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Soft Computing Modeling of Dealer Loyalty in Turkish Insurance Sector

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ABSTRACT

This study presents the application of soft computing techniques namely as Stepwise Regression (SR), Neuro-Fuzzy (NF) and Neural Networks (NN) for modeling of dealer loyalty in Turkish insurance sector. The proposed soft computing models are based on survey results conducted in insurance sector of Turkey. The accuracies of the proposed soft computing models are quite satisfactory as compared to actual results. The results show that the dominating factors affecting dealer loyalty are found to be dealer satisfaction, dealer trust, dealer perceived value, dealer perception of customer perceived value and relationship time. The analyses of effects of research variables on dealer loyalty are an important contribution to understanding relationships between dealer and manufacturer. Finally, theoretical and managerial implications of the study findings are discussed.

Keywords: Dealer Loyalty, Satisfaction, Soft Computing, Neural Networks, Turkish Insurance Sector.

INTRODUCTION

Plank and Newell (2007, p. 59) stressed that before the 1980s, market researchers often focused on the transactional nature of business, however, after 1980s, the relational structure of business was studied in many researchers. Since this time, marketing practitioner and theoretician have recognized the importance of long-term business relationships and offered opportunities and competitive advantages of the long-term relationships for firms. In long-term channel relationships, especially, researchers have focused on concepts such as trust, loyalty, interdependence, commitment, and satisfaction.

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Any remaining errors or omissions rest solely with the author(s) of this paper.

The concept of loyalty is one of the cornerstones in long-term relationship. However, numerous studies have examined the antecedents of loyalty in business-to-consumer (B2C) markets, relatively a little effort has been made in business-to-business (B2B) market (Sanchez *et al*. 2010). Thus, this study was focused on the concept of loyalty in relationship between manufacturer and dealer in insurance sector as a service industry in Turkey. Why is this study focused on Turkish insurance sector? According to Insurance Association of Turkey; report entitled "2023 Targets and Expectations of Insurance Sector" (Insurance Association of Turkey 2012): (a) The Turkish insurance and pension market has been growing by an average of about 30% each year for the last 10 years. (b) The Turkish insurance market has a very low level of GDP penetration, as measured by insurance premiums, compared to other countries with similar GDP per capita. For example, the GDP penetration of Turkish insurance market is almost half of the Bulgaria's, which has a lower GDP per capita, and almost one third of Poland's, which is slightly higher levels of GDP per capita. This situation illustrates the growth potential for Turkish insurance market. (c) As noted the report, Turkish insurance sector has lower market profitability than other developing or developed markets. To raising profitability on the on hand financial and/or technical instrumentations is applied, on the other hand relational instrumentation should be put into practice such as more communication, more closely relationships. Firms in this market must limit transaction costs. (d) In addition, nearly 66 insurance companies (64 insurance firms and 2 reassurance firms) operate in Turkey. More than half of these companies have foreign partner. The share of foreign capital is 50% and over. Considering above potentials of Turkish insurance market, there is an attractive target market and competitive market for investors. Thus, the relationship network in the market is considered exploration as significant. Further, the study discussed dealer trust (Dtrst), dealer perceived value (Dpvl), dealer satisfaction (Dstsft), dealer transaction specific investments (Dtsi), dealer perception of manufacturer transaction specific investments (Mtsi), dealer perception of manufacturer corporate reputation (Mcorep), dealer perception of customer trust (Ctrst), dealer perception of customer perceived value (Cpvl), dealer perception of customer satisfaction (Cstsft), and dealer perception of customer transaction specific investments (Ctsi) as antecedents of dealer loyalty (Dlylt). We also investigated the effects of dealer firm age (Fage) and relationship time between manufacturer and dealer (Frtime).

Trust is defined as "confidence in an exchange partner's reliability and integrity" (Morgan and Hunt 1994, p. 23). Especially, trust is probably the most widely studied and accepted construct in relationship marketing (Skarmeas *et al*. 2008, p.24). Trust is an essential component in any relationship such as person to person, person to organization and/or organization to organization and at the each stage of relationship. Reichheld and Schefter (2000, p. 107) highlight the importance of trust in that "to gain loyalty of customers, you must first gain trust" (Rauyruen and Miller 2007, p. 24). Consequently, trust was seen and examined as an important antecedent of Dlylt in this research.

The concept of satisfaction has been deeply studied in marketing channels literature and its importance in the area of distribution channel relationships have been emphasized by many competent authors in this area (e.g. Brown *et al*. 1991; Dwyer and Oh 1987; Geyskens and Steenkamp 2000; Hunt and Nevin 1974; Selnes 1998). Geyskens and Steenkamp (2000, p. 11) defined as channel member satisfaction "has been typically defined as a channel member's appraisal of all outcomes of its working relationship with another firm, including economic as well as social outcomes". Although previous research showed that there was a strong relationship between satisfaction and loyalty, the relationship has been investigated. Similarly, we aim to bring out Dstsft and Cstsft as antecedents of Dlylt and whether or not the strong linkage between satisfaction and loyalty, particularly in insurance sector. We thought that the relationship was not investigated adequately in developing country and the east socuity. Espicially, the effects of dynamics of east culture on this issue was more investigated.

Transaction specific investments (TSIs) are a very important concept in the transaction cost (Ganesan 1994; Joshi and Stump 1999). TSIs are those investments intended to support a specific mutual relationships in marketing channels, for example manufacturer—dealer, manufacturer—supplier or buyer—supplier (Yu *et al*. 2006). TSIs can have different forms. It can be a physical asset, a monetary asset, knowledge, a personal relationship, and/or skills, etc. (Williamson 1991). Such an investment can include a risk for the investing firm; if the relationship ends, the investing firm may lose the almost full value of the TSIs. Therefore, linkage between TSIs and loyalty must be very strong in distribution channel relationships. In case of insurance sectors, dealers may have less of intention to switch to other manufacturer if they have invested assets as invisible human, knowledge, relationship, and/or skills; the same is true for manufacturers. Therefore, TSIs concept is one of the most important variables for understanding the mechanisms of loyalty in insurance sector.

