ICED13
INTERNATIONAL CONFERENCE ON ENGINEERING DESIGN, ICED13
19-22 AUGUST 2013, SUNGKYUNKWAN UNIVERSITY, SEOUL, KOREA

ANALYZING SOCIAL INFLUENCE THROUGH NETWORK SIMULATIONS IN CHOICE MODELING

Peilin TIAN, Wei CHEN
Northwestern University, United States of America

ABSTRACT

In this paper, we study how to capture social influence on customer choice based on rich consumer data. The created choice model helps achieve a better understanding of consumer preferences in product design. Social influence attributes are employed to quantify the social impact a customer receives from interactions with other individuals in product selection. Data analysis technique is first adopted to identify critical social profile attributes based on a large amount of consumer information. To quantify social influence at the individual level, the paper presents a data-driven approach that integrates social network simulation based on consumers' social profile attributes in product choice modeling. Later the network is simulated to estimate the social influence on individual consumer's choice behavior. This paper provides new understanding of how consumers are socially influenced. A Hybrid Electric Vehicle case study is implemented to demonstrate the proposed methodology using National Household Travel Survey data. Choice modeling prediction results and consumers green attitude towards hybrid electric vehicle are examined over multiple years.

Keywords: user centred design, design methods, human behaviour in design, social network simulation, consumer choice modeling

Contact:
Peilin Tian
Northwestern University
Mechanical Engineering
Evanston
60208-0834
United States of America
P8S4E2@u.northwestern.edu

1 INTRODUCTION

The objective of this research is to develop a data-driven analytical approach to capture consumer preferences with the consideration of social influence in product design. Traditional product design is product-centric to achieve the best engineering performance subject to economic constraints. However, consumer choice is not only determined by engineering attributes, but it should also take into consideration the heterogeneity of consumers, who are differing in their preferences based on their socio-demographics, their usage profiles, and the social influence. It is challenging to take into consideration some of the heterogeneities because of their qualitative nature. How can designers capture the consumer social influence quantitatively? This paper proposes a methodology that integrates the social network construction and social influence evaluation into a choice modeling framework.

As an integral part of Decision Based Design (Lewis, Chen and Schmidt 2006), choice modeling (Wassenaar and Chen 2003) considers heterogeneity of consumers by implementing the Discrete Choice Analysis (DCA) method in which each respondent selects preferred options among competing products, taking into consideration customer-specific attributes at an individual level. In recent development, He and Chen (2011) integrated usage context information into choice modeling. Traditional choice modeling methodologies assume that consumers' choice behaviors are rational, which means that consumers pick a product based on its performance attributes (including price) in comparison with those of other competing products. However, this is not always the case in the real world, since consumers' decisions are often influenced by their surroundings through social influence processes such as compliance, identification, and internalization (Kelman 1958). Each of these processes represents a distinct way of how people interact. Social influence has a great impact on a consumer's purchase attitude as well as his or her choice behavior towards certain products (Case 1992). The primary task for integrating social influence into choice modeling is to quantitatively assess social influence.

In marketing research and transportation research respectively, Manski (1995) and McFadden (2010), along with many others, showed the need for integrating social influence into choice modeling. Social network influence has been labeled as 'contagious' (Leenders 1995), modeled by communications through the existence of links among people in a social network. Brock and Durlauf (2002) considered the interaction of various decision-makers in making choices and introduced social interactions in binary discrete choice models. Dugundji and Gulyas (2003a, 2003b) made a distinction between social network interactions (at individual level) and spatial network interactions (at global level). Páez, Scott and Volz (2008) demonstrated a method that uses simulated social influence data for a multinomial logit application to residential location choice. In travel demand research, Walker et al. (2011) developed a comprehensive discrete choice model to capture the interdependencies among decision makers. Nevertheless, one existing problem that hinders the study of social influence in product selection is a lack of empirical data for either social influence or social network construction. He and Chen (2012) proposed to simulate a consumer network using principles of small world network. However, the network was constructed based on consumers' geographic location information alone, which is not sufficient to capture all consumer aspects that influence the social connections.

