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Trust Prediction Using Z-numbers and Artificial Neural Networks

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***Abstract* -Trust modeling of both the interacting parties in a virtual world, is a critical element of business intelligence. A key aspect in trust modeling is to be able to accurately predict the future trust value of an interacting party. In this paper, we propose an intelligent method for predicting the future trust value of a trusted entity. We propose the use of Z-number to represent both the trust value and its corresponding reliability. Subsequently, we apply Artificial Neural Network (ANN) to predict future trust values. We generate a large number of synthetic time series, with a view to model real-world trust values of trusted entity. We validate the working of our methodology using the generated time series.**

I. Introduction

TRUST technology, in the virtual world, seeks to help build business reputation, consumer confidence, fair trading and mutual relationships. In e-transactions, trust between interacting parties is a critical aspect in having and maintaining a fair trading marketplace. One of the main goals of managing and modeling trust is to have the capability of forecasting future trust values of the interacting parties accurately [1, 2]. Interactions based on mutual trust, in both business and society, have fewer risks and bring greater satisfaction than those where there is no previous knowledge about the interacting counterpart [3]. There are few approaches to forecasting trust between organizations in the existing body of work [1]. Additionally, in the context of recommendations-based trust computation, when an agent is asked to express the amount of trust that he or she has in another agent, the response may sometimes be as a linguistic expression rather than a real trust value. The reliability of an agent's judgment is a crucial factor in decision making; hence, we are interested in using the concept of Z-number to convert such linguistic expressions (expressing the trustworthiness of the trusted agent) to quantitative values to enable future trust value prediction. Marsh [4] was the first researcher that defined trust in distributed artificial intelligence. Several researchers in the area of computing use the definition given in [5] by Gambetta, who defines trust as "Trust is a particular level of the subjective probability with which an agent will perform a particular action, both before we can monitor such action and in a context in which it affects our own actions".

The concept of predicting values has existed for many years. Different methods such as Markov model, Bayesian models, Neural networks etc., have been developed and used for various applications such as forecasting energy, weather, demands, and resources [6-8].

In some of the existing proposed trust models, the assigned trust value is qualitative, and this assigned trust value forms the basis for recommendations. Given that these linguistic expressions of trust values (which form the basis for recommendations), and the reliability of the recommendations needs to be taken into account, for predicting trust values, in this paper we utilize Z-number introduced by Zadeh [16] to convert qualitative expressions to real numbers. In this paper, we consider time series for trust prediction in two broad scenarios – trust prediction in the short-term (or immediate future time slot) and trust prediction in the medium term. In order to validate the working of our prediction approach, we generate a time series for each of these scenarios and make use of Artificial Neural Networks (ANNs) for trust prediction.

A. Z-number

The concept of Z-number has been proposed by Zadeh et al [16]. As pointed out by Zadeh [16], a Z-number models and encapsulates the reliability of information and has two components Z= (A, B). The variable *A* is a fuzzy subset of the domain, and the variable *B* captures the degree of reliability or certainty of *A*. The variable *B* could be perception-based and can be described in a natural language such as *High*, *Sure*. The variable *A* denotes the fuzzy restriction R(X) on the values which X can take. In other words A is the possibility distribution over X. More specifically,

$$R(X): X \text{ is } A \equiv \quad Poss\ (X = u) = \mu_A(u) \tag{1}$$

Where $\mu_A(u)$ is the membership function of A and u is a generic value of X. $\mu_A(u)$ may be viewed as a constraint which is associated with R(X).

A Z-number is used to give information about the uncertain variable X, where *A* represents the value of the variable and B represents the degree of certainty with which the variable takes on the value of *A* [17]. A Z-valuation indicates that X takes the value of A with the degree of certainity specified by variable B.

For example, some of these Z-valuations are:

- Trust in the service provider (High, Likely);
- Demand for product (Low, Sure);
- Anticipated budget increase (About 5 million, Not Sure)

As pointed previously, a Z-number is closely related to the linguistic variables, and Z-valuations provide additional information about the associated variable. In [18], a theorem that converts the Z-number to the usual fuzzy sets was proven. In this work, we use this theorem to convert the linguistic expressions of trust values, and model then as Z-numbers.