According to Zeithaml (1988) definitition, perceived value is defined as "the judgment or evaluation made by the customer of the comparison between the advantages of, or the utility obtained from, a product, service or relationship and the perceived sacrifices or costs" (Forgas *et al*. 2010, p.230). Chen and Tsai (2008) found that perceived value has direct effect on loyalty; their finding overlaps previous many research findings. In order to better understand the effect of perceived value on loyalty, we tested whether or not both dealer and dealer perception of customer perceived value was antecedent of loyalty.

Corporate reputation is popular topic of management and marketing researches. According to Walsh and Beatty (2007, p. 130), corporate reputation was related with relationship variables (e.g. customer satisfaction, loyalty, trust, and positive word of mouth). Bontis *et al*. (2007) stated that corporate image – part of reputation –is an antecedent to customer loyalty (Andreassen and Lindestad 1998) and may be loyalty's strongest driver (Andreassen 1994; Ryan *et al*. 1999). Thus, a company's reputation should be positively associated with loyalty to the firm (Walsh and Beatty 2007). However, in this regard, the link between manufacturers' reputation and their dealers' loyalty should be more investigated.

Given the above assessments, the first objective of this paper is to propose and empirically analyze a conceptual framework that considers trust (dealer and dealer perception of customer), perceived value (dealer and dealer perception of customer), satisfaction (dealer and dealer perception of customer), transaction specific investment (dealer, dealer perception of customer, and manufacturer), manufacturer corporate reputation (dealer perception of customer), Fage, and Frtime as antecedents of Dlylt in mutual channel relationship context (manufacturers and their dealers).

The second aim of this study is to model the dealer loyalty of insurance sector in Turkey in terms of affecting factors described above by using soft computing approaches such as Stepwise Regression (SR), Neuro-Fuzzy (NF) and Neural Networks (NN). The degree of dealer loyalty is measured by means of converted numerical values ranging from 1 to 5 obtained from survey results conducted in insurance sector of Turkey. As a result of soft computing models, the dominating factors on dealer loyalty will be determined. The significance of the study is that dealer loyalty has not been modeled in terms of numerical values so far where this study will be a pioneer research in this field.

Researches on loyalty cover both B2C and B2B context, but B2B loyalty studies are less than B2C. Davis-Sramek *et al*. (2008) summarized that existing studies for B2B context. Customer loyalty is important variable on long term financial performance (Lai *et al*. 2009, p.980 stressed that) in competitive B2C markets. The present study contributes that our knowledge of the antecedents of loyalty in service sector such as insurance sector and B2B markets extend. This research tries to complete this gap.

LITERATURE REVIEW

Loyalty

The concept of loyalty is similar mean of relationship commitment (Anderson and Weitz 1992; Moorman *et al*. 1992; Morgan and Hunt 1994) and it has been defined as a long-term commitment to repurchase involving both repeated patronage and a favorable attitude, by Dick and Basu (1994) (Ellinger *et al*. 1999, p. 122). In organizational buyer-seller relationships, according to Lam *et al*. (2004, p. 293), loyalty lead to to focus on long-term benefits and engage in cooperative actions beneficial for the all parties, so on the one hand firms may enhance competitiveness on the other hand they may reduce transaction costs in distrubition channels (Doney and Cannon 1997; Ganesan 1994; Morgan and Hunt 1994). Many studies has been emphasized that loyalty has a favorable effect on business performance (Morgan and Rego 2006). The development, maintenance, and enhancement of loyalty between the parties in both B2C and B2B markets represent a fundamental marketing strategy for high business and marketing performance.

Trust

Trust is defined as the willingness to rely on an exchange partner in whom one has confidence (Moorman *et al*. 1992) and it has assumed a central role in the development of buyer–seller relationship models (Cannon and Perreault 1999; Doney and Cannon 1997; Dwyer *et al*. 1987; Ganesan 1994). To develop mutual trust in exchange partners, they act reliably and fairly. Past research to date suggests that trust is a significant contributor of customer loyalty (Rauyruen *et al*. 2009, p. 177) and this research shows a link between trust and loyalty. The link is generally supported (Sanchez-Franco *et al*. 2009; Sirdeshmukh *et al*. 2002; Chaudhuri and Holbrook 2001; R. L. Oliver, 1999; Mutlu and Taş 2012). Ulaga and Eggert (2006) not found statistically significant relationship between trust and loyalty. Caceres and Paparoidamis (2007) empirically test a model of business loyalty in a sample of 234 advertising agencies' clients. Although their results show that the effects of trust and commitment on loyalty were verified, some authors found an indirect linkage of trust and loyalty (Garbarino and Johnson 1999). Based on previous work, trust is an antecedent of loyalty.

Satisfaction

Satisfaction has been conceptualized, measured, and tested for a long time in marketing literature. Satisfaction is a construct of vital importance in the explanation of any type of relationship between two or more participants (Sanzo *et al*. 2003, p. 329). Considering that Geyskens *et al*. (1999) approach, "satisfaction in the B2B context is often defined as a positive affective state resulting from the appraisal of all aspects of a firm's working relationship with another firm" (Lam *et al*. 2004). In addition to satisfaction includes an evaluation of the economic and noneconomic aspects of the relationship.

According to Geyskens *et al*. (1999), satisfaction is a key driver of the long-term relationship. Johnson *et al*. (2001) argue that satisfaction affects repurchase intentions largely through the ability to build strong relationships between suppliers and customers (Davis-Sramek *et al*. 2008).

Lages *et al*. (2008) examined relationship satisfaction as an assessment of the customer's previous interactions with the supplier (Roberts *et al*. 2003) and Cannon and Perreault (1999) stated that relationship satisfaction is critical for the development of future business exchanges.

Several theoretical and empirical evidences indicate influence of satisfaction on customer retention and/or customer loyalty as a company or supplier. Therefore, satisfaction may be accepted predictive of future actions by partner firm managers. Therefore, satisfaction is an an affective and direct antecedent of loyalty (Dick and Basu 1994; Oliver 1999, Szymanski and Henard 2001, Mutlu and Taş 2012).

Given the above discussion, it may appear to be unnecessary to study the relationship between satisfaction and loyalty as many studies have confirmed that there is a significant positive relationship between these two variables. However, we may display the loyalty-satisfaction relationship in the dynamics of manufacturer and their dealer relationships in Turkish Insurance Sector.

