Improved Trust Prediction in Business Environments by Adaptive Neuro Fuzzy Inference Systems

Ali Azadeh
School of Industrial Engineering, College of Engineering, University of Tehran, Tehran, Iran
E-mail: aazadeh@ut.ac.ir

Mansour Zarrin
School of Industrial Engineering, College of Engineering, University of Tehran, Tehran, Iran
E-mail: mansour.zarrin@gmail.com

Morteza Saberi
School of Information Systems, Curtin University of Technology
Perth, Australia
E-mail: m.saberi.ie@gmail.com

Zohre Ebrahimi
School of Industrial Engineering, College of Engineering, University of Tehran, Tehran, Iran
E-mail: z.ebrahimi@ut.ac.ir

Abstract—Trust prediction turns out to be an important challenge when cooperation among intelligent agents with an impression of trust in their mind, is investigated. In other words, predicting trust values for future time slots help partners to identify the probability of continuing a relationship. Another important case to be considered is the context of trust, i.e. the services and business commitments for which a relationship is defined. Hence, intelligent agents should focus on improving trust to provide a stable and confident context. Modelling of trust between collaborating parties seems to be an important component of the business intelligence strategy. In this regard, a set of metrics have been considered by which the value of confidence level for predicted trust values has been estimated. These metrics are maturity, distance and density (MD2). Prediction of trust for future mutual relationships among agents is a problem that is addressed in this study. We introduce a simulation-based model which utilizes linguistic variables to create various scenarios. Then, future trust values among agents are predicted by the concept of adaptive neuro-fuzzy inference system (ANFIS). Mean absolute percentage errors (MAPEs) resulted from ANFIS are compared with confidence levels which are determined by applying MD2. Results determine the efficiency of MD2 for forecasting trust values. This is the first study that utilizes the concept of MD2 for improvement of business trust prediction.

Keywords—key words Trust prediction; Adaptive neuro-fuzzy inference system (ANFIS); Maturity, distance and density (MD^2)

I. INTRODUCTION

For all business systems, designing a model for trust prediction is really essential, since it is one of the important business intelligence strategies for all organizations. The primary goal of modelling trust is to acquire the capability of forecasting future trust values correctly [1], [2].

Considering trust in communications among parties is a growing concern. In this context, Trust gives an opinion to choose a partner which suits the requirements best. Interactions based on mutual trust in both business and society environments have less risks and more satisfaction than interactions which have no previous knowledge about it [3]. Trust in these kinds of trade means being provided by an environment in which agents have knowledge about each other and are relieved and satisfied with received services. In some cases, there is no need to interact directly with a partner in order to assign him/her a trust value. Actually, users rely on agents in similar situations and contexts in which agents have proved to be trustworthy. In addition, trust and security are two closely related concepts which can be mistaken. In fact security prepares a safe environment without any defined agent, but trust helps the trusting agent to choose trusted partner [4]. So, the concept of trust is crucial when the relationships among parties are considered.

Trust has been studied widely in the field of social and cognitive sciences. Interested readers can refer to [5]-[17].

Initially, concept of trust was presented by [18] in distributed artificial intelligence. Reference [18] and many other researchers considered the following definition for trust provided by [19] in the field of computing:

"Trust is a special degree of the subjective possibility with which a party will execute a specific act, both before we can monitor such action and in a setting in which it touches our own actions."

Predicting behavior of the trusted party at future point of time is a typical case. In this regard, different methods have been developed for prediction including Markov model [20], Bayesian models [21] and neural networks [22]. These methods have been used for different types of applications like forecasting energy, demand, weather, revenue, resources and etc. Considering trust concept in communications among

IJARER

parties has proved to be a growing concern, for trust gives an opinion to choose a partner which suits the requirements best. Nowadays, because of the communication tools developments, relationship among people moves from face-to-face and personal relevance to peer-to-peer or mobile networks [4], [23]. Trust in this context means being provided by an environment in which agents have knowledge about each other and are relieved and satisfied with received services. In some cases, users rely on agents in similar situations and contexts in which trustees have proved to be trustworthy.