B. *Artificial Neural Network*

Artificial Neural Networks (ANN) are inspired by the way the biological nervous system processes information. ANNs usually are applied when there is no theoretical evidence about the functional form, thus ANNs are data-based, not model-based. The key element of ANNs is the novel structure of the information-processing system, which is composed of a large number of highly interconnected processing elements (neurons) working in unison to solve specific problems. An ANN is defined for specific tasks, such as data classification, function approximation and so on. ANNs are normally arranged in three layers of neurons and hence are referred to as multilayer structures: input layer, hidden layer and output layers. The input layers are neurons (nodes or processing units), and the hidden layers combine the inputs with weights during the learning process. The output layer provides the estimation of the network [25]. In this work we make use of the Multilayer perception.

The rest of the paper is organized as follows. In Section II we review the existing work on trust prediction, trust evaluation and uncertainty, and explain the related works. In Section III we explain the method of converting the Z-numbers to real-valued numbers, describe the construction of time series for short-term and medium-term for trust prediction, and make use of the ANN to predict future trust values. In Section IV, we describe the experimental results after running the proposed method, and Section V concludes our work.

II. Related work

In the past decade, a number of trust models have been proposed with increased research attention and focus on online provision and social communities [1,28]. Trust prediction models intelligently determine the future trust values of a given agent (or service) [9]. In [10] the SVM-based model was developed to infer the trust relationships between two users based on their individual interactions with other users. Prediction techniques were used to measure bidirectional effects on trust values on online social networks [11]. In [12], Wang et al. proposed the method to study situational transaction trust, which binds the trust ratings of previous transactions with a new transaction. Wang et al. used a fuzzy regression model in [14] to predict the trust values in uncertain areas. This model uses Fuzzy Linear Regression Analysis (FLRA) to mine qualitative knowledge from trust values and then models trust in the future. Markov Chains were proposed in [15] to predict trust and reputation values. This model has the ability to model three kinds of input data: data with seasonal variations, data with trend, and random data sets. The literature on trust forecasting and estimation can be divided into two main classes. In the first class of approaches, a deduction of the "existence of trust" among agents is determined or carried out. It focuses on determining whether trust exists between two agents. The other class of trust prediction work focuses on the estimation of "trust values" in a future time spot. A key shortcoming of stated studies is that there that they do not model (or account for) the reliability of a future trust value. To address this shortcoming, in this paper we make use of Z-number for trust modeling and develop an approach to reliability predict future trust values.

III. Proposed model

The goal of this work is to predict the trustworthiness of a trusted agent (or trusted party). To carry out this process, it is necessary to use the historical data of trust values; in the other words, the past interactions between the given trusted agent and all its interacting parties (or trusting agents), and the value assigned to the trusted agent by each of them. The prediction of trustworthiness has various applications; however in every application the period of time over which data is predicted is a crucial factor. The overall trust value (of a given trusted agent) may change as a function of time, due to the following reasons:

1) The volume of trust assessment related information about the trusted agent may vary as a function of time;
2) The satisfaction levels with the service provided by the trusted agent may change as a function of time or over time randomly;
3) The opinion of other agents (who have interacted with the trusted agent) may influence the overall trustworthiness of the trusted agent.

Trust predictions can be carried out in a short-term, middle-term or long-term period. In this work, we focus on the short-term and middle-term trust prediction. For short-term trust prediction, in our work we assume the time slot to be one month; thus, an interaction between other agents in the community and the trusted agent has to take place once in a month. Correspondingly, in this scenario, the trusted agent is assigned a trust value once per month. In this paper, we consider the length (or duration) of the short-term period to be 12 months and the middle-term period to be 21 months. In our experimentation, in the short-term period, we have 12 interactions between other agents in the community and the trusted agent, from which we try to predict the future trust value of the trusted agent (corresponding to its behavior). In the middle-term period, the available number of trust values from which we try to predict the future trust value is 21. The reason for constructing the scenarios in two categories, i.e., short-term period and middle-term period in this work is to model that the available trust-related information of the trust entity will be different. The time series we build for short-term trust prediction is premised on the assumption that trusting agent has insufficient information about the trusted agent because of the inadequate number of interactions between the two agents (relative to the medium-term period). The constructed time series models the overall trust value of the given trusted agent as a function of time, and all the trust values are given equal importance or weight during trust value prediction. Based on this time series, we make use of ANN to predict trust values. Our proposed model defines each trust value as a Z-valuation. The rationale for using Z-numbers is that they implicitly model and support the reliability of the trust values either assigned to the trusted agent in each interaction time slot or after each interaction.

