

# An Integrated Fuzzy Trust Prediction Approach in Product Design and Engineering

A. Azadeh<sup>1</sup> · Sh. Sadri<sup>2</sup> · M. Saberi<sup>3</sup> · J. H. Yoon<sup>4</sup> · E. Chang<sup>3</sup> ·  
O. Khadeer Hussain<sup>3</sup> · N. Pourmohammad Zia<sup>2</sup>

Received: 30 March 2016/Revised: 20 December 2016/Accepted: 13 March 2017/Published online: 11 May 2017  
© Taiwan Fuzzy Systems Association and Springer-Verlag Berlin Heidelberg 2017

**Abstract** Nowadays, the success of a company is dependent to the novelty of the company in developing new items. Product design and engineering are a basic phase in developing new commodities which examines the product economically and technologically. In the proposed study, “Trust” is identified as an effective factor on the life cycle of the new designed product. This study addresses a simulation structure to generate all the possible trust modes between two agents over time and implements four prediction methods to forecast the trust value of the new item. The time horizon is considered to be short term and middle term, and 27 and 108 scenarios are designed, respectively, based on three categories involving high, medium and short trust. Here, three prediction techniques: conventional time series, artificial neural networks and adaptive neuro-fuzzy inference system, are recommended and compared. By comparing MAPEs of all prediction methods, the best technique is identified.

**Keywords** Product engineering · Trust prediction · Conventional time series analysis · Artificial neural networks · Adaptive neuro-fuzzy inference system

## 1 Introduction

Today, companies must be more conscious about the changes in the market in order to have competitive advantages. Recently, life cycle of products has gotten shorter; hence, satisfaction of customers decreases. Therefore, there is an essential need to develop a new product to satisfy the customers’ demand [9]. One of the most important phases of developing new items is product engineering. Product engineering refers to the process of designing and developing an item considering issues of costs, predictability, quality, performance, reliability, serviceability and user features. The life cycle of a newly developed product is affected by different controllable and also external factors, and there is a trade-off between cost of producing the product and life cycle.

Reliability in product design is a technological indicator which represents the performance of the product in its operating environment. Over time, this indicator influences the customer satisfaction about the product and “Trust” between customer and company in terms of an external factor.

Trust is a subjective concept arises between two parties to indicate the success of the relationship [12]. As the trust of customers to the developed items increases, the risk of failure in the development of new product decreases.

Considering this factor in product design necessitates managers to predict the trust level of new item based on previous data. Prediction of agent trustworthiness is so valuable, because direct the trusting agent to take better decision in the future. Prediction has two classes: 1) predicting whether an interaction between two parties had been formed and consequently trust would exist among agents and 2) prediction of the trust values and the level of satisfaction by trusting agent [16]. As the number of time

---

✉ J. H. Yoon  
jin9135@gmail.com

<sup>1</sup> School of Industrial and Systems Engineering, College of Engineering, University of Tehran, Tehran, Iran

<sup>2</sup> Department of Industrial Engineering and Management Systems, Amir Kabir University of Technology, Tehran, Iran

<sup>3</sup> Business School, UNSW Canberra, Canberra, Australia

<sup>4</sup> Department of Mathematics, Yonsei University, Seoul, South Korea

slots (i.e., a particular time in which an interaction happens between two parties, and based on it a trust value is assigned to trusted agent by trusting agent) [4] consisting of historical data increases, the data tend to be static. It means sometimes in early relations fluctuation of trust values is high, while as the time passes the values converge. Different methods have been used to predict the trustworthiness. In the proposed study, to predict the trust of customers to the new product as a stage in product design, we consider all possible scenarios for a short-term and middle-term horizon. Owing to the complexity of considering all scenarios in a long-term horizon, it is ignored in this study. Here, the authors utilized the artificial neural network method to predict the trust value based on historical data. Also, time series is applied as another method of prediction. Autocorrelation (ACF) is a basic calculation of both methods. In Sect. 2, a brief review of related literature in both product design and trust field is provided. The proposed methodologies of data simulation and prediction procedures are described in Sect. 3. Section 4 describes a numerical example to infer the proposed algorithm. The most and less complex scenarios are determined by calculating and comparing the complexity of each scenario which is referred in Sect. 5. Finally, Sect. 6 implies a conclusion of the study.

## 2 Literature Review

Concurrent engineering (CE) is an approach which integrates the product design and process design. There is a rich literature in the product design field. A few of the studies are reviewed below. Furthermore, a brief review of studies which considered the trust concept is provided.

For several years, researchers concentrated on CE issues and studied different aspects of it. For the first time, Fine [8] defined 3D-CE approach in which supply chain design was incorporated into product and process design. Dowlatshahi [5] investigated the role of product safety and liability in the early stages of product design in a concurrent engineering environment. Years later, Tchidi et al. [19] introduced an extended quality functional deployment process, in a 3D-CE environment that transforms customer requirements into product design, process design and supply chain design, through an extended house of quality. Demoly et al. [6] described the application of a novel product relationship management approach, in the context of product life cycle management, enabling concurrent product design and assembly sequence planning. Karningsih et al. [11] studied the difficulties of CE implementation in company X, one Indonesian high-technology industry. The aim is achieved through implementing Simultaneous Engineering Gap Analysis (SEGAPAN) and

analytical hierarchical process (AHP). Recently, [23] evaluated the impact of organizational culture on the new product development practices and product safety performance.