The rest of study is organized as follows: a survey on relevant literature is provided in Section II. Proposed model is included in Section III. Analysis and results are addressed in Section IV. Finally, we conclude this paper in Section VI.

II. LITERATURE REVIEW

Trust has recently turned to be an interesting topic for many researchers and has stimulated developing new models to evaluate mutual interactions in business and social environments. These models can be classified into three main classes: prediction of trust, propagation of trust and evaluation of trust. Trust prediction models exploit prediction methods to predict the future trust values for continuing interactions among agents [25]. Liu et al., [26] developed a model based on Naive Bayes and SVM classifiers to predict trust relationships between two users according to their individual interactions. Ma et al., [27] used prediction techniques for measuring the bidirectional effects of trust and rating for online social networks.

Marsh et al., [28] used supervised learning method to explore the influence of temporary trust assessment in forecasting trust for online trust networks. They incorporated historical data of trust in the context of relationships to forecast current state of trust. In experience sharing online publics, the existence of a robust trust system is essential. Matsuo et al., [29] proposed a framework of computational trust to forecast level of trust between two users that was normally distributed. Their framework was not based on a Web of Trust, because it was not always available. They used rating data obtained from the feedback of users. This approach guaranteed availability of information with a density greater than the Web of Trust. Morrow et al., [30] employed data available from a survey on 134 exporting companies to discover the influences of trust, relation-oriented adequacies, commitment, and entrepreneurial capabilities on efficiency of export. The main advantage of this method was that they assumed effective commitment had an indirect influence on efficiency, rather than a direct influence.

Newton [31] introduced a new model called relative trust model. They assumed that trusting a certain agent was relied on experiences with that agent and with other agents which were competitors of that agent. Parameters of the proposed model denoted a specific dependency among trust values of different agents. They proved that this relative trust model was able to forecast trust for human relationships considerably better than a benchmark model. Onolaja et al., [32] presented a dynamic model for trust prediction of mobile ad hoc networks considering prediction rules in fuzzy logic. They assessed mobile node trustworthiness according to historical and future manners of the nodes.

Raza et al., [33] proposed a new framework which uses the paradigm in the area of trust-based systems and reputation in mobile networks. Then, the proposed framework was compared with other exciting structures to classify trust and to find risky areas. Rilling [34] proposed an incentive method to simulate cooperation of trust prediction in wireless networks through a game scheme. They showed that their method had more advantageous and less game cost in compression with previous studies. Rondeau et al., [35] presented a new version of BDI interpreter which helped agents in assigning responsibilities to others. Actually, they incorporated trust into BDI construction.

During international financial crisis, Rothstein et al., [36] examined influence of media interpretations on the level of trust from a media-user viewpoint. They discussed influences of communicator-centered and audience-centered methods in forecasting policies during crises. Roventa and Spircu [37] examined efficiency of different electronic communication channels used by bank managers to increase number of customers and to improve existing service. Also, they investigated quality of online banking services impacts on trust, satisfaction, and e-loyalty of client.

Singh et al., [38] suggested a method to assess the situational business trust that binds trust ratings of previous business interactions with a novel one. Taibi [39] focused on trust-based interactions in which a trustee pair was allocated either a trust or non-trust tag according to the features generated by users. Terzidis [40] used discrete Markov to predict values of trust and reputation for three types of data: data with seasonal fluctuations, data with a trend, and random data sets.

So, concept of trust prediction can be classified into two main categories; the first of which is predicting the "existence of trust" that determines whether trust exists between parties or not, and the second is to predict "trust values" among parties. These works have not focused on trust trends which depend on time of interactions between two agents. In this work, we consider all possible scenarios obtained from simulation. Including uncertainty to these scenarios is also the contribution of this study. We utilize the concept of Z-numbers to include uncertainty and subjectivity to data. Then, we measure the reliability of trust data created subjectively in context of three criteria of MD^2. Results of confidence level obtained from MD^2 are compared with MAPEs obtained from ANFIS. Results determine the efficiency of MD^2 for forecasting trust values.