Transaction Specific Investments (TSIs)

As stressed by TCA, transaction-specific assets are investments in assets that are highly specialized to the exchange relationship. TSIs are also defined as the tangible and intangible assets that are devoted to a relationship and support a given transaction (Heide and John 1988). Wouters *et al*. (2007) indicate that TSIs are not limited to physical capital; human-capital investments that are transaction-specific commonly occur as well (Williamson 1979, p. 240). Therefore Williamson (1985) emphasized that TSIs refer to the assets that cannot be easily redeployed in other exchange relationships (Skarmeas *et al*., 2008). TSIs are assets that have considerably less value if they are employed in a relationship with another exchange relationship (Wouters *et al*. 2007). Vazquez *et al*. (2007, p.498) sign that TSIs are more efficient, effective and confidence assets for managing, ongoing and monitoring or controlling relationship between partners. Considering all of these discussions, the formation of loyalty must be examined the role of TSIs in distribution channels.

Perceived Value

The perceived value definition of Zeithaml (1988, p. 14) is the most universally accepted trade-off definition of perceived value in the literature. Zeithaml (1988) defined that value may be viewed as a consumer's overall assessment of product utility based on perceptions of what is received (benefits) compared to what is given (costs) in a service encounter (Chen and Tsai 2008, p.1167). Value is the trade-off between received benefit and cost and past research has shown that perceived value is an important antecedent for overall satisfaction and future purchase intention (Chiou 2004, p.687). Thus, perceived value is also important in the distribution channel context, where it is essential for the firm to establish an ongoing and positive relationship with channel members (Zeng *et al*. 2011). Previous work has defined a direct relationship between perceived value and loyalty (Forgas *et al*. 2010).

Corporate Reputation

Drawing on the conceptualizations offered by Selnes (1993) and Fombrun (1996) corporate reputation is conceived of as a perceptual representation of the firm's overall appeal when compared with competitors (Hansen *et al*. 2008, p.208). Lai *et al*. (2010) indicate that corporate reputation contributes to firms three respects: Firstly, a good corporate reputation differentiates a company from its competitors; secondly a good corporate reputation is an important strategic asset, and thirdly a good corporate reputationis an inimitable asset (Fombrun and Shanley 1990; Roberts and Dowling 2002). However, a good corporate reputation is not quite easily practicable resource, it require cumulitave efforts. According to Walsh and Beatty (2007, p. 127), corporate reputation is critical because it helps to reduce transaction costs, and positively influences both financial and customer outcome variables, such as consumer trust and loyalty. In distribution channels reputation of an organization is a reflection of its corporate identity. Companies and/or customers tend to prefer to deal with companies that have proven reliable in the past (Walsh and Beatty 2007).

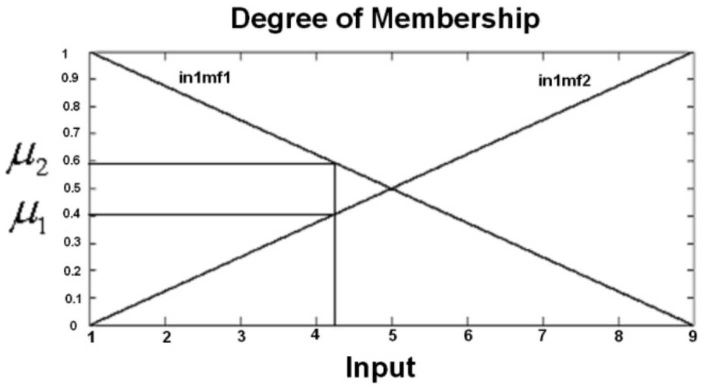

Figure 1 Demonstrated the antecedents of dealer loyalty in this study

SOFT COMPUTING

The definition of soft computing is not precise. Lotfi A. Zadeh, the inventor of the term soft computing, describes it as follows (Zadeh 1994): "*Soft computing is a collection of methodologies that aim to exploit the tolerance for imprecision and uncertainty to achieve tractability, robustness, and low solution cost*. Its principal constituents are fuzzy logic, neurocomputing, and probabilistic reasoning. Soft computing is likely to play an increasingly important role in many application areas, including software engineering. The role model for soft computing is the human mind." This study encompasses the applications and Stepwise Regression (SR), Neuro-fuzzy and Neural Networks (NN).

Brief Overview of Stepwise Regression

While dealing with large number of independent variables, it is of significant importance to determine the best combination of these variables to predict the dependent variable. Stepwise regression serves as a robust tool for the selection of best subset models i.e. the best combination of independent variables that best fits the dependent variable with considerably less computing than is required for all possible regressions (Campbell 2001; Cevik 2007).

The determination of subset models are based on consecutively by adding or deleting, the variable/variables that has the greatest impact on the residual sum of squares. The selection of variables may be either forward, backward or a combination of them. In forward selection, the subset models are chosen by adding one variable at a time to the previously chosen subset. At each successive step, the variable in the subset of variables that are not already in the model that causes the largest decrease in the residual sum of squares is added to the subset. Without a termination rule, forward selection continues until all variables are in the model. On the other hand, backward stepwise selection of variables chooses the subset models by starting with the full model and then eliminating at each step the one variable whose deletion will cause the residual sum of squares to increase the least and continues until the subset model contains only one variable (Rawlings 1998; Cevik 2007).

Regarding forward and backward procedures, it should be noted that the effect of adding or deleting a variable on the contributions of other variables to the model is not being considered. Thus stepwise regression is actually a forward selection process that rechecks at each step the importance of all previously included variables. If the partial sums of squares for any previously included variables do not meet a minimum criterion to stay in the model, the selection procedure changes to backward elimination and variables are dropped one at a time until all remaining variables meet the minimum criterion. Stepwise selection of variables requires more computing than forward or backward selection but has an advantage in terms of the number of potential subset models checked before the model for each subset size is decided. It is reasonable to expect stepwise selection to have a greater chance of choosing the best subsets in the sample data, but selection of the best subset for each subset size is not guaranteed. The stopping rule for stepwise selection of variables uses both the forward and backward elimination criteria. The variable selection process terminates when all variables in the model meet the criterion to stay and no variables outside the model meet the criterion to enter (Rawlings 1998; Cevik 2007).

Fuzzy Logic

Over the last decade, fuzzy logic invented by Lotfi Zadeh (1965) by has been applied to a wide range of covering engineering, process control, image processing, pattern recognition and classification, management, economics and decision making (Rutkowski 2004).