This paper presents an advanced choice modeling approach that integrates social influence into the conventional discrete choice analysis framework. Statistical data analysis techniques are first employed to identify critical attributes to include for the choice model and the social network simulation. To address the aforementioned limitation in the work of He and Chen (2012), the social influence simulation goes beyond the geographic location based small world network and follows the social distance method (Akerlof 1997) considering both demographic and usage context attributes in the social space. A widely used theory developed by Snijders et al. (Snijders 2001, Steglich, Snijders and Pearson 2010) is followed to evaluate the social effects for capturing social influences among consumers. The values of the social influence attributes are integrated into the choice model together with the engineering and consumer attributes. Hybrid Electric Vehicle is taken as a case study to illustrate the proposed methodology.

2 TECHNICAL BACKGROUND OF DCA AND SOCIAL NETWORK THEORY

The first attempt at using the Discrete Choice Analysis (DCA) technique for demand modeling in engineering design was made by Wassenaar and Chen (2003). DCA provides probabilistic choice models, where individual's true choice utility consists of an observed part W and an unobserved random disturbance. The observed utility W is expressed as a function of customer-desired attributes A and customer demographic attributes S. Lately, usage context attributes U (He and Chen 2011) were integrated into the choice model. In recent work of He and Chen (2012), social influence attributes N are introduced into the choice utility function to capture the social influence.

In this research, social network interactions are simulated to capture the social influence at the individual level. Social network provides the mechanism of customer communication which enables a customer to be influenced by others. Social network theory has been developed for decades to study the real world network among people. The links in social network provide channels for the flow of social influence. Messages passing through a network include data, information, knowledge, and other symbolic forms that can move from one point in a network to another or can be created by network members (Monge and Contractor 2003). A typical social network is formed by two important elements, *actors* (dots shown in Figure 1) and *relations* (black lines shown in Figure 1). Actors represent the participants in the network. Relations are central to network analysis because they define the nature of the communication connections among actors. A rich set of literatures exists on network concepts, measures, methods and applications (Monge and Contractor 1988). In this research, actors in a social network are consumers and the relations represent the social influence between two consumers in product selection.

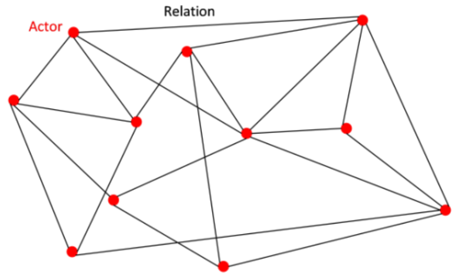

Figure 1. Actors and relations in a social network

3 METHODOLOGY OF SOCIAL INFLUENCE INTEGRATION

The step-by-step procedure of integrating social network influence into choice modeling is separated into three phases as shown in Figure 2. The key idea of the proposed methodology is to integrate the social influence in the form of social influence attributes into conventional choice models, while the values of social influence attributes are assessed through social network simulations. In the absence of real social network data, this research employs social network construction as the basis for social network simulations. In Phase I, data is collected for customer-desired product attributes of competing choices, consumer demographic attributes, consumer usage context attributes, and consumer choice. Data analysis of the relationship among multiple consumer attributes is conducted in this phase to test the correlations and to identify the critical social profile attributes. Phase II aims to construct the social network based on the social profile attributes and to evaluate the social influence using network simulations. In Phase III, the values of social influence attributes are integrated into choice modeling together with the other attributes in conventional choice modeling.

3.1. Data Collection and Data Analysis

Both social influence evaluation and choice modeling rely on empirical data. In this Phase, consumers' choice set information, engineering attributes of competing products, demographic and usage context attributes of consumers and ideally the social network information are collected. In the absence of real social network data, we propose to use the information of consumer demographic attributes and usage context attributes to represent independent social dimensions of consumers in forming the social network. Choice modeling surveys can be divided into either Stated Preference (SP) (Kroes and Sheldon 1988) or Revealed Preference (RP) (Samuelson 1948) surveys. National Highway Travel Survey (NHTS) data set employed in this paper belongs to RP data. Data analysis using statistical techniques is a critical step in this phase to determine which attributes to include in a choice model and the social network construction. Correlation test is employed to examine the independency among consumer's social profile attributes to ensure the uniqueness of each social dimension.