III. PROPOSED MODEL

The goal of this paper is to predict trustworthiness of a trusted party in a mutual relationship. We use historical data of trust values which trusting agent has assigned to trusted agent. Trust prediction has various applications and the time period for which we forecast data, is a crucial factor in this research. The trust values will change with time, according to the following reasons:

IJARE

- The information about the trusted agent increases during the time
- The satisfaction of trusting agent may change during the time
- The opinion of other agents may be influenced by the trustworthiness of trusted agent.

The prediction can be applied for a short-term period, middle-term period and long-term period. Here, we focus on short-term period prediction, and the time slot is considered to be at monthly basis. Thus, any interaction between two parties occurs once in a month and the trusting agent assigns a trust value to trusted agent. We also classified trust values as "Low", "Medium", and "High" with a trapezoid fuzzy membership function. x=0, denotes very low trust and x=1, denotes very high trust, and each value between them denotes a trust value between low and high. Fig. 1 show the membership functions.

Therefore, three defuzzification methods called "Centroid", "Middle of maximum", and "Largest of maximum" are applied randomly to convert this trapezoid fuzzy set to real-value numbers [43]-[45].

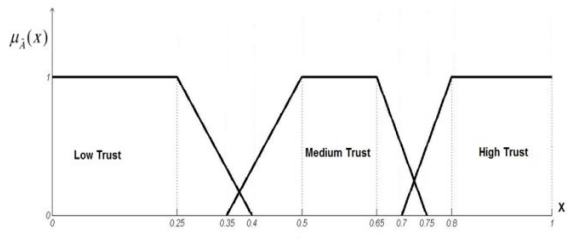


Fig. 1. Fuzzy membership functions of trust.

As discussed above, to predict the future values of trust, we first need to create data. So, we simulate all rational scenarios for each time slot and then predict the future trust values. In the following, we explain scenarios for each time period. Fig. 2 shows the roadmap of our method.

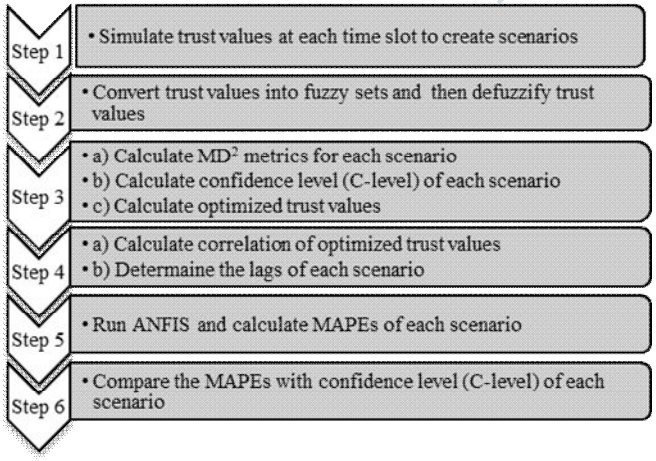


Fig. 2. Road map of our proposed method.

A. Definition of MD2 metrics for calculating confidence level

Prediction of trust values considering confidence level (C-level) can be taken as a strategy to improve business intelligence [4]. The C-level associated with values of predicted trust data relies on multiple characteristics and features of available trust data. The three indicators influencing C-level are: Maturity, Distance and Density (MD^2) [4]. More descriptions regarding these metrics and the impacts that they have on C-level are provided below.

The formula for calculating C-level related to the predicted trust values is as follows

$$c-level = \frac{m + ds + dy}{\max(m) + \max(ds) + \max(dy)} \quad (9)$$

where, m, ds and dy denote maturity, distance, and density in that order. We have assumed $\max(m) = \max(ds) = \max(dy) = 2$ in this case study.