Fuzzy systems can be defined as rule-based systems that are constructed from a collection of linguistic rules which can represent any system with accuracy, i.e., they work as universal approximators. The rule-based system of fuzzy logic theory uses linguistic variables as its antecedents and consequents where antecedents express an inference or the inequality, which should be satisfied and consequents are those, which we can infer, and is the output if the antecedent inequality is satisfied. The fuzzy rule-based system is actually an IF–THEN rule-based system, given by, IF antecedent, THEN consequent (Sivanandam *et al*. 2007).

FL operations are based on fuzzy sets where the input data may be defined as fuzzy sets or a single element with a membership value of unity. The membership values (μ_1 & μ_2) is found from the intersections of the data sets with the fuzzy sets as shown in Figure 2 which illustrates the graphical method of finding membership values in the case of a single input (Haris 2006).

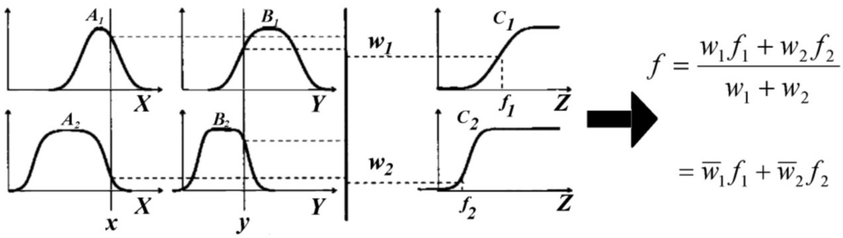

Figure 2 The Sugeno fuzzy model (Jang *et al*., 1997).

A fuzzy set contains elements which have varying degrees of membership in the set, unlike the classical or crisp sets where a member either belongs to that set or does not (0 or 1). However a fuzzy set allows a member to have a varying degree of membership and this partial degree membership can be mapped into a function or a universe of membership values (Bai *et al*. 2006).

The implementation of fuzzy logic to real applications considers the following steps (Bai *et al*. 2006):

- Fuzzification which requires conversion of classical data or crisp data into fuzzy data or Membership Functions (MFs)
- Fuzzy Inference Process which connects membership functions with the Fuzzy rules to derive the fuzzy output
- Defuzzification which computes each associated output.

Neuro-Fuzzy Systems

Fuzzy systems can also be connected with Neural Networks to form neuro-fuzzy systems which exhibit the advantages of both approaches .Neuro-fuzzy systems combine the natural language description of fuzzy systems and the learning properties of neural networks. Various neuro fuzzy systems have been developed that are known in literature under short names. Adaptive Network-based Fuzzy Inference System-ANFIS developed by Jang *et al*. (1997) is one of these Neuro-fuzzy systems which allow the fuzzy systems to learn the parameters using adaptive back propagation learning algorithm (Rutkowski 2004).

Mainly three types of fuzzy inference systems have been widely employed in various applications: Mamdani, Sugeno and Tsukamoto fuzyy models. The differences between these three fuzzy inference systems are due to the consequents of their fuzzy rules, and thus their aggregation and defuzzification procedures differ accordingly (Jang *et al*. 1997). In this study the Sugeno FIS is used where each rule is defined as a linear combination of input variables. The corresponding final output of the fuzzy model is simply the weighted average of each rule's output. A Sugeno FIS consisting of two input variables x and y, for example, a one output variable f will lead to two fuzzy rules:

Rule 1: If x is A1, y is B1 then f1 = p1x + q1y + r1

Rule 2: If x is A2, y is B2 then f2 = p2x + q2y + r2

where pi, qi, and ri are the consequent parameters of its rule. Ai, Bi and Ci are the linguistic labels which are represented by fuzzy sets shown in Figure 3.

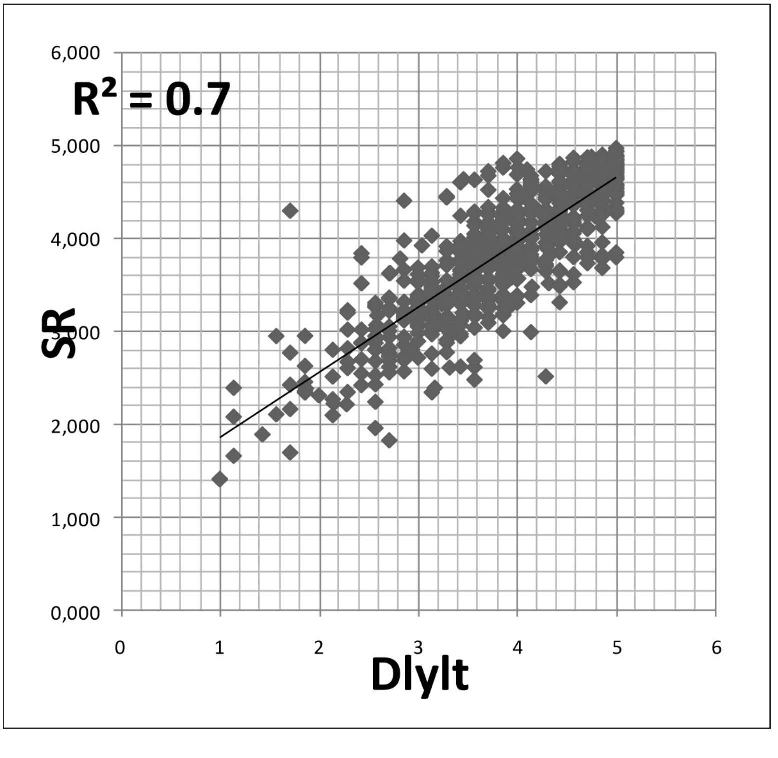

Figure 3 Performance of SR formulation vs. actual results

Neural Networks

A Neural Network is a 'machine' that is designed to model the way in which the brain performs a particular task or function of interest, the network is usually implemented using electronic components or simulated in software on a digital computer. Neural networks are an information processing technique built on processing elements, called neurons that are connected to each other (Hecht-Nielsen 1990).

