Linguistic Fuzzy Logic Enhancement of a Trust Mechanism for Distributed Networks

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Abstract—Trust is, in some cases, being considered as a requirement in highly distributed communication scenarios. Before accessing a particular service, a trust model is then being used in these scenarios to determine if the service provider can be trusted or not. It is done usually on behalf of the final user or service customer, and with little intervention of him/her. This is usually happening with the main aim of automatizing the process, but also because trust models are normally making use of reasoning mechanisms and models difficult to understand by humans. In this paper we propose the adaptation of a bio-inspired trust model to deal with linguistic fuzzy labels, which are closer to the human way of thinking. This Linguistic Fuzzy Trust Model also uses fuzzy reasoning. Results show that the new model keeps the accuracy of the underlying bio-inspired trust model and the level of client satisfaction, while enhancing the interpretability of the model.

Index Terms—Linguistic Fuzzy models, Trust management, wireless networks.

I. INTRODUCTION

The Internet, with its services, has changed our life in the last few years. In fact, we are using it as a way to access online services and applications ranging from simple web pages with news to on-line payment systems or e-banking solutions. For the first set of services, trust is advisable, but in most cases it is not a must. However, for the latter trust represents a key requirement that should be considered by any user before getting access to a service.

Traditional ways of managing trust are no longer applicable when dealing with highly distributed scenarios. To deal with these scenarios new models have been designed and implemented in the last few years. They are based on different techniques, including fuzzy systems, Bayesian networks, bio-inspired models, social networks or analytic expressions, among others.

However, most of these techniques usually offer a low level of interpretability of the results being provided as part of the model. As trust is such a sensible issue for humans, clients feel more comfortable if they understand how the trust management process works. Poorly interpretable models makes difficult both the interaction between the final client and the model, and the sense that users can make of the results being provided by the trust model.

The human mind has the remarkable capability to perceive and reason using words instead of numbers. It is, in fact, the more natural way in which people expresses and acquire its experience and knowledge. Interestingly, most of the words used to describe perceptions or categories are rather vague and imprecise. Temperature perceptions are usually referred to with words like “warm”, “hot” or “cold” instead of precise measurements or numbers. Science and computers usually work with numbers. In fact, Science has been working quite hard to go from perceptions to measurements.

Nevertheless, even with the great successes of this numeric approach, the description of the systems based on measurements tend to be quite difficult to understand, even for experts. It would be interesting to express knowledge about a system using these rather vague words and allow automatic optimization techniques to provide useful models that, using such human words, still provide competitive performances.

Fortunately there exists a representation and inference tool that allows for that hybridization in a natural way. Such a tool is fuzzy logic. In the work proposed in this paper, linguistic fuzzy logic and fuzzy reasoning provides the framework for knowledge representation, model transparency and inference for a trust model for distributed environments. An ant-colony optimization would be guided using such Linguistic Fuzzy Trust Model (LFTM). The resultant system is able to provide a platform that achieve very high levels of client satisfaction. A system that is, at the same time, easy to interpret, thanks to the use of linguistic fuzzy logic, and very efficient in its job of providing a very good service.

The paper is structured as follows. Section II describes the linguistic fuzzy approach and mentions some related work for trust and reputation management. Next, in section III the underlying base trust model is described. Section IV covers the newly proposed linguistic fuzzy enhanced trust model. The experiments and results are described in section V. Finally, the paper ends in section VI where the main conclusions and some future work is presented.

II. BACKGROUND

A. Fuzzy Sets

“Everything is vague to a degree you do not realize till you have tried to make it precise, and everything precise is so remote from everything that we normally think, that you can not for a moment suppose that is what we really mean.
when we say what we think” [1]. Bertrand Russell states here
that humans do not normally think in very precise terms. He
also suggests that precision move us away from what we
really think. In fact, it is interesting to note that validity of
most human concepts is a matter of degree [2]. Therefore any
natural way to express our thinking should allow for the use
of vague words.