TABLE I. *DESCRIPTION OF THE SYMBOLS.*

Symbol	Description
t_c	Current time slot
t_f	Time slot related to the first interaction
t_p	Time slot to be predicted
t_m	Median time slot ($(t_c + t_f)/2$)
$n(t_f - t_m)$	Total number of interactions taken place between t_f and t_m
$n(t_m - t_c)$	Total number of interactions taken place between t_m and t_c
LRI	Least Recent Interactions (The number of interactions in the first half of maturity period is more than the second half.)
MRI	Most Recent Interactions (The number of interactions in the first half of maturity period is smaller than the second half.)
ND	Normally Distributed (The number of interactions in both halves of maturity period is equal)
C-level	Confidence level

TABLE II. *DESCRIPTION OF METRICS AND ITS ALGORITHM FOR QUANTIFICATION.*

Metric	Symbol	Description	Mathematical formula	Relation with c-level*	Algorithm for quantification
Maturity	m	The total lifetime of a unit that it has been in existence	$m = \lvert t_c - t_f \rvert$	$\uparrow m \Rightarrow \uparrow c\text{-level}$	If $\lvert t_c - t_f \rvert = \lvert t_p - t_c \rvert$ then m = normal (= 2) else if $\lvert t_c - t_f \rvert < \lvert t_p - t_c \rvert$ then m = min (= 1) End If

HARE

Distance	ds	An indicator that shows the distance in which prediction procedure is being conducted	$ds = \frac{\lvert t_y - t_x \rvert}{\lvert t_m - t_0 \rvert}$	$ds \in [0,1]$	If $\frac{t_y - t_x}{t_m - t_0} = 1$ then ds = normal (= 2) else if $\frac{t_y - t_x}{t_m - t_0} < 1$ then ds = min (= 1) End if
Density	dy	An indicator that shows the distribution and density of interactions during maturity	$dy = \frac{n(t_m - t_x)}{n(t_y - t_m)}$	$dy \in [0,2]$	If $n(t_m - t_x) = n(t_y - t_m)$ then dy = ND (= 2) Else if $n(t_m - t_x) < n(t_y - t_m)$ then dy = LRI (= 1) End if
* C-level indicates for confidence level					

B. *Data Simulation Procedure for Short-Term Period*

Estimation of future trustworthiness is based on historical data of trust values which trusting agent has assigned to trusted agent. Trust prediction has various applications. It can be defined for a short-term period, middle-term period and long-term period. Simulation process differs based on the prediction period. Time duration between two consecutive transactions of agents is called time slot. Here, it is defined on a monthly basis. Thus, an interaction happens between two parties once in a month and the trusting agent assigns a trust value to trusted agent. Here three types of time slots are taken into account which are representatives of trust modes which are: "Low", "Medium", and "High".

Since in short-term scenarios, the time period is short and trusting agent has not sufficient information about trusted agent, former trust values do not seriously influence last or new trust values. For short-term scenarios, the period of time is supposed to be 12, 13 and 14 months randomly. Each period of time (length of scenario) is divided into three intervals. The length of first and second intervals are equal to 4 months, and the third interval according to the period of time can be 4 (if time of period = 12) or 5 (if time of period = 13) or 6 (if time of period = 14) months. In each scenario, interactions have been assumed to happen monthly. After defining the length of each scenario, the level of reliability and the value of three metrics (maturity, distance and density) are determined for all intervals.

Level of reliability and value of each metric (MD2) should be determined for each interval. Levels of reliability are classified as low, medium and high with indexes 1, 2, and 3, respectively. Also, each metric can be equal to 1 or 2 to express low and medium values, respectively.

Then, all possible permutations of three numbers: 1, 2, 3 are generated to determine the level of reliability. Number 1 is representative of high level of trust, number 2 refers to medium level of trust and number 3 is related to a low level of trust. The procedure is defined as follows:

If the random number is 1, the values are procreated in [0.7 1] interval, else if the random number is 2, the values are procreated in [0.3 0.75] interval, else the values would be in [0 0.35] range.