Some papers have quantitative attribute to CE and developed mathematical models. Xu et al. [21] proposed a fuzzy multi-stage decision-making system for product design in the concurrent engineering. Shidpour et al. [18] used a multi-objective linear programming model integrated to the TOPSIS method in order to determine the best configuration of product design assembly process and suppliers of components. Maier et al. [13] developed a discrete-event simulation model to investigate priority policies in the design. In the proposed study, design progression is modeled as an increase in the maturity of parts.

As stated above, trust is another effective factor in product design which is ignored in the literature. A comprehensive work on defining and managing trust and reputation can be found in Change et al. [4]. Prediction of trust values is a key element of modeling and managing trust. Raza et al. [16] employed a few approaches for predicting trust. Mashinchi et al. [14] introduced a new approach based on fuzzy linear regression analysis (FLRA) to extract qualitative information from quantitative data and so use the obtained qualitative information for better modeling of the data. Xia et al. [20] provided a dynamic trust prediction model to evaluate the trustworthiness of nodes and enhance the security of mobile ad hoc networks. Azadeh et al. [2] implement the concept of trust in terms of performance measurement. They establish different scenarios based on Number DMUs and Timeslot. The proposed approach incorporates time series forecasting in order to predict the future efficiency rate. Nunez-Ganzalez et al. [15] believed that machine learning is an approach to predict the trust in social networks based on reputation features which are gained from the available trust information. To implement the conventional machine learning methods, the variable size reputation information must be reduced to a fixed-size vector. To this aim, they proposed two approaches: (1) a naïve selection of reputation features and (2) a probabilistic model of these features. Fang et al. [7] considered the complexity of trust with multiple facets and proposed a (dis) trust framework with consideration of both interpersonal and impersonal aspects of trust and distrust.

Up to now, the product design and engineering issues were concentrated on product features, and some external criteria are ignored. The trustworthiness of a company is an influential factor addressed in the proposed study to investigate the role of trust in product engineering. In this study, trust rate of new product is predicted based on some historical data. To cope with the complexity of relations between agents in a market, a simulation structure is established to simulate all possible trust scenarios in a

short-term and middle-term horizon. Classical time series, ANN and ANFIS are three prediction techniques implemented to forecast the new items trust value.

### 3 Proposed Methodology

In the proposed study, a new concept is considered to distinguish the feasibility of developing a new item. The authors are motivated to predict trustworthiness of new item based on historical data in a short-term and middle-term horizon. To cope with the complexity of relations among agents, almost all possible scenarios of trust are simulated and finally a trust value is predicted for each one by implementing adaptive neuro-fuzzy inference system, artificial neural network and also conventional time series analysis. The short-term horizon is considered to involve 12 months, whereas the middle-term horizon contains 21 time slots. The simulation structure of historical data and prediction methods is explained below, and comparing the mean absolute percentage error (MAPE) values for all techniques represents the efficiency of each one in prediction trust value. Figure 1 represents the steps of simulation and prediction algorithm of next trust value.

*Step 1 Data Simulation* Estimation of future trustworthiness is based on historical data on trust values which trusting agent assigned to the trusted agent. Time duration among two consecutive transactions of agents is called time slot. In this work, it is assumed to be a month; thus, a deal happens between two parties once in a month. Here, three concepts are assumed which are representative of trust modes: low, medium and high. In the rest of the paper,  $z_t$  represents the simulated historical data at time  $t = 1, 2, \dots, T$  (for short-term horizon  $T = 12$ , while for middle-term horizon  $T = 21$ )

*Step 1.1 Short-Term Horizon* For short-term planning, the time horizon is considered to be one year. Each third of whole refers to a concept: low, medium and high (i.e., Each 4 time slots are supposed to have the same concept. The reason is that it is considered that it takes 4 months for trusting agent to change the trust level about trusted agent based on previous experiments). In simulation of scenarios, first all possible permutations of 3 numbers: 1, 2 and 3, are generated. Number 1 is equal to the concept high, number 2 is equal to the concept medium, and number 3 is equal to the concept low. The trust level interval is assumed to be  $[0, 1]$ . Zero refers to the completely distrust/low trust, and 1 represents the completely trust/high trust. According to the permutations of the numbers and related trust concepts, values are generated in  $[0.7, 1]$ ,  $[0.4, 0.7]$  and  $[0, 0.4]$  intervals for high, medium and low concepts, respectively. Following this

algorithm results in generation of 27 scenarios of short-term horizon.

*Step 1.2 Middle-Term Horizons* Middle-term horizon contains 21 time slots, and previous structure is not appropriate to apply. The proposed structure for middle-term horizon includes three stages following which leads to simulation of 108 scenarios. As mentioned in short-term period, here three consecutive time slots refer to one concept. In the first stage, all possible permutations of the numbers 1, 2, 3 are generated (this stage is similar to short-term horizon, and 27 scenarios are generated). As before, three trust concepts are supposed. According to the generated permutations and related concepts, data are created randomly in  $[0.7, 1]$ ,  $[0.4, 0.7]$  and  $[0, 0.4]$  for high, medium and low concepts, respectively. In the second stage, per a scenario created in the first stage, there are four different trust models. Based on the tendency to converge, the mean of last three data of first stage is calculated; if it was in  $[0, 0.3]$  range, the initiate concept of the second stage is low, but if the mean was in  $[0.3, 0.6]$  range, the next stage starts with concept medium, else the next stage starts with the high concept. Through passing time and more interactions between two parties of a relationship, the trust values tend to be stable. So for the second stage, when the mode begins with concept low, the other values tend to have low and medium concepts. Also, for modes started by medium, the rest will refer to medium and high concepts, and finally, to modes initiated with high concept, the rest will include medium and high concepts. These modes are generated randomly in  $[0.6, 1]$ ,  $[0.3, 0.6]$  and  $[0, 0.3]$  ranges for high, medium and low batches, respectively.