Artificial neuron is the basic element of a neural network which consists of three main components namely as weights, bias, and an activation function

Where
$$u_i = \sum_{j=1}^{H} w_{ij} x_j + b_i \tag{1}$$

The summation u_i is transformed as the output using a scalar-to-scalar function called an "activation or transfer function" as follows:

$$O = f(u_i) \tag{2}$$

Neural networks are commonly classified by their network topology, (i.e. feedback, feed forward) and learning or training algorithms (i.e. Supervised, Unsupervised). For example a multilayer feed forward neural network with back propagation indicates the architecture and learning algorithm of the neural network. Back propagation algorithm is used in this study which is the most widely used supervised training method for training multilayer neural Networks due to its simplicity and applicability. It is based on the generalized delta rule and was popularized by Rumelhart *et al*. (1986).

Optimal NN Model Selection

The performance of a NN model mainly depends on the network architecture and parameter settings. One of the most difficult tasks in NN studies is to find this optimal Network architecture which is based on determination of numbers of optimal layers and neurons in the hidden layers by trial and error approach. The assignment of initial weights and other related parameters may also influence the performance of the NN in a great extent. However, there is no well defined rule or procedure to have optimal network architecture and parameter settings where trial and error method still remains valid. This process is very time consuming.

In this study Matlab NN toolbox is used for NN applications. Various Back propagation Training Algorithms are used. Matlab NN toolbox randomly assigns the initial weights for each run each time which considerably changes the performance of the trained NN even all parameters and NN architecture are kept constant. This leads to extra difficulties in the selection of optimal Network architecture and parameter settings. To overcome this difficulty a program has been developed in Matlab which handles the trial and error process automatically. The program tries various number of layers and neurons in the hidden layers both for first and second hidden layers for a constant epoch for several times and selects the best NN architecture with the minimum MAPE (Mean Absolute Percentage Error) or RMSE (Root Mean Squared Error) of the testing set, as the training of the testing set is more critical. For instance NN architecture with 1 hidden layer with 7 nodes is tested 10 times and the best NN is stored where in the second cycle the number of hidden nodes is increased up to 8 and the process is repeated. The best NN for cycle 8 is compared with cycle 7 and the best one is stored as best NN. This process is repeated N times where N denotes the number of hidden nodes for the first hidden layer. This whole process is repeated for changing number of nodes in the second hidden layer. More over this selection process is performed for different back propagation training algorithms such as trainlm (Levenberg-Marquardt), trainscg (Scaled conjugate gradient) and trainbfg (BFGS quasi-Newton). The program begins with simplest NN architecture i.e. NN with 1 hidden node for the first and second hidden layers and ends up with optimal NN architecture. This algorithm has been successfully applied to various NN problems (Cevik and Guzelbey 2008; Guven *et al*. 2006; Cevik and Guzelbey 2007; Guzelbey *et al*. 2006a, 2006b; Tapkin *et al*. 2009).

METHOD

Sampling Procedures and Characteristics

Insurance dealers in Turkey have been defined as the population of this study. The key informative person in a sampling unit is the dealer owner, manager, or executive. A questionnaire was developed to test the hypotheses by measuring the insurance dealers' responses to perceptions of research components. An e-mail list of insurance dealers prepared from insurance company Web sites was used. The questionnaire forms were e-mailed to the insurance dealers. Of the 850 questionnaires answered, 816 were usable[1].

Table 1 summarizes the descriptive statistics. More than 99% of the firms were between 1 and 57 years old. The average duration of the relationship between the dealer and its company was 9.06 years. Over 94.5% of the respondents held positions

[1] The data set were used in Mutlu, H. M., & Taş, İ. (2012). Antecedents of Insurance Agents' Loyalty for Different Forms of Transaction-Specific Investments in the Turkish Insurance Sector. Journal of Relationship Marketing, 11(4), 215-232.

concerned with the owners and general managers. Most of the respondents were from small businesses with fewer than 20 employees.

Table 1 Respondents of descriptive statistics

Title of respondent	Owner	74.8%
	Manager	19.7%
	Another	5.6%
Firm age	Min.	1
	Max.	90
	Mean	11.74
	SD	10.83
Relationship time	Min.	1
	Max.	51
	Mean	9.06
	SD	7.09
Firm size	Less than 20 employers	98.6%
	20-99 employers	1.4%

Measures

All constructs are measured using multiple-item, five-point scales with anchors ranging from Strongly Disagree (= 1) to Strongly Agree (= 5). We modified the measures of research variables and used control variables such as firm age and relationship time. Table 2 is shown the scales of this research variables and their reliability. Nunnally (1978, p.245) recommends that instruments used in basic research have a reliability of about 0.70 or better. The Cronbach's α of each construct was over 0.75 (see Table 2). According to Nunnally (1978), all the factors are reliable.

Table 2 Scales and its Cronbach's α

Variables		Scales	Items	Cronbach's α
Loyalty	a. Dealer loyalty	Zeithaml *et al.* (1996)	a. 7	a. 0.863
Trust	a. Dealer trust b. Dealer perception of customer trust	Morgan & Hunt (1994) and Garbarino & Johnson (1999)	a. 6 b. 4	a. 0.841 b. 0.934
Satisfaction	a. Dealer satisfaction b. Dealer perception of customer satisfaction	Oliver (1980)	a. 3 b. 3	a. 0.879 b. 0.940
Transaction spesific investments	a. Dealer TSI b. Dealer perception of manufacturer TSI c. Dealer perception of customer TSI	Joshi and Stump (1999)	a. 8 b. 5 c. 4	a. 0.815 b. 0.768 c. 0.833
Perceived value	a. Dealer perceived value b. Dealer perception of customer perceived value	Dodds *et al.* (1991)	a. 4 b. 3	a. 0.837 b. 0.742
Corporate reputation	a. Dealer perception of manufacturer corporate reputation	Morgan & Hunt (1994)	a. 3	a. 0.749

ANALYSES AND NUMERICAL APPLICATION

The main aim in this study is to obtain a soft computing models of dealer loyalty in Turkish insurance sector by means of affecting factors such as dealer trust (Dtrst), dealer perceived value (Dpvl), dealer satisfaction (Dstsft), dealer transaction specific investments (Dtsi), dealer perception of manufacturer transaction specific investments (Mtsi), dealer perception of manufacturer corporate reputation (Mcorep), dealer perception of customer trust (Ctrst), dealer perception of customer perceived value (Cpvl), dealer perception of customer satisfaction (Cstsft), dealer perception of customer transaction specific investments (Ctsi), dealer firm age (Fage) and relationship time between manufacturer and dealer (Frtime) using soft computing techniques such as Stepwise Regression (SR), Neuro-Fuzzy (NF) and Neural Networks (NN).