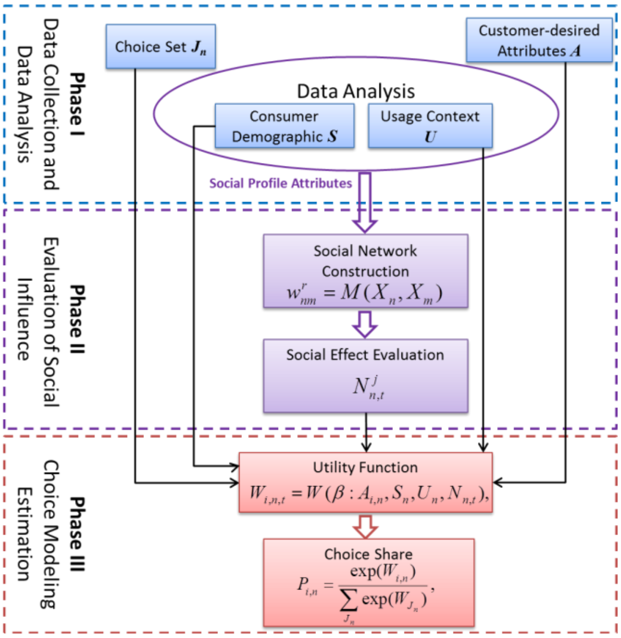

Figure 2. Proposed Methodology

3.2. Social Network Construction

This paper employs social network theory to assist the evaluation of social influence on customers' choice behavior. However, social network information is often absent because it requires huge efforts to complete the survey of each consumer's relationships with others. An alternative way of obtaining social network information is based on the proximity of customers' social profile attributes.

$$w_{nm}^r = M(X_n, X_m), \tag{1}$$

where w_{nm}^r denotes the existence (0 or 1) of social network link between respondent n with individual m; X_n and X_m denote social profile attributes. Function M denotes the rule for defining how n and m are socially related. In this paper, the social distance method is employed to construct a social network. Social distance is defined by Krugman (1991) as the distance between social locations of two nodes in a social geography (social space) formed over multiple social dimensions. Sociologists have a whole lexicon of their own for what can be considered as social geography dimensions, such as geographic, education level, etc. Akerlof (1997) introduced a method of constructing a social network, in which he suggested that two nodes with closer social distance are more likely to be connected. Our method implements a distance-decay function to reflect the hypothesis that the degree of influence between actors should decrease as their opinions or behaviors become more dissimilar (Festinger 1954). The strength of a connection w_{nm} in social space would then be a function of the intervening distance between individuals, shown as (Paez et al. 2008):

$$w_{nm} = \begin{cases} \gamma_1 \exp(-\gamma_2 d_{nm}^2), & for\ n \neq m \\ 0, & for\ n = m \end{cases}, \tag{2}$$

where d_{nm} is the distance in social space between individuals n and m, defined as:

$$d_{nm} = \sum_i (x_{i,n} - x_{i,m})^2 \tag{3}$$

γ_1 is the parameter controlling the magnitude of the effect and γ_2 is the one controlling the rate of decay. Whether a social network connection exists or not is defined by the following principle: $w_{nm}^r = 1$ if individual m is significant to individual n (defined by w_{nm}), otherwise, $w_{nm}^r = 0$ .Threshold of significance level is set for the value of w_{nm} obtained in equation (2) to define whether individual m is significant to individual n. If significant, m and n form an existing link in the social network. There are many different criteria for defining the social connections, and more extensive discussions of different criteria are covered by Leenders (2002). One of the criteria, "average degree criterion", means that for each person in a social network, he or she has a certain number (degree) of connections on average.