The third stage consists of three time slots. For simulation of this part, in addition to the mean of last three data created in the second stage, the variance of all generated numbers is calculated. Variances are normalized by dividing them to the maximum variance. Variance is an indicator of variation or convergence rate of data during passed time. 0.7 is supposed to be a boundary in variance range. Thus, if the variance of one scenario is more than boundary, the variation between trust values is high and the mode does not tend to converge.

*Step 2. Autocorrelation (ACF)* ACF calculation is a basic calculation to use time series and ANN techniques. Autocorrelation (ACF) is a mathematical representation of the degree of similarity between a time series and a lagged version of itself over successive time intervals to detect non-randomness in data and to identify the appropriate time series model. It is the same as calculating the correlation between two different time series ( $z_t, z_{t+k}$ ; correlation of lag  $k$ ), except that the same time series is used

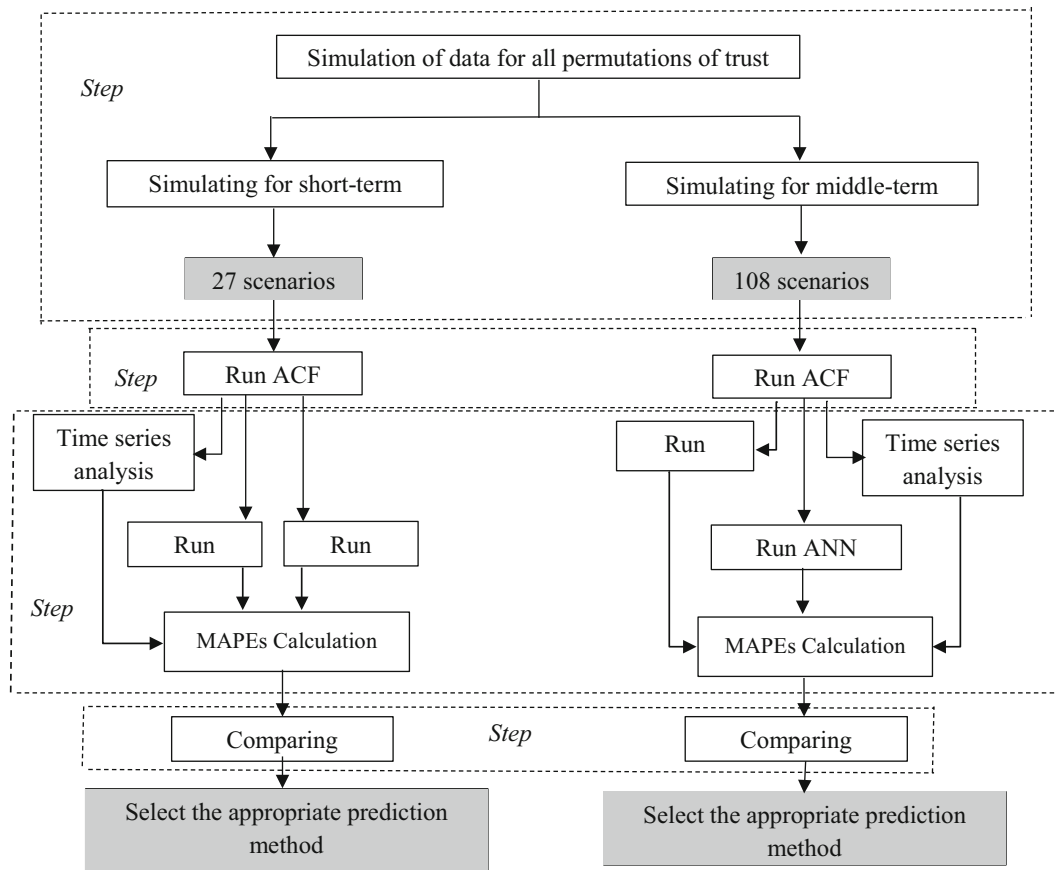


Fig. 1 Proposed algorithm of prediction of future trust value

twice—once in its original form and once lagged one or more time periods.

Given measurements  $y_1, y_2, \dots, y_T$  at time  $z_1, z_2, \dots, z_T$ , the lag  $k$  autocorrelation is defined as:

$$r_k = \frac{\sum_{i=1}^{T-k} (y_i - \bar{y})(y_{i+k} - \bar{y})}{\sum_{i=1}^T (y_i - \bar{y})^2} \tag{1}$$

The results are eventuated from coding up ACF in MATLAB. Based on ACF quantities, maximum and minimum numbers are determined. Related time slot to the maximum number is supposed to be lag. Lag is representative of the time slot which impacts more on future trust value.