Fuzzy sets [3] are sets where a member can have partial
membership. This provides a good tool to represent the
aforementioned vague concepts, categories or perceptions that
human mind is so familiar with. A typical fuzzy set (see
Figure 1) usually has some members with full membership
in a kind of core, prototype or canonical elements. There
are also some other members with decreasing membership
as we move away from the core. This can easily represent
the usual category that has some elements that comply with
all the characteristics and therefore we are certain of its
categorization. At the same time there are some other elements
that may not comply with all the characteristics, or maybe
there is not enough information to be sure, or perhaps the case
presents other sources of uncertainty about the membership.
These latter elements may still be considered in such category
but, by using fuzzy sets, they will belong with a reduced
or partial membership. The fuzzy membership of a value \(x\),
defined on a domain \(D\), to a fuzzy set \(S\) is usually represented
as \(\mu_S(x) \in [0..1]\).

B. Linguistic Fuzzy Logic

One of the most useful features of fuzzy sets is the
possibility of attaching a linguistic label, that is, a word, to
them [4]. This allows the membership value of an element
to the set to represent the confidence of such element being
described by the word. In order to be useful for our purposes
this is performed in the reverse order. That is, given a word
or a linguistic label, a human user defines a fuzzy set that
matches his subjective semantics about that word. So, elements
with total confidence of being represented by the word get
full membership values to the underlying fuzzy set. Likewise
elements with less confidence get reduced fuzzy membership
proportional to the decrease in confidence.

This use of linguistically labelled fuzzy sets is called
linguistic fuzzy approach. This use is not to be confused
with the most commonly found precise fuzzy approach. In
the precise approach the fuzzy sets are defined to better fit
the data instead of being defined to better fit the words given
by humans. Precise fuzzy models are universal approxima-
tors with similar performances to neural networks and, with
some minors restrictions, functionally equivalent to them [5].
Unfortunately, precise fuzzy modeling also share with neural
networks the poor understandability.

In this work a pure linguistic fuzzy approach is used [6].
This provides transparent models easy to understand. Although
this usually comes at the cost of precision the proposed model
is powerful enough as to produce underlying models that
match the human given definitions for the linguistic fuzzy sets
without a loss in performance.

C. Fuzzy partitions and the linguistic approach

So fuzziness allows a quantitative domain to be transformed
into a quasi-quantitative one with soft boundaries between the
different categories. The process of converting a number into a
fuzzy word is called fuzzification. Note, however, that not any
group of fuzzy sets definitions can be used naturally as cate-
gories for a variable. In order to be a useful set of categories
defined over a domain some properties should be taken into
consideration for the fuzzy definitions and domain partitions.
These constrains on the membership functions increases its
semantic interpretability [7].

One of such important properties is called completeness or
coverage, that states that any value of the domain should have
some membership to at least one fuzzy set. This means that
the categories should cover all possible values. Normality, or
that each category have, at least, a value with full membership,
is also important to have because a concept which is always
somewhat vague is rather questionable and not too representat-
tive. Yet another useful property is distinguishability, that is,
that no point can have full membership to more than one
fuzzy set. This means that the categories do not overlap in
its representative values. If they do overlap then one of the
categories would be superfluous and confusing and may easily
lead to inconsistencies.

In the current work a strong fuzzy partition will be used to
define the underlying fuzzy sets (that will be linguistically
labelled). A strong fuzzy partition has the following properties
being \(S_i\) fuzzy sets defined over the domain \(D\) and \(x\) a value
of such domain:

\[
\forall i, \exists x \in D, \mu_{S_i}(x) = 1 \quad (1)
\]

\[
\forall x \in D, \exists i, j \forall k \ i \neq j, k \neq i, k \neq j, \mu_{S_i}(x) + \mu_{S_j}(x) = 1 \quad (2)
\]

The first expression ensures normality. The second expres-
sion states that any particular value of the domain can belong,
at most, to two different fuzzy sets \((S_i, S_j)\) and that the
addition of the membership values for any given value of the
domain is equal to one. Note that this last expression implies
both: \(\forall x, \sum_i \mu_{S_i}(x) = 1\) (sum of all memberships equals one)
and \(\forall x, \exists i, \mu_{S_i}(x) > 0\) (coverage). Figure 1 shows a typical
strong fuzzy partition. Linguistic labels \(L_i\) will be associated
with each defined fuzzy set \(S_i\).