Next all the possible permutations of high, medium, and low levels of trust and also low and medium levels of three metrics (MD2) are considered together and therefore 216 scenarios are generated for short-term period. Therefore, the defuzzification methods are applied to transform fuzzy values into real numbers. These real numbers indicate trust values for each time slot. Crisp values of trust obtained from defuzzification stage are included in Fig. 3. The first 10 scenarios identified based on the previous description.

Then a multistep algorithm for predicting trustworthiness of future time slots is proposed. First of all, the algorithm simulates data for all permutations of modes. Then, by applying ANFIS on each scenario, MAPEs are calculated. Finally these values are compared with C-level computed based on MD2 metrics.

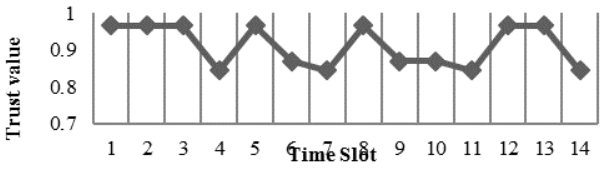


Fig. 3. The values of trust for a specific scenario.

1) *Auto correlation (ACF)*

ACF calculation is one of the fundamental techniques for investigating patterns in time series. Autocorrelation can be utilized for following purposes:

- ✓ To detect that data is random or not
- ✓ To estimate a suitable model of time series when data isn't random

Autocorrelation (ACF) is a mathematical illustration that shows the similarity degree between a time series and a lagged record of itself over repeated time periods. It is identical to the investigation of relationship between two different time series, except that just one time series is considered twice - once with its original form and once with a lag of one or more time periods. The pattern of autocorrelation is modeled in any time-series study, before the forecasting procedure, or prior to tests of an intervention. When ACF is calculated, the numerical results can take values between [-1, +1]. An autocorrelation of +1 denotes perfect positive correlation while a value of -1 denotes perfect negative correlation[1].

2) *Adaptive Neuro-Fuzzy Inference System (ANFIS)*

ANFIS is considered as an approach in neuro-fuzzy development, proved to have significantly acceptable results in modeling nonlinear functions [46], [47]. Neuro-fuzzy modeling refers to the way of applying various learning techniques developed in the neural network literature to fuzzy modeling or a fuzzy inference system [48]. ANFIS uses a feed-forward network to optimize parameters of a given fuzzy inference system (FIS). The learning algorithm for ANFIS is a hybrid algorithm, which is combination of the gradient descent and least squares methods [49].

To select the best model for each output, 12 ANFIS models with different architectures have been designed and

[1]http://www.investopedia.com/terms/a/autocorrelation.asp

IJARE

run and their MAPE values are determined. For each scenario 80% of the data set is used as the training data and 20% as test data. The architecture with the minimum MAPE value is selected as the preferred one. It should be mentioned that each of ANFIS architecture has been run 100 times to deal with possible noise. The architecture of preferred ANFIS model is shown in Table 4.

TABLE III. ARCHITECTURE OF THE PREFERRED ANFIS

AND	OR	Implication	Aggregation	Defuzzification	Type
prod	max	prod	sum	Weighted average	Sugeno

IV. ANALYSIS THE NUMERICAL RESULTS

Data are simulated for each scenario and then lag values are calculated in last step. Then, prediction method is utilized to predict future trustworthiness values. Inputs and outputs for time series method has been identified based on lag values that were obtained from ACF. Then, MAPEs of scenarios for short-term period scenarios are calculated. MAPE is the only technique that lacks scaled output. Since the input data is considered to estimate the model, the preprocessed data and the original data have distinct scales. MAPE approach is the most appropriate method for estimating relative error.

$$MAPE = \frac{1}{N}\sum_{k=1}^{N}\left|\frac{Actual_k - Forecast_k}{Actual_k}\right| \quad (10)$$

The minimum value of MAPE for the mentioned scenario (scenario {High, Medium, Low} with its MD^2 {min, max, min}) in short-term is equal to 0.2569.