**Step 3. Prediction Methods** According to the importance of future event prediction, there are some methods which predict based on historical data and estimate next time slot’s value. In this study, four different prediction tools are applied, and by comparison with MAPEs, the best one is selected. Each method has different efficiency. Mentioned methods are described in below.

**Step 3. 1. Time Series Analysis** Time series analysis comprises methods for analyzing time series data in order

to extract meaningful statistics and other characteristics of the data. Time series data have a natural temporal ordering. This makes time series analysis distinct from other common data analysis problems, in which there is no natural ordering of the observations. A stochastic model for a time series will generally reflect the fact that observations close together in time will be more closely related than observations further apart. (en.wikipedia.org).

Mean absolute percentage error (MAPE) is an appropriate criterion for assessing the efficiency of predicted value. It would be computed by following formula (2):  $x_t$  : predicted value,  $x'_t$  : the value of identifying lag,  $n$  : number of rows (in this study,  $n = 1$ )

$$MAPE = \frac{\sum_{t=1}^n \left| \frac{x_t - x'_t}{x_t} \right|}{n} \tag{2}$$

**Step 3.2. Artificial Neural Network (ANN)** Neural networks can be used for prediction with various levels of success [22]. The advantage of them includes automatic learning of dependencies only from measured data without any need to add further information (such as type of dependency like with the regression). The neural network is trained from the historical data with the hope that it will

discover hidden dependencies and that it will be able to use them for predicting into the future.

Figure 2 represents the structure of the artificial neural network.

Data from the past are provided to be the inputs of neural network, and data for future are expected from the outputs of the network. For neural networks that can have outputs only in a certain interval, it is important to realize that it is not possible to predict values outside of this interval. The backpropagation algorithm is used in layered feedforward ANNs. This means that the artificial neurons are organized in layers and send the signals forward, and the errors propagated backward [17]. The activation function of the neurons in the case of the implementing backpropagation algorithm is weighted sum which can be defined as:

$$A_j(\bar{z}, \bar{w}) = \sum_{i=0}^n z_i w_{ji} \tag{3}$$

Obviously, the activation function depends only on the inputs and weights. The commonly used output function is sigmoid function which is represented in Eq. 4.

$$O_j(\bar{z}, \bar{w}) = \frac{1}{1 + e^{A_j(\bar{z}, \bar{w})}} \tag{4}$$

In prediction of trust values, three basic error estimation methods as mean absolute error (MAE), mean square error (MSE) and mean absolute percentage error (MAPE) are applied [1]. Equations (5) and (6) refer to MAE and MSE, respectively. MAPE formula is similar to Eq. (2).  $x_t$  : predicted value,  $x'_t$  the value of identifying lag,  $n$  : number of rows

$$MAE = \frac{\sum_{t=1}^n |x_t - x'_t|}{n} \tag{5}$$

$$MSE = \frac{\sum_{t=1}^n (x_t - x'_t)^2}{n} \tag{6}$$

By applying ANN, trust value for future time slots can be estimated and also predicted.

*Step 3.3. Adaptive Neuro-Fuzzy Inference System* ANFIS, which is considered as an approach in neuro-fuzzy development, proved to have significantly

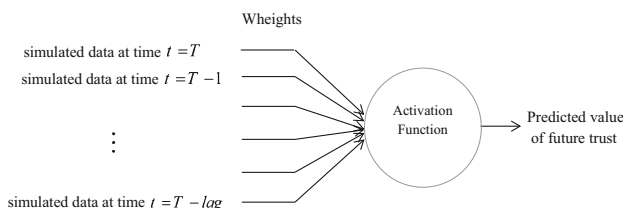


Fig. 2 ANN structure

acceptable results in modeling nonlinear functions [10]. 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 [3]; in fact, neuro-fuzzy system combines neural networks and fuzzy logic. ANFIS uses a feedforward network to optimize parameters of a given fuzzy inference system (FIS). The learning algorithm for ANFIS is a hybrid algorithm, which is a combination of the gradient descent and least squares methods [10].

### 4 Numerical Example

In this section, the simulation structure and prediction process of one scenario for each time horizon are explained in details.

#### 4.1 Short-Term Horizons

As stated before, for short-term horizon trust values of 12 time slots are simulated.

##### 4.1.1 Data Simulation

Suppose permutation {1, 2, 3} as an example of all possible permutations of these three numbers. This permutation is representative of (high, medium and low) scenario. Based on related concepts and identified intervals in step 1.1, 4 random numbers are created in [0.7 1] range, whereas other 4 number are created in [0.4 0.7] range which refer to medium concept. As last number is 3, 4 random numbers are generated in [0, 0.4] range. Figure 3 depicts the trend of scenario and its trust values.

##### 4.1.2 Autocorrelation (ACF)

ACF is a basic calculation to use time series and ANN techniques. ACF determines lag values for each scenario. Table 1 illustrates ACF values for short-term planning time scenarios.