D. Trust and reputation management

Regarding trust and reputation management there are some
authors who have applied bio-inspired algorithms in order
to perform such management. Some examples are QDV [8],
AntRep [9], TDTM [10] and the one which constitutes the
basis of our new proposal, called BTRM-WSN [11].

Moreover, some other researchers exploited the benefits of
fuzzy logic and fuzzy representation in order to deal with this
topic, leading this way to the development of models such as
PATROL-F [12], AFRAS [13] or PTM [14], amongst others.
However, as far as we know, this is one of the first works combining both methodologies in this field, profiting from the advantages of each. Bio-inspired techniques have been proved to obtain quite good outcomes. At the same time, the expressivity achieved by the use of fuzzy logic and linguistic labels make the models which use them human interpretable.

III. Base Trust Model

Our enhancement proposal is based on a previous trust and reputation management scheme for wireless sensor networks called BTRM-WSN [11]. In this section we will summarize the functionality of this trust and reputation mechanism.

BTRM-WSN is a bio-inspired algorithm based on an Ant Colony System [15], following the 5 generic steps for a trust and reputation model proposed in [16], [17]:

1) Gathering information
When the algorithm is launched, a set of artificial ants are deployed over the network. Those ants leave some pheromone traces throughout the paths they travel. Their goal is to find the most trustworthy node providing a certain service, required by the client executing BTRM-WSN. To do so, they follow the pheromone traces left by previous ants. Thus, the greater the pheromone trace a specific path has, the more feasible such route is to be selected as the one leading to the most reputable node.

2) Scoring & ranking
Once the ants have found a path leading to a node providing the requested service, a score has to be given to each of those paths. Such assessment is done through the following expression:

\[ Q(S_k) = \frac{\tau_k}{\text{Length}(S_k)PLF} \cdot \%A_k \]  

(3)

where \( S_k \) is the path returned by ant \( k \), \( \tau_k \) is the average pheromone of such path, \( PLF \in [0, 1] \) is a path length factor and \( \%A_k \) represents the percentage of ants that have selected the same solution as ant \( k \).

3) Entity selection
The path \( S_i \) with a highest value of \( Q(S_i) \) is selected by BTRM-WSN as the one leading to the most trustworthy server in the network.

4) Transaction
The client explicitly requests the service to the selected node, who will provide such service (the one he was offering) or even a worse one, depending on his goodness. The client then evaluates the received service and computes his satisfaction with the performed transaction.

5) Reward & punish
If the client was satisfied with the received service, a reinforcement in terms of pheromone addition to the path leading to the final service provider is done. Otherwise, if the server cheated, a punishment in terms of pheromone evaporation is carried out. Thus, we either promote such path (so future ants will choose it with higher probability), or we downgrade it (having less opportunities to be selected again).

IV. Linguistic Fuzzy Trust Model

The main objective of the current proposal is to assess the application of linguistic fuzzy sets and fuzzy logic to several concepts within our trust and reputation model. On one hand it will be enjoyed the representation power of linguistically labeled fuzzy sets, as is the case, for instance, of the satisfaction of a client or the goodness of a server. On the other hand, it will be exploited the inference power of fuzzy logic, as in the imprecise dependencies between the originally requested service and the actually received one, or the punishment to apply in case of fraud. The expected outcome will be an easy to interpret system with competitive performance.

As mentioned, a set of linguistic labels describing several levels of a variable or concept could be associated to a fuzzy set. The set is defined in a way that captures the underlying notion of such word for that particular concept. Typical linguistic labels include: “Very Low”, “Low”, “Medium”, “High” and “Very High”. The defined fuzzy sets associated to such labels for the case of client satisfaction are depicted in Figure 1.