3.3. Evaluation of Social Influence Attributes

Social network theory generalizes the basic principles of communications between consumers, hence the mechanism of quantifying the social influence. The social influence effects are distinguished by three types (Snijders 2001, Steglich, Snijders and Pearson 2010): structural effects for network dynamics, effects for network dynamics associated with covariates and effects on behavior evolution. In this research, the social network influence effect is assumed to be constant, namely only the static social network is considered. Hence, among the three types of social influence effects, effects on behavior evolution are the most relevant. For models with a dependent behavior variable, the widely considered effects for the behavior dynamics (Steglich et al. 2010) include the tendency effect, the average similarity effect, the total similarity effect, the average alter effect, the indegree effect and the outdegree effect. All these social effects can be derived based on both the social network information and the social behavior information of a respondent (consumer). Two social effects, "indegree effect" and "average alter effect" are considered in this work. Both of them are explained in detail in Appendix A, where $y_{n,t}$ represents the social behavior (choice behavior=1 or 0) of respondent n at time t. All social effects are represented by the social influence attributes, where $N^{j}_{n,t}$ denotes the value of effect j of individual n. Social influence attribute $N_{n,t}$ of all effects at time t for individual n is the vector collection of multiple social effects expressed as,

$$N_{n,t} = (N^1_{n,t}, N^2_{n,t}, ...N^j_{n,t}), \qquad (4)$$

Social influence attributes quantify the influence of social network on individual's social behavior. Since social behavior of one customer is affected by the pre-existing social behavior of other customers connected, we note that social influence attribute at time t depends on social behavior of other customers at time t-1.

3.4. Integration of Social Influence into Choice Modeling

In Phase III, a predictive model of consumer choice is established using the Discrete Choice Analysis (DCA). DCA assumes that individuals seek to maximize their personal choice utility, the deterministic part of which is shown in Eqn (5). Compared to the traditional DCA model, social influence attributes N are now integrated into the observed part of utility $W_{i,n,t}$ as additional attributes. The coefficients β are estimated based on the choice data collected during different time periods.

$$W_{i,n,t} = W(\beta : A_{i,n}, S_n, U_n, N_{n,t}), \qquad (5)$$

4 CASE STUDY OF HYBRID ELECTRIC VEHICLE CHOICE

Alternative fuel vehicles have drawn increasing attention in the past few years due to their potential to reduce greenhouse-gas emissions and to utilize renewable energy sources. However, understanding consumer choices of alternative fuel vehicles is challenging because the preference construction process involves many aspects beyond traditional engineering considerations, which calls for a comprehensive modeling framework to incorporate social influence into engineering design. Taking hybrid electric vehicles (HEVs) as an example, consumers' attitude to hybrid electric vehicles is often affected by their friends or those who have similar social status. In this section, a hybrid electric vehicle case study is implemented to illustrate the choice modeling framework with social influence attributes integrated. Consumer data collected by the National Household Travel Survey (NHTS) for both HEVs and conventional vehicles (CVs) is utilized for model estimation. It should be noted that in our current study, the impact of HEV policies and other purchase incentives are not considered. The NHTS data contains vehicle purchase and consumer data from nearly 300,000 nation-wide respondents for multiple years. The respondent's demographic attributes, purchased vehicle product information and their usage patterns are collected in the questionnaire. Model estimation is focused on the state of California as it has the highest percentage of hybrid vehicle ownership in the US with data of 8964 respondents.

4.1 Phase I: Data Collection and Analysis

There are 193 car models covered in the data set, and each was chosen by at least one respondent. Among the large number of attributes included in the NHTS data set, 17 (9 product attributes and 8 consumer attributes)are chosen to be included in choice model based on statistical analysis of correlations with consumer choice. In addition, two social influence attributes derived from social network simulations are included in the choice model as shown in Appendix A.