Therefore, an extensive survey was conducted in Turkish insurance sector which measured the effects of factors stated above on dealer loyalty.

To achieve generalization capability for the models, the experimental database is divided into two sets as training (80%) and testing (20%) sets. The models are based on training sets and are further tested by test set values to measure their generalization capability. The patterns used in test and training sets are randomly selected.

Numerical Application of SR

Possible forms for all combinations of independent variables used for the stepwise selection process are given as follows:

$$X_i\ ,\ 1/X_i,\ X^2,\ \ln(X),\ 1/\ln(X)$$

Where X_i stands for the independent variables.

Models considered for the stepwise regression process are given in Table 3 for 2 independent variables (x1, x2) and 1 dependent variable (y) with possible corresponding equations.

Table 3 Models considered in SR process (Inputs vs. Equations)

Model	Inputs	Equation
Linear	x1, x2	y = b0 + b1*x1 + b2*x2
Linear + Interaction	x1, x2, x1*x2	y = b0 + b1*x1 + b2*x2 + b3*x1*x2

All possible combinations of independent variables with models considered and corresponding equation of best subset are given in Table 4. The stepwise regression analysis in this study is performed by SPSS which are a well known statistical and data management software package for analysts and researchers and the following SR equation has been obtained for the best subset (R2 = 0.70):

$$\begin{aligned} Dlylt = {} & 0.376 + 0.172*Dstsft*Dtrst + 1.039*Dpvl \\ & - 0.131*Dpvl*Dtrst - 0.086*Dpvl*Dstsft + \\ & 0.0155*Cstsft*Mtsi + 0.001*Ctsi*Fage \end{aligned} \tag{3}$$

Table 4 Statistical Details and equations of best subsets for each stepwise regression model

Model	Equation of best subset	Constants	R2	COV
Linear	Dlylt = b0 + b1*Dstsft + b2*Dtrst + b3*Dpvl + b4*Mtsi + b5*Fage + b6*Ctsi	b0=0.202 b1=0.427 b2=0.285 b3=0.153 b4=0.05468 b5=0.00346 b6=0.04478	0.69	0.15
Linear + Interaction	Dlylt = b0 + b1*Dstsft*Dtrst + b2*Dpvl + b3*Dpvl*Dtrst + b4*Dpvl*Dstsft + b5*Cstsft*Mtsi + b6*Ctsi*Fage	b0=0.376 b1=0.172 b2=1.039 b3=-0.131 b4=-0.08579 b5=0.01550 b6=0.00101	0.70	0.14

The performance of the proposed SR formulation vs. actual results is given in Figure 4 and the accuracy of the formulation is observed to be quite good with standard deviation of 0.14and correlation coefficient of 0.70.

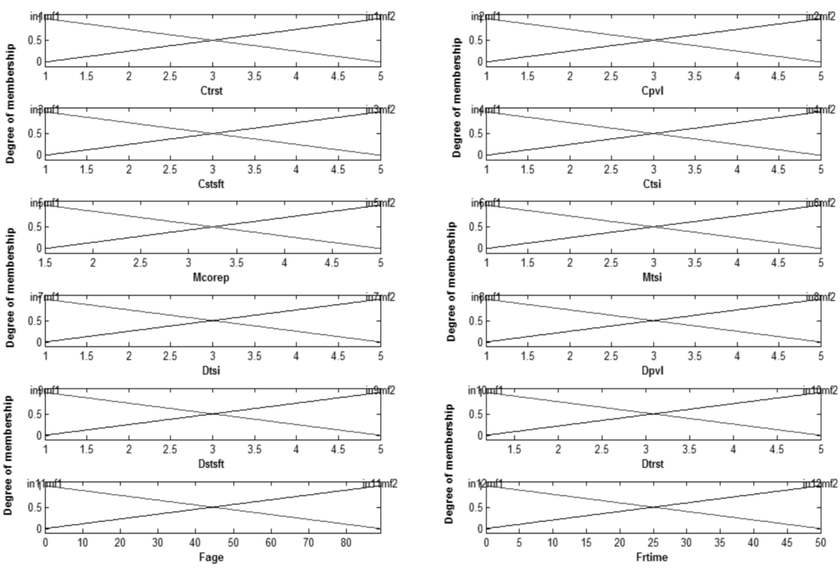

Figure 4 Fuzzy rules of NF model

Numerical Application of NF

The simplest ANFIS model is selected to illustrate the effectiveness of the NF approach which has 2 fuzzy rules only. The proposed ANFIS model uses triangular input membership functions with minimum number of fuzzy rules which is 2. The output membership function is chosen as the simplest one available which is a constant value. Features of the proposed ANFIS model are given in Table 5.

Table 5 Features of the proposed ANFIS models

Type	SUGENO
Aggregation Method	Maximum
Defuzzification Method	Weighted Average
Input Membership Function Type	Trapezoidal
Output Membership Function Type	Constant

The membership functions (fuzzy rules) for inputs are presented in Figure 5. The performance of the proposed NF model vs. actual results are given in Figure 6 and the accuracy of the formulation is observed to be quite good with a COV (coefficient of variation) of 0.09 and correlation coefficient of R2=0.73.