![Linguistic Labels and its defining Fuzzy Sets](image)

Fig. 1. Linguistic Labels and its defining Fuzzy Sets

Human users usually have a common sense or an experience based notion of the dependencies between related concepts. It is also quite common that such perceived dependences are imprecise in nature. A simplistic example is the common sense based notion that states that a tall person tend to be quite heavy in weight. That can be expressed as “IF person is Tall then person is Heavy”, with Tall or Heavy being fuzzy concepts. Linguistic fuzzy if-then rules are an adequate representation and inference tool for such type of knowledge.

Fuzzy rules can be expressed in several forms. For the case of study a fuzzy grid will be used and explained later. A rule is composed of an antecedent part, where the activation condition is expressed, and a consequent part where an action or a conclusion is presented. The antecedent is usually a logic expression. In fuzzy rules a basic logic expression is the membership of a variable value to a set as in "person is Tall". Those basic expressions are then connected with logic connectives, being the most common the AND operator. Likewise, the most common consequent is the membership of an output variable to a fuzzy concept. These are known in fuzzy terminology as Mamdami-Type rules. In fuzzy logic the truth value of logical expressions is not binary but ranges from zero to one allowing for partial truth. The fuzzy logic operators, AND, OR, NOT are adapted to allow for

\[ \text{AND} \]

\[ \text{OR} \]

\[ \text{NOT} \]
such partial truth. Fuzzy operators also produce a partial truth value to the whole logic expression. A typical if-then linguistic fuzzy rule would look like as:

If quality is Good AND price is Low
THEN satisfaction is Very High (4)

The perception of quality being Good or price being Low may vary from total confidence to no confidence at all. But, unlike traditional logic, it may also be any value in between. In other words, a price being Low can be partially true. This partial truth for each condition is combined through the fuzzy AND operator and the whole logic sentence of the antecedent is so evaluated. As can be guessed, the truth value of the consequent part is precisely that one achieved by the whole antecedent logic expression.

So if, for example, the truth value of the expression “quality is Good AND price is Low” is 0.3, then the system concludes that the expression “satisfaction is Very High” has a truth value of 0.3. When in a given situation several fuzzy rules are activated a collection of conclusions is produced. These separate conclusions are aggregated into a final result and, if needed, defuzzified back into a numerical value. Details of how fuzzification, fuzzy inference, aggregation and defuzzification work can be found in [18], [19]. The defuzzification method chosen to be used in this research work is Center of Gravity.

A fuzzy grid is a collection of fuzzy rules in a matrix form. Each row/column represent one of the input variables. In order to represent the whole input space each row and column includes all the linguistic labels defined over the represented input variable. Remember that, the way in which the fuzzy sets were defined, using a strong fuzzy partition, ensures that any measured value in a variable would have some membership to, at least, one linguistic fuzzy concept (and at most to two) so full coverage is obtained. Each cell in the matrix represent an AND combination of its row/column truth valued labels, that is, the antecedent of the fuzzy rule. The content of the cell represents the consequent of the rule. Therefore a fuzzy grid represents as many rules as cells it has. Of course a fuzzy grid can have more than two dimensions.

Each domain has linguistic variables that are more appropriate to use than others. Temperature uses “warm” or “hot”, length uses “long” or “short”, and width uses “wide” or “thin”. In this work, to keep things simple and avoid distractions, very generic labels, that can be used in most domains, were used. Nevertheless it is strongly encouraged to use the most natural words/labels for the categories in each variable domain when applied for real. In table I the sets of labels used in each variable are shown.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Labels</th>
</tr>
</thead>
<tbody>
<tr>
<td>Price, Server Goodness, Quality of service, Client Satisfaction, Client Conformity</td>
<td>Very Low, Low, Medium, High, Very High</td>
</tr>
<tr>
<td>Attribute Comparison</td>
<td>Much worse, Worse, Similar, Better, Much Better</td>
</tr>
</tbody>
</table>

Table I: Sets of linguistic labels used in the different variables

Figure 2 depicts the flow of our approach, emphasizing those steps where we actually applied linguistic fuzzy sets and fuzzy logic. Such steps are:

