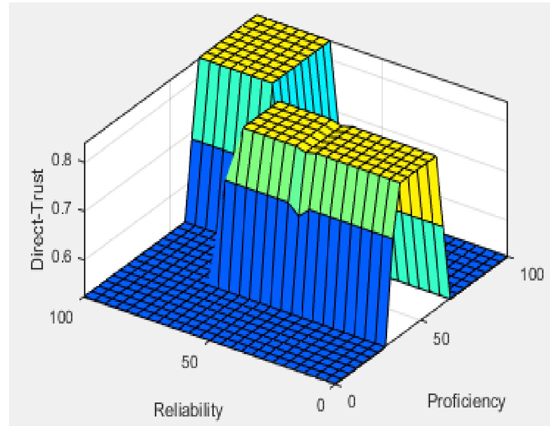


Fig. 7 Direct Trust level Dependency on Proficiency and Reliability.

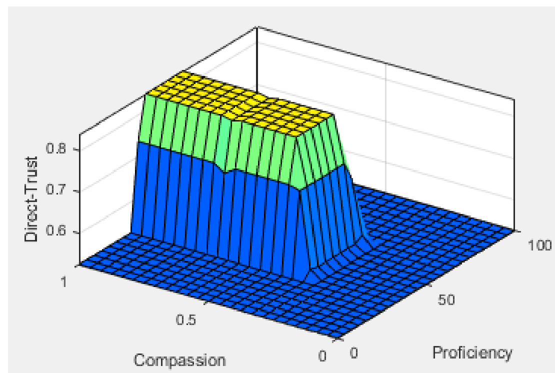


Fig. 6 Direct Trust level Dependency on Compassion and Proficiency.

Figure 7 shows the accumulative effect of reliability and proficiency on direct trust. In the absence of details for information security, the trust level is moderately influenced by compassion and proficiency.

While estimating virtual trust a node with neighboring to build direct trust is very persuasive.

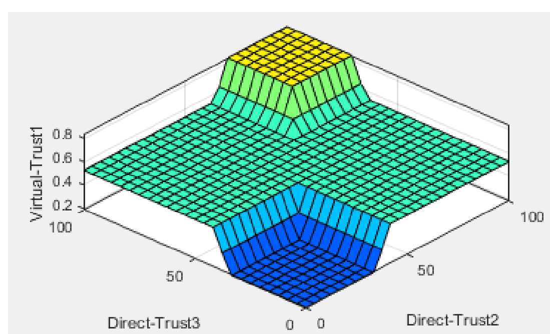


Fig. 8 Virtual Trust level Dependency upon DirectTrust3 and DirectTrust2.

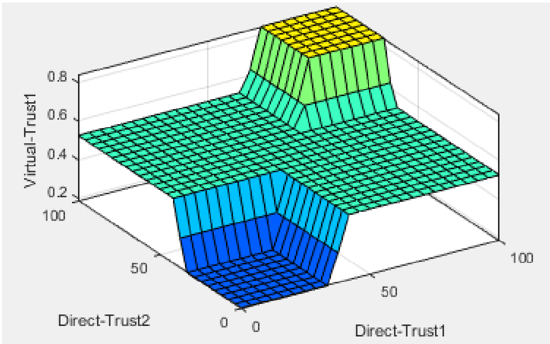


Fig. 9 Virtual Trust level Dependency upon DirectTrust2 and DirectTrust1.

Information sensitivity is the control of access to information that might result in loss of security if exposed to every node. No matter at which reliability level a cognitive node is, it will compromise over mutual trust level to maintain security level. This situation is depicted in the simulation graph shown in Figure 7. While estimating virtual trust a node's correspondence with neighboring nodes to build direct trust is very persuasive. As shown in scenario depiction in Figure 2 node A is trying to establish a virtual trust on X through its neighboring nodes B and C. Direct trust levels in multi-node systems extremely effect the level of virtual trust. This fact is clearly shown in Figure 8 and Figure 9. The virtual trust level depends not only on the neighboring trust levels but also on the relativity of the level.

9. Conclusion

Estimating preliminary trustworthiness has been a significant aspect of networking to avoid malicious activities. This paper has presented one of the potentials for a multi-network system to communicate between networks and perform cognitively to estimate virtual trust level. The computational fuzzy inference system simulation model has been proposed to measure virtual trust to start communication between heterogeneous and homogeneous networks. The relative impact of neighboring trust on virtual trust estimation has also been experienced. In the future, the development may be implemented using deep learning techniques, artificial neural networks, and some other advanced techniques of machine learning to make the system more dynamic.