The theorem below is proven in [18] and transforms the Z-number to a classical fuzzy set according to the Fuzzy Expectation of fuzzy numbers.

A. Convert Z-numbers to Classical Fuzzy Numbers

Definition 1: Let a fuzzy set A be defined on a universe X which may be given as: A = {(x; $\mu_A(x)$) |x $\in$ X} where A: X → [0; 1] is the membership function of set A. The membership value $\mu_A(x)$ describes the degree of belongingness of x $\in$ X in A.

Definition 2: The Fuzzy Expectation of a fuzzy set is denoted as:

$$E_A(x) = \int_X x.\mu_A(x)dx \tag{2}$$

Assume Z-number $\widetilde{Z} = (\widetilde{A}, \widetilde{B})$. Let $\widetilde{A} = \{x, \mu_{\widetilde{A}}(x)) \mid x \in [0.1]\}$ and $\widetilde{B} = \{x, \mu_{\widetilde{B}}(x)) \mid x \in [0.1]\}$. $\mu_{\widetilde{B}}(x)$ is a triangular membership function and $\mu_A(x)$ is a trapezoid membership function. The three steps shown below are performed to convert the Z-numbers to normal fuzzy numbers.

1) Convert the reliability part (second part) of Z-number to a crisp number

$$\alpha = \frac{\int x\, \mu_{\tilde{B}}(x)dx}{\int \mu_{\tilde{B}}(x)dx} \tag{3}$$

2) Add α of the second part of Z-number to the first part

The weighted Z-number can be denoted as:

$$\tilde{Z}^{\alpha} = \{(x, \mu_{\tilde{A}^{\alpha}}(x)) | \mu_{\tilde{A}^{\alpha}}(x) = \alpha.\mu_{\tilde{A}}(x), x \in [0,1]\} \tag{4}$$

$$E_{\tilde{A}^{\alpha}}(x) = \alpha E_{\tilde{A}}(x), \quad x \in X \tag{5}$$

$$\text{s.t.} \quad \mu_{\tilde{A}^{\alpha}}(x) = \alpha.\mu_{\tilde{A}}(x) \tag{6}$$

3) Convert a weighted restriction to the normal fuzzy number:

After converting Z-numbers to fuzzy restrictions, these equations are used to convert the weighted fuzzy sets to classical fuzzy sets.

$$\tilde{Z}' = \{(x, \mu_{\tilde{Z}'}(x)) \mid \mu_{\tilde{Z}'}(x) = \mu_{\tilde{A}}(\frac{x}{\sqrt{\alpha}}), x \in [0,1]\} \tag{7}$$

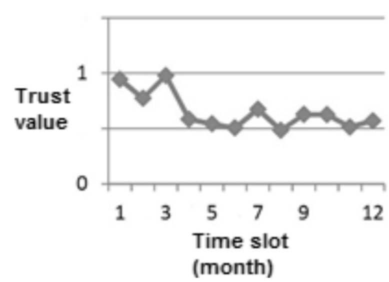
$$E_{\tilde{Z}'}(x) = \alpha E_{\tilde{A}}(x) \qquad x \in \sqrt{\alpha}X \tag{8}$$

$$\text{s.t.} \quad \mu_{\tilde{Z}'}(x) = \mu_{\tilde{A}}(\frac{x}{\sqrt{\alpha}}) \quad x \in \sqrt{\alpha}X \tag{9}$$

As discussed above, we define three linguistic terms (with each other term corresponding to a different trust level) to model and to construct the time series (comprising of sequential trust values) of a given trusted agent. In this work we consider that the interactions have taken place in the short-term period and middle-term period only. In the next section, we outline and discuss the procedures for simulating interactions, both in the short-term and medium-term.