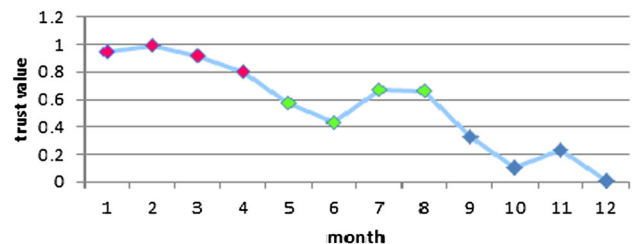


Fig. 3 Scenario (high, medium, low)



Lag value refers to the time slots which have more impact on prediction. It is calculated based on the maximum ACF value of scenario. Maximum, minimum and the large number of discussed example is represented in Fig. 4.

For all scenarios, ACF value of first time slot equals 1 and is ignored in calculation maximum and lag values.

#### 4.1.3 Time Series Analysis

Inputs and outputs of time series method are identified based on the lag which is obtained from ACF calculation.  $X$  represents inputs and  $Y$  represents outputs for each case. The results of applying time series for considering scenario are illustrated in Table 2.

#### 4.1.4 Artificial Neural Network (ANN)

Inputs and outputs of this method are determined based on the lag. These values are as same as values for time series. Three error estimations and predicted values which are eventuated by running ANN for scenario are represented in Tables 3.

#### 4.1.5 Adaptive Neuro-Fuzzy Inference System (ANFIS)

As last methods, lag number has an impact on determining inputs and outputs. Here, for the sake of brevity, only MAPEs of scenarios as an essential factor in determining the efficiency of method are calculated. MAPE of discussing scenario is 0.1019, and the predicted value is 0.743.

### 4.2 Middle-Term Horizon

It is stated in step 1.2 that middle-term time horizon consists of 21 time slots and 108 different scenarios are simulated by following the developed structure. In this section, a numerical example to represent the simulation and prediction process for middle-term horizon is presented.

#### 4.2.1 Data Simulation

As mentioned earlier, scenarios of middle-term horizon are divided into three parts. {1, 2, 3} is an example of all 27 different permutations for the first part of middle-term scenarios. According to identified intervals in step 1.2, trust

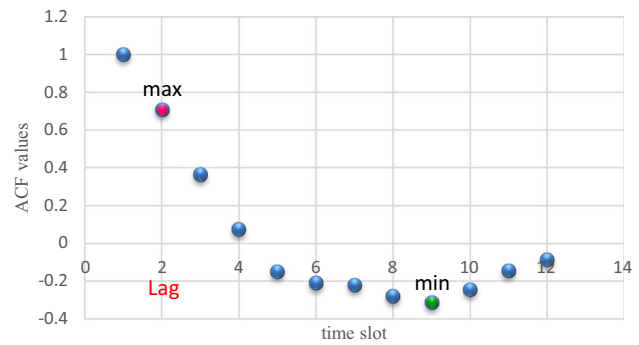


Fig. 4 Max, min, lag for short-term planning time

values are created in [0.7 1], [0.4, 0.7] and [0, 0.4], respectively, which refer to high, medium and low trust concepts. Table 4 demonstrates creating numbers for the first part of the scenario ( $z_t, t = 1, 2, \dots, 9$ ).

Mean of last 3 data is 0.18262. As it is in [0 0.3] range, the next part starts with concept low and the rest slots can have medium and low concepts. The simulated data ( $z_t, t = 10, 11, \dots, 18$ ) are shown in Table 5.

Then, the variance of whole 18 data is computed, and also the mean of the last three numbers is calculated. Mean of last three data is in [0.3 0.6] range, and also variance is less than 0.7; so next three values are in the medium range. Table 6 refers to the generated data ( $z_t, t = 19, 20, 21$ ).

These values represent the scenario (high, medium, low, low, medium, medium, medium) and are shown in Fig. 5.

#### 4.2.2 Autocorrelation (ACF)

Similar to short-term horizon, before implementing prediction methods ACF calculation is done to determine the maximum, minimum and lag values which represent the most effective time slot on next slot's trustworthiness value. Results of the ACF are depicted in Table 7.

Considering these values results in determining lag value, which is equal to 2.

#### 4.2.3 Time Series Analysis

Classical time series analysis technique predicts values based on inputs and outputs derived from historical data. Considering lag number, inputs and outputs of each scenario are identified. Obtained results by implementing this approach is shown in Table 8.

Table 1 ACF results for short-term planning time

ACF values											
1	2	3	4	5	6	7	8	9	10	11	12
1	0.709	0.3642	0.0745	-0.15	-0.21	-0.221	-0.28	-0.311	-0.244	-0.145	-0.086

**Table 2** Time series result for short-term planning time

	Trust value										Constant	Coefficient	Predicted value
x	0.947	0.994	0.919	0.803	0.575	0.432	0.672	0.664	0.327	0.104	0.702	0.022	0.721
y	0.919	0.803	0.575	0.432	0.672	0.664	0.327	0.104	0.238	0.009			

**Table 3** Results of ANN for short-term planning time

MAPE	MAE	MSE	Prediction
0.3013	0.0474	0.0022	0.6608

**Table 4** Trust values of first part

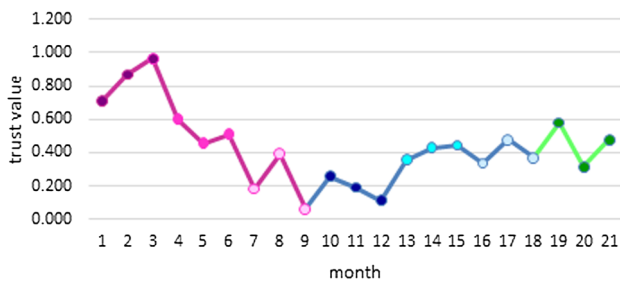
$z_t$
0.710 0.868 0.965 0.601 0.457 0.511 0.184 0.393 0.063