Among the 17 attributes, eight key consumer attributes covering both demographic and usage context are utilized to measure the social distance in constructing the social network. Statistical data analysis is utilized to test the correlations among the eight key customer attributes to determine the attribute set for defining the social dimension. Consumer attributes include both demographic attributes *S* and usage context attributes *U*. Ideally these attributes are desired to be independent from each other in defining the social dimension. If a variable does not have correlations with other variables, it becomes an independent social dimension of a consumer. Correlations among attributes are listed in the matrix form as shown in Table 1.

*Table 1. Correlation Matrix of all **S** and **U** Attributes*

	income	vehicle	State	Age	sex	children	education	Miles Driven
Income	1							
Vehicle	0.2451	1						
State	-0.0005	0.0279	1					
Age	-0.2519	-0.2751	-0.018	1				
Sex	-0.0378	-0.0635	0.0034	-0.024	1			
Children	0.1657	0.1313	0.0141	**-0.4734**	-0.0012	1		
Education	0.2247	-0.0457	-0.0188	0.067	-0.0052	-0.0114	1	
Miles Driven	0.1592	0.1578	0.0413	-0.1471	-0.1972	0.1012	0.0795	1

It is noted that the only moderately correlated coefficient is at -0.4734 (in bold) between "children number in household" and "age". All other attributes are considered as not correlated, which means they can be treated as independent social dimensions. The correlations of usage context attribute 'miles driven' with all other attributes are low. This indicates that 'miles driven' should be included as an additional consumer attribute in the social dimension. The t-values of correlation coefficients are assessed based on the definition of t-statistic. The largest t-value obtained is 1.422, which is not far away from 0 (compared to infinity maximum) meaning the correlation between attributes is not significant. It is concluded that each of the seven consumer demographic attributes listed represents one unique dimension of consumer and will be included as one of the social dimension attributes in network construction and simulation.

Two social influence attributes, indegree and alter, are introduced and evaluated based on the simulation of social network, which will be discussed further in Section 4.3. It should be noted that social influence attributes of the current year are simulated based on the social behavior from the past year. Therefore, for social influence consideration, it is necessary to employ multiple year survey data for calibrating the model coefficients of social influence attributes.

4.2 Phase II Evaluation of Social Influence Attributes Using Network Simulation

As discussed previously in Section 3.2, social network is constructed based on the social distance associated with the proximity of customers' demographic and usage context attributes. The social distance is first evaluated by the social distance of two consumers based on equation (3). Seven demographic attributes and one usage context attribute are used to describe the social dimensions $x_{i,n}$ of respondent n when using the social distance method. Social network strength w_{nm} between respondents n and m are evaluated by equations (2), with ($\gamma_1 = 1, \gamma_2 = 1$).

For our case study, the average degree criterion (Paez et al. 2008) is used to define social significance. We assume that in making a product choice, each consumer is connected to the same number of other customers on average. The obtained relative influence serves as the probability to form a connection ($w^r_{nm} = 1$) in the network between respondent *n* and respondent *m*. This probability is linearly correlated with the relative social influence, which is calculated as the ratio between social connection strength w_{nm} and the sum of all social connection strengths for person *n*. The criterion ensures that on average each person has a certain number of connections. Meanwhile, each consumer may be different in the actual link number due to the randomness in forming connections. After a social network is constructed, the value of social influence attributes is evaluated next.

Based on Snijders's work in 2001 (Snijders 2001), multiple social effects such as tendency effect, average similarity effect, total similarity effect, average alter effect, indegree effect and outdegree effect may be important. We have examined these six effects by testing the statistical significance of choice modeling coefficients, but only two effects, average alter effect and indegree effect, are shown to be important based on the choice modeling result. The indegree effect N_1 captures the influence due to the number of connections in the social network. Higher number of connections indicates that customers are more likely to be influenced by others' behavior and the information received. The average alter effect N_2 captures the influence a person receives based on the percentage of customers in his (her) network who have purchased an HEV. It should be noted that due to the social influence, consumers' purchasing behavior becomes dynamic. The amount of hybrid electric vehicle purchasing is expected to grow with respect to time as the social influence propagates through the network.