B. Short-term Period Simulation

For short-term trust prediction, the time period is 12 months, as opposed to 21 months for medium-term prediction. Correspondingly, assuming one trust value per time slot, we assume the volume of trust-related information available to the trusting agent, in short-term trust prediction is relatively less as compared to medium-term trust prediction. We define each trust value, in the time series, as a Z-valuation. We make use of three linguistic terms to represent trust values ("*Low*", "*Medium*", or "*High*"). Each of the linguistic terms is assumed to be a trapezoid fuzzy set. x=0 denotes *Low* trust; x=1 denotes *High* trust; and values between are used to denote *Medium* trust. We also classify the reliability of each trust value (that the trusting agent assigns to the trusted agent), in three triangular fuzzy sets "*Likely*", "*Usually*", and "*Sure*". Figures 3 and 4 show the membership functions of each component of the trust Z-valuation. In a time period of one year, while constructing the time series, we assume that a third of all the interactions, between two agents correspond to the trust value indicated by one linguistic term.. We then generate all the possible permutations of *Low*, *Medium* and *High* trust for each third of one year to construct the 27 scenarios for the short-term period. As mentioned previously, we categorize the reliability of the trust values that the trusting agent gives to the trusted agent in three classes that represented in Fig. 4. The defined reliability classes are: *Likely*, *Usually*, *Sure*. The reliability value is randomly selected for each trust value. The theorem represented in A is used to convert each trust value (in the form of a Z-number) to a normal fuzzy set, and defuzzification methods are then used to change this fuzzy set into real numbers that show the trust values in each time slot. Three defuzzification methods "*Centroid*", "*Middle of maximum*", and "*Largest of maximum*" are applied randomly to convert these trapezoid fuzzy sets to real-valued numbers [19-21]. For example, the {High, Medium, Medium} scenario is shown in Fig. 1 below. Lastly, we apply ANN to predict future trust values. ANN is considered an appropriate tool for approximating nonlinear problems and is also useful in forecasting various values in a time series [22], which is the main reason of utilizing it in our algorithm.



C. Middle-term Period Simulation

The number of time slots during medium term, are more than that in the short-term period, and hence it is not appropriate to use approach for generating the time series for short-term trust prediction in this case. In the medium-term trust prediction, relative to the short-term trust prediction, there would be more information about the trusted entity. The approach for generating the time series used for medium term trust-prediction approach should implicitly model and consider this when carrying out trust prediction.

We assume that the time period for the middle-term is 21 months. Similar to the previous section, there is one trust value available for the trusted agent at each time slot. This trust value could be from one of the three different trust levels (*Low Trust*, *Medium Trust*, *and High Trust*). For simulating the time series in over a medium-term, we divide the time period into three parts.

Part 1 of the time series corresponds to trust values for the first 9 months, in which the trusting agent has no information about the trusted agent. For the Part 1, we make use of the same approach as that of short-term prediction. Following construction, the theorem in Section 3.1 is used and defuzzification methods are applied to convert the trust values into real-valued numbers.

Part 2 of the time series corresponds to the trust values for the subsequent 9 months. In this part of the time series, we assume that the behavior of the trusted entity corresponds to one trust level only. We model the reliability values of trust values under the assumption that in the last three months of Part 1 and in Part 2 more information of the trusted entity is available than before. Consequently the reliability of the trust assessment in these time slots are more higher than those in the previous time slots. In our simulation, during these time slots, we model them such that the trust values assigned over these time slots have lower variance, compared to the trust values assigned in the previous time slots. Hence to construct the time series for Part 2, we compute the mean of the last three trust values of Part 1. If this value belongs to the *Low trust* fuzzy set, the second part will begin with the concept *Low trust* and continue with the concepts *Low trust* and *Medium trust*. If this value belongs to the *Medium trust* fuzzy set, the second part will begin with the concept *Medium trust* and continue with the concepts *Medium trust* and *High trust*; and if it belongs to the *High trust* fuzzy set, the second part will begin with the concept of *High trust* and continue with the concepts *High trust* and *Medium trust*. The reliability of each trust value in this part is randomly selected between the three classes of fuzzy sets "Likely", "Usually", and "Sure". After constructing the trust values in the form of Z-numbers, these are converted to real-valued numbers as before.