Hence, we analyze MAPE values calculated for each scenario in comparison with the confidence level (C-level). First, we classify C-levels into 4 classes. class 1, has the minimum value of confidence level equal to 50%, class2 with 66.7% of C-level, class 3 with 83.3% of C-level, and the last class has the maximum C-level equal to 100%. Next, we input all scenarios into their appropriate classes; for example, all scenarios that have C-levels equal to 50% are included to class 1, class two contains scenarios with confidence levels of 66.7%, and so on. At the end, we calculate the average of MAPEs separately to obtain the average values of MAPEs for each class. Table 5 shows the numerical results of calculating average values for each class. Based on Table 3 we conclude that when the value of C-level increases, the average of MAPE decreases. Fig. 9 shows the relation between C-level and average of MAPEs for each class.

We can find the polynomial trend line with order 3 between the value of C-level and average of MAPEs. The non-linear relation between C-level values and average MAPE is depicted in Fig. 8. The figure shows that as confidence level gradually increases, average MAPE values decreases. The mathematical formula representing the relation between C-level and the average of MAPEs is as follows:

$$y = 5.62x^3 - 13.09x^2 + 9.55x - 2.07, \; R^2 = \quad (11)$$

Where:

y = Average value of MAPE

x = *C*-level value

These results show that confidence level approach is efficient according to low MAPE values obtained. So, the three indicators MD^2 can be used to compute the confidence and reliability level of trust prediction in business environments with a high level of certainty.

V. CONCLUSIONS

Trust prediction for future time slots is essential to evaluate the probability of continuing a transaction between two agents. According to subjectivity feature of trust, the prediction is dependent on historical data which are collected from last experiments. In this study, all permutations of trust modes consisted of high trust, medium trust and low trust level are created with simulation techniques. ANFIS is recommended for predicting trust value of future, since it is an appropriate method for predicting data with uncertainty and vagueness. In this study, before implementing ANFIS, Auto correlation method is applied as a basic calculation of prediction tools. Based on amount of lag in ACF calculation, ANFIS is applied for each scenario. MAPEs are compared for level of confidence and reliability. During this study complexity of scenarios are taken into account. As mentioned before, simulation structure of data for long term planning would be different. Simulation method would differ because time horizon increases and therefore historical data for each scenario would be different. Finally it shows efficiency of these metrics for evaluating confidence level of trust prediction. It is recommended to develop simulation methods for long term planning for future work directions.

VI. NUMERICAL RESULTS OF CLASSIFICATION

Average of MAPEs	Class of C-level			
	50%	66.7%	83.3%	100%
	0.130045644	0.138454244	0.04881535	0.00760353

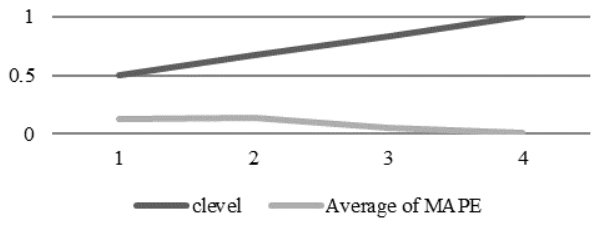


Fig. 4. The relation between C-level and average of MAPEs

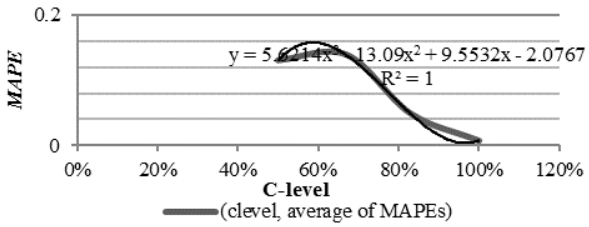


Fig. 5. Trend line between c-level and MAPEs.

IJARER

REFERENCES

[1] Al–Kandari, A. A., Caldwell, L. G., & Alduwaila, N. (2013). The use and impact of media during the 2008 global financial crisis: a media–user perspective. International Journal of Business Continuity and Risk Management, 4(3), 246-265.

[2] Andrade, F., Novais, P., Machado, J., & Neves, J. (2010). Software agents and virtual organisations: consent and trust. International Journal of Services and Operations Management, 6(3), 352-361.