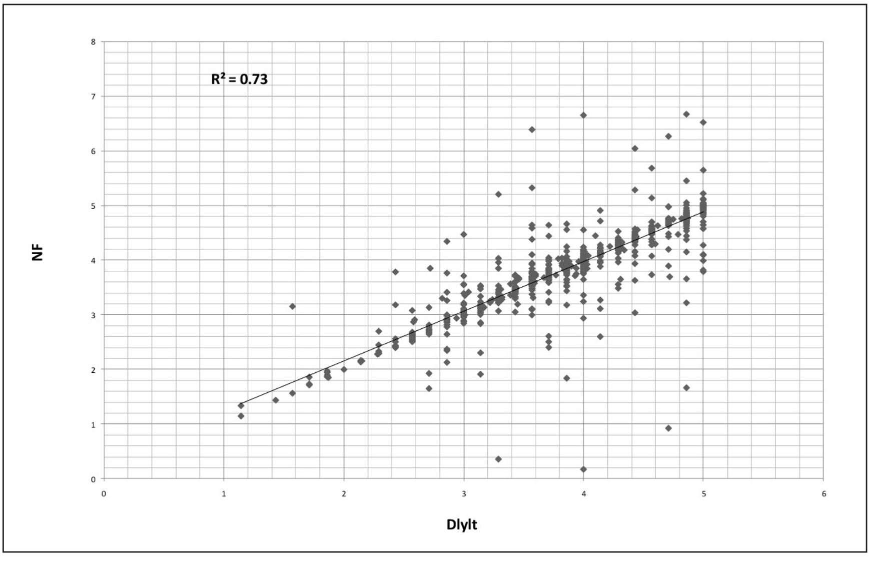

Figure 5 Performance of NF model vs. actual results

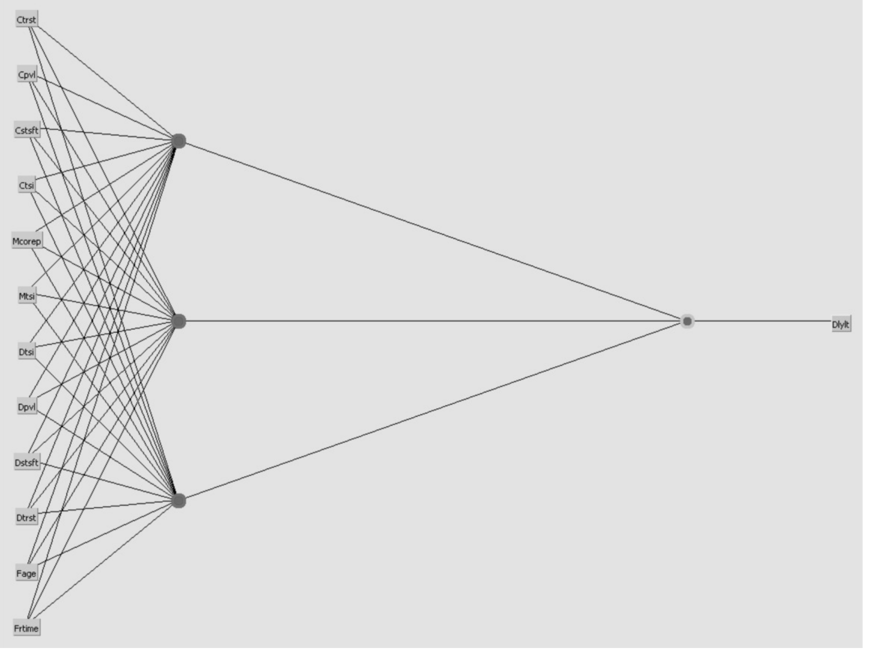

Figure 6 Optimum NN architecture

Numerical Application of NN

The optimal NN architecture in this part was found to be 12-3-1 (12 inputs- 3 hidden neurons- 1 output) NN architecture with logistic sigmoid transfer function (logsig). The training algorithm was quasi-Newton back propagation (BFGS). The optimum NN model is given in Figure7. The performance of the proposed NN model vs. actual results is given in Figure 8. The accuracy of the formulation is observed to be quite good with a COV (coefficient of variation) of 0.14 and correlation coefficient of 0.73. Moreover the closed form solution of dealer loyalty based on the trained NN parameters (weights and biases) can also give as follows:

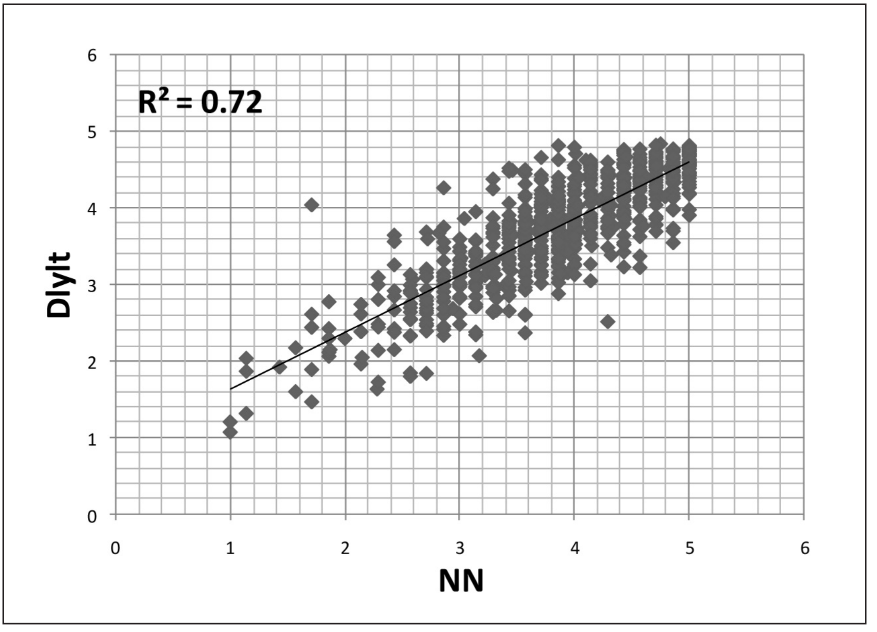

Figure 7 Performance of NN formulation vs. actual results

```
// sigmoid(x) = 1/(1+exp(-x))
Input0 = Ctrst*0.2 - 0.1
Input1 = Cpvl*0.2 - 0.1
Input2 = Cstsft*0.2 - 0.1
Input3 = Ctsi*0.2 - 0.1
Input4 = Mcorep*0.228571 - 0.242857
Input5 = Mtsi*0.2 - 0.1
Input6 = Dtsi*0.2 - 0.1
Input7 = Dpvl*0.2 - 0.1
Input8 = Dstsft*0.2 - 0.1
Input9 = Dtrst*0.2 - 0.1
Input10 = Fage*0.00898876 + 0.1
Input11 = Frtime*0.016 + 0.1
HidLayer0 = sigmoid(–1.181*Input0 + 0.172113*Input1 +
            1.03538*Input2 + 0.357974*Input3 - 0.275785*Input4 +
            0.719372*Input5 + 0.432261*Input6 - 0.0539904*Input7
            + 3.32026*Input8 + 3.4133*Input9 + 0.845255*Input10
            – 0.761312*Input11 – 6.0246 )
```