**Table 5** Values of second part

$z_t$
0.257 0.193 0.113 0.357 0.428 0.445 0.336 0.477 0.368

**Table 6** Values of third part

$z_t$
0.578 0.315 0.478



**Fig. 5** Scenario (high, medium, low, low, medium, medium, medium)

**Table 7** ACF results for middle-term planning time

ACF values												
1	2	3	4	5	6	7	8	9	10	11	12	
1	0.601	0.511	0.188	0.020	-0.100	-0.301	-0.303	-0.355	-0.291	-0.296	-0.073	
ACF values												
13	14	15	16	17	18	19	20	21				
-0.082	-0.003	-0.042	-0.017	0.041	-0.010	0.012	-0.013	0.012				

4.2.4 Artificial Neural Network (ANN)

For this technique, inputs and outputs are as same as time series analysis. The results of ANN for discussing example are illustrated in Table 9.

As stated in Sect. 3 (step 3.2), three error estimation methods are defined: Mean absolute percentage error (MAPE), mean absolute error (MAE) and mean square error (MSE), respectively. The predicted value is based on the trained function.

4.2.5 Adaptive Neuro-Fuzzy Inference System (ANFIS)

As mentioned in Sect. 4.1.5, for this technique only MAPE is estimated. Estimated value of MAPE of discussing example is 0.0341, and the predicted value equals to 0.7915.

4.3 MAPE Comparison

Comparison with MAPEs, commonly used error estimation measurement, results in examining each technique’s efficiency in prediction of value for provided simulation structure. The summary of obtaining MAPEs for discussing examples for each time horizon is depicted in Table 10.

Obviously, ANFISN is an appropriate method for prediction of future experiment trust value which trusted agent assigns to trusting agent in a short-term and middle-term horizon. One other point is that, given that middle-term horizon has more information about the trend of relationship, it is well-trained and an appropriate model is fitted to predict the future.

**Table 8** Time series result of middle-term planning

Trust value											
X	0.710	0.868	0.965	0.601	0.457	0.511	0.184	0.393	0.063	0.257	0.193
Y	0.965	0.601	0.457	0.511	0.184	0.393	0.063	0.257	0.193	0.113	0.357
Trust value									Constant	Coefficient	Predicted value
X	0.113	0.357	0.428	0.445	0.336	0.477	0.368	0.578	0.522	0.168	0.738
Y	0.428	0.445	0.336	0.477	0.368	0.578	0.315	0.478			

**Table 9** Results of ANN for middle-term planning

MAPE	MAE	MSE	Prediction
0.0507	0.0229	0.0008	0.7869

**Table 10** Comparison with MAPEs for short-term and middle-term samples

Short-term planning			Middle-term planning		
Conventional time series	ANN	ANFIS	Conventional time series	ANN	ANFIS
0.5019	0.3013	0.1019	0.3399	0.0507	0.0341

### 5 Evaluating Complexity of Scenarios

The complexity degree of simulated scenarios has been calculated according to the formula (7).

$$\text{Complexity degree} = \frac{\sum_{i=1}^m \text{CB}(A_i, T)}{m} \tag{7}$$

That:  $CB$  city-block<sup>1</sup> distance,  $m$  number of training dataset members,  $T$  test data vector,  $A$  Training dataset vector Complexity of short-term sample which mentioned above is 0.27, and for middle-term scenario this index is 0.34.

### 6 Conclusion

Nowadays, there is an essential need to be conscious about market trends to respond to the market demand in an appropriate way. One approach to survive in a competitive market is developing new items in desired times.

One of the most important phases of developing new items is product engineering. Product engineering is the

process of developing new commodity considering cost, applicability and other features.

The reputation of company and trust of customers to a company is an effective factor in new items features such as lifecycle, revenue and durability. Trust is a subjective belief of an agent about another that can be altered during the time. Prediction of trust value for future time slots is an essential process in evaluating the probability of continuing the transaction between two agents. In the proposed study, a simulation structure is provided to generate all possible permutations of trust models consisted of high trust, medium trust and low trust for short-term and middle-term horizon. This process leads to consideration of 27 scenarios in short-term horizon and 108 scenarios in middle-term time horizon. Conventional time series analysis, ANN and ANFIS are recommended tools for prediction of trust values of the future. Autocorrelation is a basic calculation in utilizing time series, ANN and ANFIS. Based on amount of lag in ACF calculation, Time series, ANN and ANFIS are applied for each scenario. MAPE is an index of efficiency for each method that represents the accuracy of predicted value. The results address the applicability of ANFIS in prediction of next slot’s trust value which helps the designers to improve the quality of product. Based on the achieved values, the managers decide about the important features of the new product.

As mentioned before, the simulation structure of data for long-term planning is different. Due to increasing the time horizon and historical data for each scenario, simulation method is complicated from one for short-term and middle-term planning. It is recommended to develop simulation methods for long-term planning in future.