1) The trust and reputation model BTRM-WSN selects the server to have a transaction with
2) Such server has a perceived certain goodness (“Very high”, “High”, “Medium”, etc.)
3) According to the required service attributes and the server goodness, the later provides a better, worse or equal service than the expected
4) Both the required service and the actually received one are compared, using certain subjective weights for the services attributes
5) The client satisfaction is assessed by means of the services comparison performed in previous step, and the client conformity
6) Finally, the punishment level is determined by the client satisfaction with the received service, together with his/her goodness

Next, it will be described the different fuzzy grids used in the proposed model. The tables were created using the knowledge of a human expert and follows a very intuitive notion of...
the relation among variables. Table II.(a) represents the fuzzy rules followed by a server when decides the quality of the service to be provided. Such decision depends on the Server Goodness and the requested quality of the service. As can be seen in the grid, very good servers actually provide better services than the requested ones and vice versa. Table II.(b) shows the rules used by the servers to decide the price of the service to be provided. In this case the decision depends on Server Goodness and the price of the requested service. By looking at the grid it is easy to see that, for example, if the goodness of the server is “Very High” and the price of the requested service is “High”, then the price of the actually provided service will be “Low”.

In this work it has been defined a service as composed by four perceived properties: price, cost, quality and delivery time. Tables II.(c) and II.(d) shows the fuzzy rules that describe how the user perceives a comparison between same features of two services. The first table (c) is used when comparing attributes where the higher the value the better, as in quality. The second table (d) does the opposite, that is, it compares features where the lower the value the better, as in price or delivery time.

Once the client receives the service from the server, it compares its attributes individually with the corresponding attributes of the requested service. In our proposal, a client can establish certain subjective weights to each property comparison (a client might consider the price much more important than the quality or the delivery time, or vice versa, for instance). Therefore, a weighted aggregation of the two services properties comparison is performed in order to get the final services comparison.

Such comparison, together with the client conformity, provides the final client satisfaction with the received service. This assessment is performed by means of the fuzzy rules shown in table II.(e). Thus, a very conformist client will be most of the times highly satisfied, regardless the behavior of a server (even if it is malicious and provides a worse service than the requested one). On the contrary, a very exigent client will need a very good service in order to be satisfied; otherwise, his/her satisfaction will be “Low” or “Very Low”.

Finally, the client satisfaction, together with the client goodness, will decide the level of reward/punishment to be applied to the selected server. Table II.(f) shows the fuzzy rules that describe such imprecise relation. A very benevolent client might not want to apply a high punishment (small negative reward), even if he/she was highly unsatisfied (very low satisfaction). But if the client is not that benevolent, then most of the times a high or very high punishment will be carried out.

If the client satisfaction is “Medium” or higher, the client is supposed to be satisfied, and a reward is performed. Otherwise, the client is supposed to be dissatisfied and the corresponding punishment is carried out.

Usually, but not necessarily always, both client conformity and goodness might be very related issues. Nevertheless, the main reason for separating both concepts, was to make our proposal as much generic as possible, so that it can be applied in a wider variety of scenarios.

V. EXPERIMENTS AND RESULTS

In this section we present the experiments carried out in order to test the accuracy of our new proposal as well as the enhancement with regard to our previous model, where no fuzzy logic was applied.

The evaluation environment used in this research work was TRMSim-WSN [20], a generic framework aimed to serve as an assistant tool in order to easily implement and compare trust and reputation mechanisms in distributed environments.
Table III summarizes the parameters used to perform these experiments. We have measured the selection percentage of trustworthy servers, as well as the length of the path leading to such nodes, and the percentage of "types of satisfaction", all of them over static networks where neither the topology, nor the goodness of each peer varied along the time.

A. Selection percentage of trustworthy servers

The first result refers to the percentage of trustworthy service providers that each model (BTRM-WSN and LFTM) have been able to achieve. Thus, figure 3 shows the performance of BTRM-WSN on this respect. As it can be observed, the accuracy of the model decreases as the percentage of malicious servers and the total number of nodes increases. However, even in the worst case of a network composed by 500 peers where 90% of the servers are malicious, BTRM-WSN can still succeed and select the appropriate service provider in near the 80% of the cases.