[3] Bloemer, J., Pluymaekers, M., & Odekerken, A. (2013). Trust and affective commitment as energizing forces for export performance. International Business Review, 22(2), 363-380.

[4] Brown, M., & Harris, C. J. (1994). Neurofuzzy adaptive modelling and control.

[5] Chang, E., Hussain, F., & Dillon, T. (2006). Trust and reputation for service-oriented environments: technologies for building business intelligence and consumer confidence: John Wiley & Sons.

[6] Corritore, C. L., Kracher, B., & Wiedenbeck, S. (2003). On-line trust: concepts, evolving themes, a model. International Journal of Human-Computer Studies, 58(6), 737-758.

[7] Delgado, M. R., Frank, R. H., & Phelps, E. A. (2005). Perceptions of moral character modulate the neural systems of reward during the trust game. Nature neuroscience, 8(11), 1611-1618.

[8] Dillon, T., Chang, E., & Hussain, F. (2004). Managing the dynamic nature of trust.

[9] Drossu, R., & Obradovic, Z. (1996). Rapid design of neural networks for time series prediction. Computational Science & Engineering, IEEE, 3(2), 78-89.

[10] Gambetta, D. (2000). Can we trust trust. Trust: Making and breaking cooperative relations, 213-237.

[11] Gilson, L. (2003). Trust and the development of health care as a social institution. Social science & medicine, 56(7), 1453-1468.

[12] Gui, J., Chen, Z., & Deng, X. (2012). An incentive scheme in wireless access networks through a game based on trust prediction. International Journal of Ad Hoc and Ubiquitous Computing, 11(1), 11-24.

[13] Hassan, M. R., & Nath, B. (2005). Stock market forecasting using hidden Markov model: a new approach. Paper presented at the Intelligent Systems Design and Applications, 2005. ISDA'05. Proceedings. 5th International Conference on.

[14] Hoogendoorn, M., Jaffry, S. W., van Maanen, P.-P., & Treur, J. (2013). Design and validation of a relative trust model. Knowledge-Based Systems.

[15] Hou, L., Wang, L., & Yang, J. (2008). Evolutionary prediction of online keywords bidding E-Commerce and Web Technologies (pp. 124-133): Springer.

[16] Hussain, F., Chang, E., & Dillon, T. S. (2005). Markov model for managing dynamic trust.

[17] Hussain, F. K., Chang, E., & Hussain, O. (2008). A robust methodology for prediction of trust and reputation values. Paper presented at the Proceedings of the 2008 ACM workshop on Secure web services.

[18] Jang, J.-S. (1993). ANFIS: adaptive-network-based fuzzy inference system. Systems, Man and Cybernetics, IEEE Transactions on, 23(3), 665-685.

[19] Jang, J. (1997). ANFIS architecture: Prentice Hall, New Jersey.

[20] Jang, R., Sun, C., & Mizutani, E. (1997). Neuro-fuzzy and soft computation: Prentice Hall, New Jersey.

[21] Johnson, D., & Grayson, K. (2005). Cognitive and affective trust in service relationships. Journal of Business research, 58(4), 500-507.

[22] Kang, Y., Williams, L. E., Clark, M. S., Gray, J. R., & Bargh, J. A. (2011). Physical temperature effects on trust behavior: the role of insula. Social Cognitive and Affective Neuroscience, 6(4), 507-515.

[23] Khare, A., Mishra, A., & Singh, A. B. (2012). Indian customers' attitude towards trust and convenience dimensions of internet banking. International Journal of Services and Operations Management, 11(1), 107-122.

[24] Kim, Y., & Phalak, R. (2012). A trust prediction framework in rating-based experience sharing social networks without a web of trust. Information Sciences, 191, 128-145.

[25] Leekwijck, W. V., & Kerre, E. E. (1999). Defuzzification: criteria and classification. Fuzzy sets and Systems, 108(2), 159-178.