### References

1. Azadeh, A., Saberi, M., Asadzadeh, S.M., Khakestani, M.: A hybrid fuzzy mathematical programming-design of experiment framework for improvement of energy consumption estimation with small data sets and uncertainty: the cases of USA, Canada, Singapore, Pakistan and Iran. *Energy* **36**(12), 6981–6992 (2011)

<sup>1</sup> City-block metric: If  $a$  and  $b$  are vectors with  $m$ -dimension, the city-block metric has been defined to calculate distance between  $a$  and  $b$  according to the following formula:

$$\sum_{i=1}^m |b_i - a_i| \tag{8}$$



2. Azadeh, A., Zia, N.P., Saberi, M., Hussain, F.K., Yoon, J.H., Hussain, O.K., Sadri, S.: A trust-based performance measurement modeling using t-norm and t-conorm operators. *Appl. Soft Comput.* **30**, 491–500 (2015)
3. Brown, M., Harris, C.J.: *Neurofuzzy adaptive modelling and control*. Prentice Hall, Upper Saddle River (1994)
4. Chang, E., Dillon, T., Hussain, F.K.: *Trust and reputation for service oriented environments*, vol. 1(18). Wiley, Hoboken (2006)
5. Dowlatshahi, S.: The role of product safety and liability in concurrent engineering. *Comput. Ind. Eng.* **41**(2), 187–209 (2001)
6. Demoly, F., Dutartre, O., Yan, X.T., Eynard, B., Kiritsis, D., Gomes, S.: Product relationships management enabler for concurrent engineering and product lifecycle management. *Comput. Ind.* **64**(7), 833–848 (2013)
7. Fang, H., Guo, G., Zhang, J.: Multi-faceted trust and distrust prediction for recommender systems. *Decis. Support Syst.* **71**, 37–47 (2015)
8. Fine, C.: *Clockspeed*. Perseus Books, New York (1998)
9. Fine, C.H., Golany, B., Naseraldin, H.: Modeling trade-offs in three dimensional concurrent engineering: a goal programming approach. *J. Oper. Manag.* **23**, 389–403 (2005)
10. Jang, J.S.R., Sun, C.T., Mizutani, E.: *Neuro-fuzzy and soft computing: a computational approach to learning and machine intelligence*. Prentice-Hall, Upper Saddle River (1997)
11. Karningsih, P.D., Anggrahini, D., Syafi'i, M.I.: Concurrent engineering implementation assessment: a case study in an Indonesian manufacturing company. *Procedia Manufacturing* **4**, 200–207 (2015)
12. Luo, J., Liu, X., Fan, M.: A trust model based on fuzzy recommendation for mobile ad-hoc networks. *Comput. Netw.* **53**(14), 2396–2407 (2009)
13. Maier, J.F., Wynn, D.C., Biedermann, W., Lindemann, U., Clarkson, P.J.: Simulating progressive iteration, rework and change propagation to prioritise design tasks. *Res. Eng. Des.* **25**(4), 283–307 (2014)
14. Mashinchi, M.H., Li, L., Orgun, M.A., Wang, Y.: The prediction of trust rating based on the quality of services using fuzzy linear regression. In: *Fuzzy Systems (FUZZ)*, 2011 IEEE International Conference, pp. 1953–1959 (2011)
15. Nuñez-Gonzalez, J.D., Graña, M., Apolloni, B.: Reputation features for trust prediction in social networks. *Neurocomputing* **166**, 1–7 (2015)
16. Raza, M., Hussain, O.K., Hussain, F.K., Chang, E.: Maturity, distance and density (MD 2) metrics for optimizing trust prediction for business intelligence. *J. Global Optim.* **51**(2), 285–300 (2011)
17. Rumelhart, D.E., McClelland, J.L., PDP Research Group: *Parallel Distributed Processing*, vol. 1, pp. 354–362. IEEE, Piscataway (1986)
18. Shidpour, H., Shahrokhi, M., Bernard, A.: A multi-objective programming approach, integrated into the TOPSIS method, in order to optimize product design; in three-dimensional concurrent engineering. *Comput. Ind. Eng.* **64**(4), 875–885 (2013)
19. Tchidi, F.M., He, Z.: Systematic study of three-dimensional concurrent engineering based on an extended quality functional deployment. In: *Proceedings of the International Conference on Mechanical, Industrial, and Manufacturing Technologies (MIMT)*, pp. 22–24. Sanya, China (2010)
20. Xia, H., Jia, Z., Li, X., Ju, L., Sha, E.H.M.: Trust prediction and trust-based source routing in mobile ad hoc networks. *Ad Hoc Netw.* **11**(7), 2096–2114 (2012)
21. Xu, L., Li, Z., Li, S., Tang, F.: A decision support system for product design in concurrent engineering. *Decis. Support Syst.* **42**, 2029–2042 (2007)
22. Yaghini, M., Khoshraftar, M.M., Fallahi, M.: A hybrid algorithm for artificial neural network training. *Eng. Appl. Artif. Intell.* **26**(1), 293–301 (2013)
23. Zhu, A.Y., von Zedtwitz, M., Assimakopoulos, D., Fernandes, K.: The impact of organizational culture on concurrent engineering, design-for-safety, and product safety performance. *Int. J. Prod. Econ.* **176**, 69–81 (2016)