This improvement is mainly due to the reward and punishment mechanism. Since the goodness and conformity values of a client are “Medium” (according to table III), when a malicious server is unfortunately selected to provide the required service, the service actually provided is “Much Worse” than the expected one. Therefore, the satisfaction of the client is “Very Low” (table II.(e)) and the reward is “Very Low” (table II.(f)) as well, which actually means that a slight punishment is carried out.

In figure 4 the corresponding result for LFTM have been plotted. A slight enhancement has been achieved here, as it can be checked. In most of the cases the accuracy of the model is never below a 95%. Only with the biggest networks this percentage decreases to a minimum of around 90% (when the amount of malicious nodes is maximum).

B. Path length

The second experiment measured the length of the path suggested by each model, leading to the most trustworthy node found. It is worthy to mention here that by adjusting the radio range of the nodes of each network, we are able to have, on
average terms, the same number of neighbors regardless the size of the network.

Knowing this, outcomes got for BTRM-WSN model can be observed in figure 5. It shows the fact that, as the percentage of malicious servers increases, it is more difficult to find the most trustworthy one, and the ants have to explore longer paths. Additionally, the high punishment applied when a malicious provider is chosen might force ants to try alternative (and maybe longer) paths in order to find the benevolent nodes. However, in the worst case the average length of the paths is between 4 and 4.5 hops.

![Fig. 5. BTRM-WSN: Path length](image)

Regarding LFTM, figure 6 depicts its corresponding outcomes for this particular experiment. As we can see, LFTM is able to find closer reputable nodes. The reason is again the same. Since those paths leading to malicious nodes are not so strongly punished, ants can still explore in the proximity of the client. Thus, the largest average path length achieved by LFTM in this experiment is around 2.5 hops from the client.

![Fig. 6. LFTM: Path length](image)

C. Clients satisfaction

Lastly, we measured in this last experiment the percentage of clients who were “Very High”, “High”, “Medium”, “Low” and “Very Low” satisfied, respectively. Outcomes can be observed in figure 7.

![Fig. 7. LFTM: Clients satisfaction](image)

As expected, most of the clients had either a “Very High” or just a “High” satisfaction. And this proportion remains almost invariable regardless the size of the network. It slightly worsens, however, as the percentage of malicious server increases. In such situation some clients had “Low” or even “Very Low” satisfaction.

VI. CONCLUSIONS AND FUTURE WORK

Trust and reputation are concepts with which we deal every day. Trust and reputation management in distributed environments has been recently proposed as a mechanism for tackling certain risks not fully covered by traditional network security schemes, obtaining reasonably good results.

Many approaches have been followed for handling these elements. In this paper we combine two of them, getting the benefits and advantages of each. We have therefore applied linguistic fuzzy logic and fuzzy sets to a previous bio-inspired trust and reputation model for wireless sensor networks.

By doing this, we enhance the interpretability of the model, making it more human-friendly, or human-readable, while keeping, and even improving the accuracy of the underlying trust and reputation model.

As for future work, we are planning to test our proposal in a wider spectrum of scenarios like, for instance, dynamic networks with nodes continuously entering and leaving the community, or oscillating ones, where the behavior of service providers might change along the time.

Finally, it is worthy to mention that the outcomes obtained in this experiment are directly related to the definition of the underlying fuzzy sets presented in figure 1. A small variation of those underlying fuzzy definitions would likely change these results as the paths were discovered by the ants using these particular definitions. Since there is a rather long chain of fuzzy decisions
(see figure 2) the variations in results, if alternate definitions are used, would accumulate. Note, however, that this is also true for crisp systems and in a more acute way as transitions are not soft. Fuzzy rules and fuzzy reasoning are, in general, more resilient to such noise than crisp rules or systems. The degree of such resilience to small changes in the underlying fuzzy set definitions while keeping unmodified the ant discovered paths is an interesting line for future experiments. Likewise, another line would be testing the performance of the ant algorithm for very different definitions as this would show the robustness of its optimization independently of the human words utilized.

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