Part 3 of the time series is made up of the trust values for the last three months or time slots. The trust values in the last three time slots are modelled such that, they are a function of: (a) the immediate previous trust value in the time series; and (b) the variance of trusted agent's compliance with agreed service. To model the above and construct the time series for Part 3, we first compute the mean of trust values in Part 2 and then compute the variance of all trust values in Parts 1 and 2. If the value of the mean belongs to the *Low trust* fuzzy set and the variance is less than 0.07 (70 percent of variance between trust values in each trust scenario), then all the trust values in Part 3 correspond to Low trust. However, if the variance is more than 0.07, then the trust values in Part 3 are either the *Low trust* value or *Medium trust value* . If the value of the mean belongs to the *Medium trust* Fuzzy set and the variance is less than 0.07, then all the trust values in Part 3 correspond to *Medium trust*, but if the variance is higher than 0.07, then each of the trust values in Part 3 could be any of the three trust levels. This is model that given a high variance in the previous trust values of the trusted entity, it is logical to assume that this is likely to continue in.

In contrast, if the mean value belongs to the *High trust* fuzzy set and the variance is less than 0.07 then all the trust values in Part 3 correspond to the High *trust*, but if the variance is more than 0.07, then the trust values in Part 3 could be either *Medium trust* or High trust.

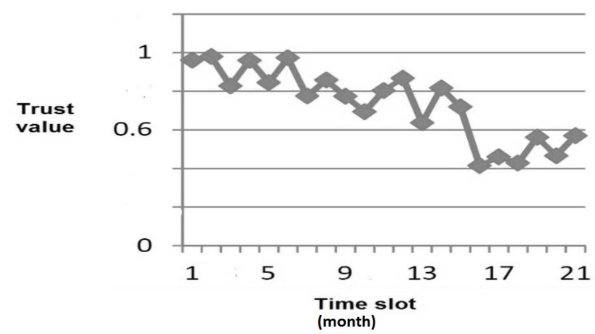


Fig. 2. {High, High, High, High, High, Medium, Medium} scenario of interactions in middle-term period simulation

After constructing the time series for medium-term prediction, as outlined above, we use the theorem to convert Z-numbers to normal fuzzy numbers. Subsequently, defuzzification methods are used to convert trust assessments to real numbers.

The 108 scenarios for the middle-term period are built to simulate the behaviors of a given trusted agent agents (over a medium term) and prepare a time series that can be used for predicting future trust values. Figure 2 shows the {High, High, High, High, High, Medium, Medium} scenario in the middle-term period.

D. *Selecting the Best ANN for each scenario*

To estimate the performance of the designed ANN, we apply cross validation technique [27]. In cross validation, the data set is first split into k parts. One part is employed for testing and the rest are used for training purposes. These steps are repeated until all parts have been used as a testing set. The final result of cross validation is the average accuracy of the total number of runs. In this study, we make use of a neural networks comprising of a single hidden layer. To find the optimum number of hidden nodes in hidden layer of the ANN, for each of the two scenarios, we design train and evaluate multiple ANN's comprising of varying number of hidden nodes ranging between one to "*p*" nodes. The error of each of the ANN is determined using Mean Absolute Percentage Error (MAPE).

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{Actualvalue_i - Setspotvalue_i}{Setspotvalue_i}\right| \quad (10)$$

The training step is executed by the scaled conjugate gradient training algorithm [24]. Usually, the training data set includes 70-90% of all data and the remaining data are used for the test data set. A critical problem that arises during neural network modeling is over-fitting [26]. In over-fitting, the error on the training set has a small value, but when the new data is presented to the neural network, the error takes on a larger value. The neural network learns about the training examples (or training data set), but when new data are given to the neural network, it is not more generally applicable to the new data. The early stopping method is utilized to address stated issue. In this method, the attainable data is divided into two subsets. The first is the training set, which is used to compute the gradient and obtain the network weights and biases. The second subset is the test data set. The error on the validation set is shown during the training process [25]. The error is only used to compare the different models and is not used during the training process.

E. Predicting Future Trust Values by Selecting ANN

By selecting the best ANN for each of the scenarios, we ensure that the ANN with highest accuracy is utilized for predicting forecasting future trust values.