**A. Azadeh** is a full eminent professor and the founder of the Department of Industrial Engineering at University of Tehran. He obtained his PhD in Industrial and Systems Engineering from the University of Southern California, in 1992. He is the co-founder of the Research Institute of Energy Management and Planning at the University of Tehran. Dr. Azadeh is the director of Simulation and Computer Aided Design Laboratory at the College of Engineering. He is a member of the Center of Excellence for Intelligent Based Experimental Mechanics. He received National Award of Merit and National Honor Award in USA, in 1983–1984. He received the 1992 Phi Beta Kappa Alumni Award for excellence in research and innovation of doctoral dissertation in USA. Professor Azadeh is the recipient of the 1999–2000 Applied Research Award, 2008–2009 Distinguished Researcher Award, 2010–2011 Eminent Researcher Award, 2012–2013 International Award for Academic Achievements at the University of Tehran. Professor Azadeh has published more than 700 papers in reputable academic journals and conference proceedings.



**Sh. Sadri** is currently PhD candidate of Industrial Engineering in AmirKabir University of Technology. Her current research interest includes time series prediction and its application in traffic management.



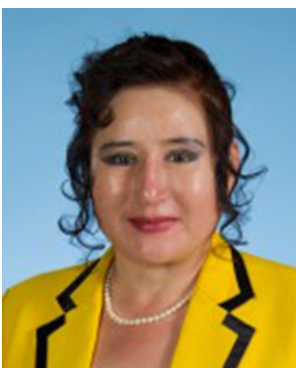
**M. Saberi Saberi** has an outstanding research records and significant capabilities in area of business intelligence, data mining and applied machine learning. He has published more than 140 papers in reputable academic journals and conference proceedings. His Google Scholar citations and h-index are 1400 and 18, respectively. He was a lecturer at the Department of Industrial Engineering at University of Tafresh. He is also the recipient of the 2006–2012

Best Researcher of Young researcher Club, Islamic Azad University (Tafresh Branch). He is also the recipient of National Eminent Researcher Award among Young researcher Club, Islamic Azad University members.



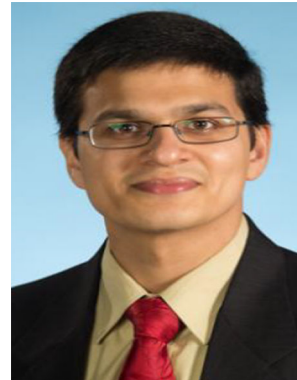
**J. H. Yoon** received Bachelor, Master and PhD degree in Mathematics from Yonsei university, South Korea. She is currently faculty of school of Mathematics and Statistics at Sejong University, Seoul, South Korea. Her research interests are fuzzy regression analysis, fuzzy time series and F-transform. She is a board member of KIIS (Korean institute of Intelligent Systems) and has been working as an editor, guest editor and editorial board member of The

Scientific world journal, Information, International journal of Applied Economics and International Journal of Fuzzy logic and Intelligent Systems, etc. Also, she has been working as an organizer and committee member of several international conferences such as 2012, 2013 NIMS Hot topic workshop, 2012, 2013 ICIS, 2014, 2015 FUZZ IEEE, 2015 ISIS, 2016 SCIS&ISIS, 2016 ICFMsquare 2016, ICMF 2016, IFSA 2017, ISIS2017, etc.

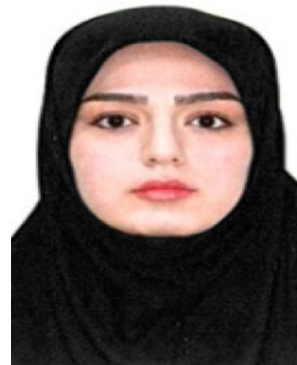


**E. Chang** is a full professor of Logistics and Canberra Fellow at UNSW at Australian Defence Force Academy (ADFA). Professor Chang leads the Defence Logistics research group at UNSW Canberra, targeting the key issues in Logistics ICT, Big Data Management, Defence Logistics and Sustainment, Predictive Analytics, Situation Awareness, IoT and Cyber-Physical Systems, Trust, Security, Risk and Privacy. In a 2012 article, published in MIS

Quarterly vol. 36 iss. 4, Professor Chang was ranked fifth in the world for researchers in Business Intelligence. She has delivered 52 Key-note/Plenary speeches largely at major IEEE Conferences and most recent in the areas of Semantics, Business Intelligence, Big Data Management, Data Quality and the like. Her academic achievement includes 24 competitive research grants, including 12 Australian Research Council (ARC) Grants worth over \$15 million. She has supervised/co-supervised 41 PhD theses to completion, 21 Master theses and 16 postdocs. She has published 7 authored books, over 500 international journal papers and conference papers with an h-index of 40 (Google Scholar) and over 8000 citations. In combining IT and Logistics, she empowers the research work and professional training in Logistics and Transportation in a way that would not otherwise be possible.



**Dr. O. Khadeer Hussain** received the B.S. degree in computer science from JNTU in 2002 and the PhD degree in Information Systems from Curtin University in 2008. His research interests include knowledge management, business intelligence and decision making. His research has been published in various international journals such as The Computer Journal, Computing and others. He is currently a senior lecturer at the University of New South Wales, Canberra, since 2014.



**N. Pourmohammad-Zia** is currently PhD candidate at Amirkabir University of Technology. Her current research interests include Marketing strategies, Inventory Control and Stochastic and Dynamic process control.