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Authors Profile:

Ayesha Tariq is the student of Minhaj University Lahore Pakistan. She is doing Master of Philosophy in Computer Science from the School of Computer Science, Minhaj University Lahore, Pakistan. Her research interest includes Knowledge Based Systems, Networking and Machine Learning.

Mr. Shahan Yamin Siddiqui is currently working as an Associate Head at the School of Computer Science, Minhaj University Lahore, Lahore, Pakistan. He is doing a Ph.D. from School of Computer Science, NCBA&E, Lahore, Pakistan. He received the B.S degree in Electrical Engineering from the School of Engineering, University of Management and Technology, Lahore, Pakistan. He completed his Master of Electrical and Computer Engineering from the School of Science and Technolog, University of Management and Technology, Lahore, Pakistan. He became the member of Pakistan Engineering Council as registered engineer in 2013. His association with IEEE was established as member in 2019 and acting as an Advisor of IEEE-MUL Student Branch. Shahan's research interests primarily include Fuzzy Systems, Computationl Intellignece, Machine Learning, Cloud Computing, Image Processing, Conginitive Machines, Intelligent Agents, IoT and Smart City with various publications in international journals and conferences.

3.Gulnaz Safdar is the student of Minhaj University Lahore, Paksitan. She is doing Master of Philosophy in Computer Science from the School of Computer Science, Minhaj University Lahore Pakistan. Her area of research is Medical Diagnosis, Fuzzy Modelings, Intelligent agents and Computational Intelligence.

Syeda Fareeha Batool Nasir is the student of Minhaj University Lahore, Pakistan. She is doing Master of Philosophy in Computer Sciences from the School of Computer Science, Minhaj University Lahore, Pakistan. Her research interests primarily include Machine Learning, IoT and Password Identification

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Muhammad Rehan Saleem was born in Jhang, Pakistan. He received the B.S degree in Electrical Engineering from University of Management and Technology, Lahore, Pakistan in 2013 and obtained M.S degree in Electrical Engineering from University of Engineering and Technology, Lahore, Pakistan in 2017.He became the member of Pakistan Engineering Council as registered Engineer in 2013. From 2014 to 2015 He served in B.Z.U Lahore Campus as Lecturer. He is currently working as Lecturer under computer science department in the University of Management and Technology, Lahore, Pakistan since 2015. His research interests include soft computing, Machine learning, Artificial intelligence and IoT.

Waqas Ali was born in Lahore, Pakistan. He received the B.S. degree in Computer Science from University of Management and Technology, Lahore, Pakistan, in 2015 and obtained M.S. degree in Software Engineering from the same University, in 2018. He worked as a Software Developer in AssortTech private limited from 2014 to 2015. He is currently working as Lecturer in Computer Science Department in UMT since 2015. He has strong programming skills and he also mentor his programming students for speed programming competitions. He won Technology and Innovation Award in 2019 from University of Balochistan and Entrepreneurship Award from UMT in January 2020. His research interests includes Natural Language Processing, Information Retrieval and Machine Learning.

Bilal Shoaib did his BS degree from Comsats Institute of Information Technology Lahore. He did his MS and PhD studies from International Islamic University Islamabad. He is an author of more than 25 international publications. He is currently working as an assistant professor in Minhaj University Lahore.

Muhammad Adnan Khan is currently working as an Assistant Professor at the Department of Computer Science, Lahore Garrison University, Lahore, Pakistan. He completed his Ph.D. from ISRA University, Pakistan by obtaining a scholarship award from the Higher Education Commission, Islamabad, Pakistan. He also completed his M.Phil. & BS degrees from the International Islamic University, Islamabad, Pakistan by obtaining scholarship award from the Punjab Information & Technology Board, Govt of Punjab, Pakistan. Before joining the Lahore Garrison University, Khan has worked in various academic and industrial roles in Pakistan. He has been teaching graduate and undergraduate students in computer science and engineering for the past 12 years. Presently, he is guiding 04 Ph.D. scholars and 04 M.Phil. Scholars. He has published about 150 research articles in International Journals as well as reputed International Conferences. Khan's research interests primarily include MUD, Image Processing & Medical Diagnosis, Channel Estimation in Multi-Carrier Communication Systems Using Soft computing with various publications in journals and conferences of international repute.