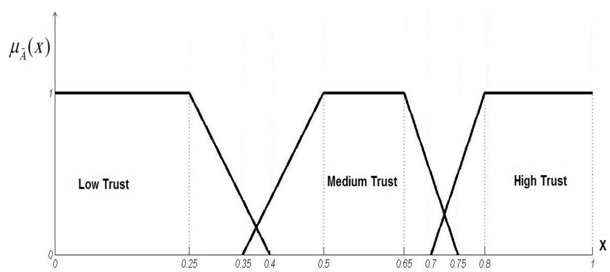


Fig. 3. Fuzzy sets of trusts

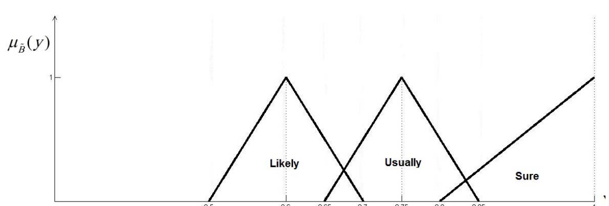


Fig. 4. Fuzzy sets of reliabilities

IV. EXPERIMENTS

The proposed approach is applied to the simulated time series in the form of Z-numbers in time periods, namely "Short-term period" and "Middle-term period". The constructed Z-numbers have two parts. As mentioned previously, we the value of that first element in the Z-number could be from the set {"High trust", "Medium trust", "Low trust"}. We assume that each of these values is presented as a trapezoidal fuzzy function. For the purposes of experimentation, the parameters of the membership function for the concept High are [0.7, 0.8, 1, 1]. The parameters of the concept Medium are [0.35, 0.5, 0.65, 0.75], and the concept Low membership parameters are [0, 0, 0.25, 0.4], as shown in Figure 2.

TABLE I
CLASSIFICATION OF TRUST VALUES IN THE FORM OF Z-NUMBERS

Z=(A,B)		Membership functions parameters
A	High	[0.7, 0.8, 1, 1]
	Medium	[0.35, 0.5, 0.65, 0.75]
	Low	[0, 0, 0.25, 0.4]
B	Sure	[0.8, 1, 1]
	Usually	[0.65, 0.75, 0.85]
	Likely	[0.5, 0.6, 0.7]

The second element of the Z-number could be from the set {"Likely", "Usually", "Sure"}. We assume that each of the values is modelled using a triangular fuzzy set. The membership parameters of the concept *Likely* are [0.5, 0.6, 0.7], and for the concepts *Usually* and *Sure* are [0.65, 0.75, 0.85] and [0.8, 1, 1] respectively, as shown in Figure 3. These parameters for Z-numbers are shown in Table I.

For short-term trust predictions, as discussed in previous sections, we construct 27 scenarios with the concepts "High", "Medium", and "Low" with random reliabilities for predicting future trust values. We assume that the time period is one year and that the agents in the community interact every month with the trusted agent. We split the time period into three parts, each of which has four interactions with the same level of trust. We construct 12 Z-numbers related to each scenario, corresponding to the trust values of the trusted agent in the past 12 months. The Z-numbers are then converted to real-valued numbers, using the previously-defined theorems.

In contrast, for medium-term trust prediction, the time period is 21 months, and the agents in the community interact with the trusted agent at the end of every month. We make use of the approach described in Section IIIC to generate the data set for medium-term trust prediction. Table II shows critical aspects and variables used for generating the data set for medium-term trust prediction.

Subsequent to these steps, the ANN models are evaluated in each constructed scenarios and finally the best network will be determined. Then these concepts are converted with random reliabilities to real numbers for each scenario, giving 108 different scenarios for the middle-term period simulation approach. The best performing ANN is selected by using error measurement variable. To calculate the value of the error, Cross Validation Test Technique (CVTT) is applied with four iterations. The data set is first divided into four sub-sets. One is used as the validation and the rest data becomes the training set.

TABLE II
SIMULATION POLICY FOR CONSTRUCTING PART THREE OF THE TRUST SERIES FOR MEDIUM-TERM TRUST PREDICTION

Range of mean of last three values of Part 2	Linguistic value of trust for first month of Part 3 is:	The variance of all past trust data	Part 3 continues with concepts:
[0, 0.35]	Low	≥ 0.07	Low or Medium
		<0.07	Low
[0.35, 0.7]	Medium	≥0.07	Low, Medium or High
		<0.07	Medium
[0.7, 1]	High	≥0.07	Medium or High
		<0.07	High