$$\text{HidLayer1} = \text{sigmoid}(0.277097*\text{Input0} + 0.568848*\text{Input1} - 0.467659*\text{Input2} - 1.13447*\text{Input3} + 0.473799*\text{Input4} - 0.664491*\text{Input5} - 0.569723*\text{Input6} - 1.87995*\text{Input7} - 1.35059*\text{Input8} - 0.253839*\text{Input9} + 0.0769175*\text{Input10} - 0.586804*\text{Input11} + 0.0694568)$$

$$\text{HidLayer2} = \text{sigmoid}(-0.933379*\text{Input0} + 1.04591*\text{Input1} + 0.299777*\text{Input2} + 0.152724*\text{Input3} - 0.186235*\text{Input4} + 0.557819*\text{Input5} + 1.04547*\text{Input6} - 2.94503*\text{Input7} - 2.45344*\text{Input8} - 1.19926*\text{Input9} - 0.182503*\text{Input10} - 1.40545*\text{Input11} + 0.706633)$$

$$\text{OUT} = (\text{sigmoid}(2.08676*\text{HidLayer0} - 1.99202*\text{HidLayer1} - 3.14176*\text{HidLayer2} + 0.350912) + 0.1) / 0.2$$

Comparative percentage effect of each factor on dealer loyalty is obtained by the weights of the given NN model shown above and presented in Table 6.

Table 6 Comparative percentage effect of each factor on dealer loyalty

Factor	% Effect	Factor	% Effect	Factor	% Effect
Dstsft	29.33	Frtime	6.74	Dtsi	2.05
Dpvl	21.70	Ctsi	4.11	Mtsi	1.76
Dtrst	19.06	Fage	3.52	Mcorep	1.47
Cpvl	6.74	Cstsft	3.52	Ctrst	0.00

Statistical parameters of testing, training and total sets of soft computing models considered in this study are shown in Table 7.

Table 7 Statistical parameters of the models considered in the study

	SR			NF			NN		
	Testing set	**Training set**	**Total set**	**Testing set**	**Training set**	**Total set**	**Testing set**	**Training set**	**Total set**
Mean	1.06	1.01	1.02	1.03	1.00	1.01	1.04	1.00	1.01
Std. Dev.	0.17	0.14	0.15	0.1	0.08	0.09	0.15	0.13	0.14
COV	0.16	0.13	0.14	0.09	0.08	0.09	0.14	0.13	0.14
R2	0.66	0.75	0.70	0.65	0.79	0.73	0.65	0.74	0.70

DISCUSSION AND CONCLUSION

This study presents a novel application of soft computing techniques namely as stepwise regression, Neuro-Fuzzy and Neural Networks for the modeling of dealer loyalty in Turkish insurance sector. The proposed soft computing models are actually empirically based on a wide range of surveys conducted among Turkish insurance companies. Factors considered in the study affecting dealer loyalty were: trust (dealer and dealer perception of customer), perceived value (dealer and dealer perception of customer), satisfaction (dealer and dealer perception of customer), transaction specific investment (dealer, dealer perception of customer, and manufacturer), and manufacturer corporate reputation (dealer perception of customer). The degree of dealer loyalty is measured by means of converted numerical values ranging from 1 to 5 obtained from survey results conducted in Turkish insurance sector. All soft computing models were found to be accurate and perform well with actual survey results.

Many studies that used soft computing techniques tested customer loyalty or brand loyalty (Buckinx *et al*. 2007; Han *et al*. 2012; Hosseini *et al*. 2010; Kim *et al*. 2007; Moutinho *et al*. 1996; Tsaur *et al*. 2002; Wong *et al*. 2009; Yang *et al*. 2009) but this article is the first study in the literature that models dealer loyalty in insurance sector using soft computing techniques and it will lead to further soft computing based modeling applications in this field in the future. In other words, the main contribution of this study is to illustrate the availability and applicability of effective use of soft computer techniques in this specific field of management which was successfully proven.

Loyalty is to be vital to all parties in distribution channels. The study find that the dealer loyalty was affected on factors (a) related to dealer, (b) related to manufacturer, and (c) related to customer. Explanatory power of all models is above 70.00%. In linear model, stepwise regression results demonstrated that loyalty is highly related to dealer satisfaction, trust and perceived value; manufacturer TSI, firm age and customer TSI. The other variables in model are not significant (e.g. corporate reputation, customer trust, customer perceived value, and customer satisfaction). Although relationship time is domain variable on loyalty, it is also not significant. The results show that dealer loyalty primarily affected on factors related to dealer. Secondly, dealer loyalty depends on TSI (manufacturer-customer). We expected that factors both related to manufacturer and to customer demonstrated indirect effect, yet. Interaction model takes into account that dealer factors interactions affect loyalty.

As a result of neural network model presented in the study, the main dominating factors on dealer loyalty were also determined as follows: dealer satisfaction, dealer trust, dealer perceived value, dealer perception of customer perceived value and relationship time between manufacturer and dealer (Frtime). The top three factors related to dealer. Neural network model' results are similar regression results. Given comparative percentage effect of each factor on dealer loyalty, dealer satisfaction, dealer perceived value, and dealer trust respectively are 29.33%, 21.70%, and 19.06%. The percentage of the effect of factors related to dealer variable is 72.14%. The percentage of the effect of factors related to customer variable is 14.38%. The total of firm age and relationship time is 10.26%. Although relationship time was not significant in regression results, it has significant effect in neural network model. The manufacturer variable effect is 3.22%. Thus, managers must establish long-term relationship with dealer. Marketing managers look for key driver of sustainable competitive advantage. The study demonstrated and empirically tested the antecedents of loyalty as a key driver in insurance market. Hence insurance market' products cannot quite easily make product diversification strategy. To create loyal dealers, the research findings suggest that push strategy should be applied by managers. Loyalty depends on satisfied dealer, the degree of perceived value and trust in relationship. The total effect of transaction specific investments on loyalty is 7.92%. The ratio is lower than total of satisfaction, perceived value and trust. Tangible and intangible TSIs in insurance sector may be neglected for dealer, manufacturer and customer or the investments have lower sunk cost in the sector.

The study also investigated comparing the results from soft computing modeling with those from regression models. Comparative results showed that dealer satisfaction, trust and perceived value are top important variables for loyalty in both models.

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