[26] Liu, H., Lim, E.-P., Lauw, H. W., Le, M.-T., Sun, A., Srivastava, J., & Kim, Y. (2008). Predicting trusts among users of online communities: an epinions case study. Paper presented at the Proceedings of the 9th ACM conference on Electronic commerce.

[27] Ma, N., Lim, E.-P., Nguyen, V.-A., Sun, A., & Liu, H. (2009). Trust relationship prediction using online product review data. Paper presented at the Proceedings of the 1st ACM international workshop on Complex networks meet information & knowledge management.

[28] Marsh, S. P. (1994). Formalising trust as a computational concept.

[29] Matsuo, Y., & Yamamoto, H. (2009). Community gravity: measuring bidirectional effects by trust and rating on online social networks. Paper presented at the Proceedings of the 18th international conference on World wide web.

[30] Morrow Jr, J., Hansen, M. H., & Pearson, A. W. (2004). The Cognitive and Affective Antecedents of General Trust Within Cooperative Organizations. Journal of Managerial Issues, 16(1).

[31] Newton, K. (2001). Trust, social capital, civil society, and democracy. International Political Science Review, 22(2), 201-214.

[32] Onolaja, O., Bahsoon, R., & Theodoropoulos, G. (2010). Conceptual framework for dynamic trust monitoring and prediction. Procedia Computer Science, 1(1), 1241-1250.

[33] Raza, M., Hussain, O. K., Hussain, F. K., & Chang, E. (2011). Maturity, distance and density (MD2) metrics for optimizing trust prediction for business intelligence. Journal of Global Optimization, 51(2), 285-300.

[34] Rilling, J. K., & Sanfey, A. G. (2011). The neuroscience of social decision-making. Annual review of psychology, 62, 23-48.

[35] Rondeau, L., Ruelas, R., Levrat, L., & Lamotte, M. (1997). A defuzzification method respecting the fuzzification. Fuzzy sets and Systems, 86(3), 311-320.

[36] Rothstein, B., & Uslaner, E. M. (2005). All for all: Equality, corruption, and social trust. World politics, 58(01), 41-72.

[37] Roventa, E., & Spircu, T. (2003). Averaging procedures in defuzzification processes. Fuzzy sets and Systems, 136(3), 375-385.

[38] Singh, A., Narain, R., & Yadav, R. (2006). A survey on relationships and cultural issues in supply chain management practices in Indian organisations. International Journal of Services and Operations Management, 2(3), 256-278.

[39] Taibi, T. (2010). Incorporating trust into the BDI architecture. International Journal of Artificial Intelligence and Soft Computing, 2(3), 223-230.

[40] Terzidis, K., Papadopoulou, E., & Kosmidis, K. (2013). Customer e-loyalty to internet banking: an empirical analysis. Global Business and Economics Review, 15(2), 148-162.

[41] Todorov, A., Baron, S. G., & Oosterhof, N. N. (2008). Evaluating face trustworthiness: a model based approach. Social Cognitive and Affective Neuroscience, 3(2), 119-127.

[42] Wang, Y., & Lim, E.-P. (2008). The evaluation of situational transaction trust in e-service environments. Paper presented at

IJARE

the e-Business Engineering, 2008. ICEBE'08. IEEE International Conference on.

[43] Winston, J. S., Strange, B. A., O'Doherty, J., & Dolan, R. J. (2002). Automatic and intentional brain responses during evaluation of trustworthiness of faces. Nature neuroscience, 5(3), 277-283.

[44] Xia, H., Jia, Z., Li, X., Ju, L., & Sha, E. H.-M. (2013). Trust prediction and trust-based source routing in mobile ad hoc networks. Ad Hoc Networks, 11(7), 2096-2114.

[45] Zolfaghar, K., & Aghaie, A. (2011). Evolution of trust networks in social web applications using supervised learning. Procedia Computer Science, 3, 833-839.

[46] Zolfaghar, K., & Aghaie, A. (2012). A syntactical approach for interpersonal trust prediction in social web applications: Combining contextual and structural data. Knowledge-Based Systems, 26, 93-102.

IJARE