TABLE III - MAPE VALUE OF THE BEST PERFORMING ANN FOR 27 SCENARIOS IN SHORT-TERM TRUST PREDICTION

Scenario	MAPE for best network	Scenario	MAPE for best network
1	0.022	15	0.037
2	0.054	16	0.049
3	0.136	17	0.093
4	0.012	18	0.032
5	0.025	19	0.002
6	0.088	20	0.041
7	0.102	21	0.196
8	0.015	22	0.052
9	0.035	23	0.015
10	0.108	24	0.1
11	0.012	25	0.044
12	0.087	26	0.049
13	0.01	27	0.018
14	0.011		

The error term is estimated by Mean Absolute Percentage Error (MAPE). The related networks for each scenario in each term are implemented with MATLAB's Neural Network Toolbox. We select the best ANN -for each scenario in each time period based on the error values. Table III shows the MAPE for the best networks for each scenario in the short-term period simulation. MAPEs for the middle-term period simulation are shown in Table IV. The minimum, maximum, average and variance of the errors of the best networks after the validation test for each term simulation are shown in Table V. These values are used for selecting the best ANN. After selecting the best network for each scenario we can forecast the future trust values for the trusted agent in a future time spot.

TABLE IV
MAPE VALUE FOR THE BEST PERFORMING ANN FOR 108 SCENARIOS IN MEDIUM-TERM TRUST PREDICTION

Scenario	MAPE for best network	Scenario	MAPE for best network	Scenario	MAPE for best network
1	0.05	37	0.048889	73	0.007937
2	0.012568	38	0.00396	74	0.009265
3	0.006272	39	0.014675	75	0.109504
4	0.014068	40	0.001265	76	0.004967
5	0.038311	41	0.075311	77	0.109796
6	0.008037	42	0.016761	78	0.033021
7	0.007488	43	0.007697	79	0.023871
8	0.067574	44	0.050546	80	0.018037
9	0.006386	45	0.040363	81	0.069238
10	0.012067	46	0.096515	82	0.095577
11	0.094765	47	0.009439	83	0.009379
12	1.61E-11	48	0.04832	84	0.104212
13	0.008604	49	0.039388	85	0.020967
14	0.015859	50	0.043417	86	0.017733
15	0.089227	51	0.098625	87	0.026697
16	0.009141	52	0.026416	88	0.006991
17	0.014596	53	0.074948	89	0.05648
18	0.010131	54	0.014109	90	0.033325
19	0.008861	55	0.012745	91	0.041243
20	0.008235	56	0.052726	92	0.011251
21	0.068726	57	0.014207	93	0.011251
22	0.018783	58	0.121592	94	0.018065
23	0.130548	59	0.007647	95	0.031781
24	0.023967	60	0.204358	96	0.052869
25	0.045803	61	0.05402	97	0.005828
26	0.063468	62	0.005643	98	0.000525
27	0.040645	63	0.018094	99	0.001409
28	0.000906	64	0.15603	100	0.087189
29	0.003009	65	0.030706	101	0.038539
30	0.09543	66	0.057862	102	0.013503
31	0.078776	67	0.044732	103	0.070796
32	0.039766	68	0.04022	104	0.003004
33	0.045415	69	0.025643	105	0.033835
34	0.042699	70	0.258188	106	0.048338
35	0.03548	71	0.058052	107	0.024069
36	0.037	72	0.103291	108	0.051338

TABLE V
PARAMETERS OF THE SELECTED NEURAL NETWORK

	MIN	MAX	AVE	VAR
Short-term period	0.002	0.196	0.054	0.002
Middle-term period	0	0.258	0.042	0.001

V. CONCLUSIONS

The proposed approach of this paper provides an mechanism to help decision makers to formulate an effective decision-making procedure for forecasting the future trust values of other entities. The purpose is to alert the decision makers to the future behavior of the trusted agent, to reduce the cost (and hence the risk) that may be sustained by the trusting agent in future interactions with the trusted agent. To achieve this, the determination and analysis of past trust values between two agents and is a useful procedure for overcoming the nonlinearity of trusted agent behavior. The proposed algorithm builds all the rational scenarios of past trust behaviors and select the best ANN for these scenarios. The major features of our algorithm are that it takes the past trust values in the form of linguistic variables, engages the reliability of trusting agent statements, and uses Z-number features to process trust values.

In future work, we will develop a methodology for predicting trust values over the long term. Additionally, we intend to make use of the developed approach in technology intelligence. This could be used to predict customer needs in markets and predict new products for future markets.

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