4.3 Phase III Integration of Social Influence into Choice Modeling

Once the social influence attributes **N** are evaluated, they are modeled explicitly in the choice utility function together with customer-desired product attributes **A**, customer demographic attributes **S** and usage context attribute **U.** Coefficients for all attributes and their interactions are obtained for the multinomial logit model and the results are listed in Appendix B. For the purpose of comparison, results from both (MNL model with N) and (MNL model without N) are provided. The model is estimated based on multiple-year data, assuming that the model coefficients stay constant throughout the years. Meanwhile, the impact of social influence on the HEV attitude grows throughout the years. All bold attributes in Appendix B are statistically significant for the choice model with p value <=0.05. It is noted that the coefficient of price/income is negative as expected. Higher price means less willingness to purchase, while higher income means more willingness to purchase. MPG's positive coefficient implies that customers prefer vehicles with higher fuel efficiency. Children*length interaction represents that families with more children prefer vehicles of larger sizes.

5 RESULT AND DISCUSSION

5.1 Choice Model Validation

Goodness-of-fit measures based upon the Log-Likelihood of the converged model, such as the likelihood ratio index $\rho^2 = 1 - L_{convergence} / L_0$ (pseudo R-square), reflect how well the estimated model predicts the actual individual choices in the data set. A higher value of ρ^2 indicates better predictions of the choices. As shown in Table 2, a slightly higher Log-Likelihood of -9614.3211 and a subsequently higher ρ^2 value of 0.1193 is achieved using the MNL model with social influence attributes N versus the MNL model without N. On average, the Log Likelihood ratio index ρ^2 shows a 3.8% improvement in MNL from 11.55% without N to 11.93% with N. The amount of improvement is not significant. However, based on the hypothesis testing of additional attributes importance, $\text{Prob} > \text{chi2} = 0 < 0.01$. Therefore, we are 99% confident that adding two social influence attributes will improve our model fitting. For behavior modeling, the choice model fitting result ρ^2 with 0.2 is considered as a good model fit. Since our obtained ρ^2 is around 0.12, the model fit is considered as acceptable. One reason behind low ρ^2 of choice model is due to the large noise associated with the data collected from consumers.

Table 2 Multinomial Logit Model ρ^2 Result

Multinomial Logit Model	Without N	With N
Log Likelihood at zero	-10917.1	-10917.1
Log Likelihood at convergence	-9656	-9614
ρ^2	0.1155	0.1193

5.2 Hybrid Technology Attitude Interpretation

In this work, the "Hybrid Technology Attitude" is assessed based on the presence of attribute "hybrid" in the choice utility function, indicating how consumers prefer the vehicles with hybrid technology. Specifically, it is the sum of the HEV related terms in the utility (Appendix B), written as $Hybrid\_Tech\_Attitude=hybrid*(-0.273870-0.0000465*miledriven+0.12636*indegree+0.22755*alter)$. As shown in Appendix B, the coefficient β_{hybrid} of hybrid attribute and the coefficient $\beta_{hybrid\_miledriven}$ of hybrid_miledriven interaction are negative, while hybrid_indegree $\beta_{hybrid\_indegree}$ and hybrid_alter β_{hybrid_alter} are positive. The positive coefficients of social influence attributes indicate that consumers value hybrid vehicle more than they did before since they are influenced by those who are connected with them and have a more positive attitude towards hybrid vehicle. The Hybrid Technology Attitude value for each year from 2003 to 2008 is plotted in Figure 3 (a). It is noted that at the beginning of year 2003, when the hybrid vehicle was first introduced to the market, the hybrid technology attitude index is low because consumers were not familiar with the HEV technology. As time goes on, the hybrid technology attitude index increases due to the positive impact of social network. Between year 2007 and 2008, attitude on HEV technology became significant and the increase rate was high. To design for different targeted markets, the attitude index can be segmented to help understand consumers' attitude towards new technology. As shown in Figure 3, consumers are segmented by income, education level and indegree. Their attitude indices for multiple years are plotted in Figures 3(b), (c), (d), respectively. The graphs illustrate that the social influence has a more significant impact on green attitude for consumers with high education, high income and high indegree.

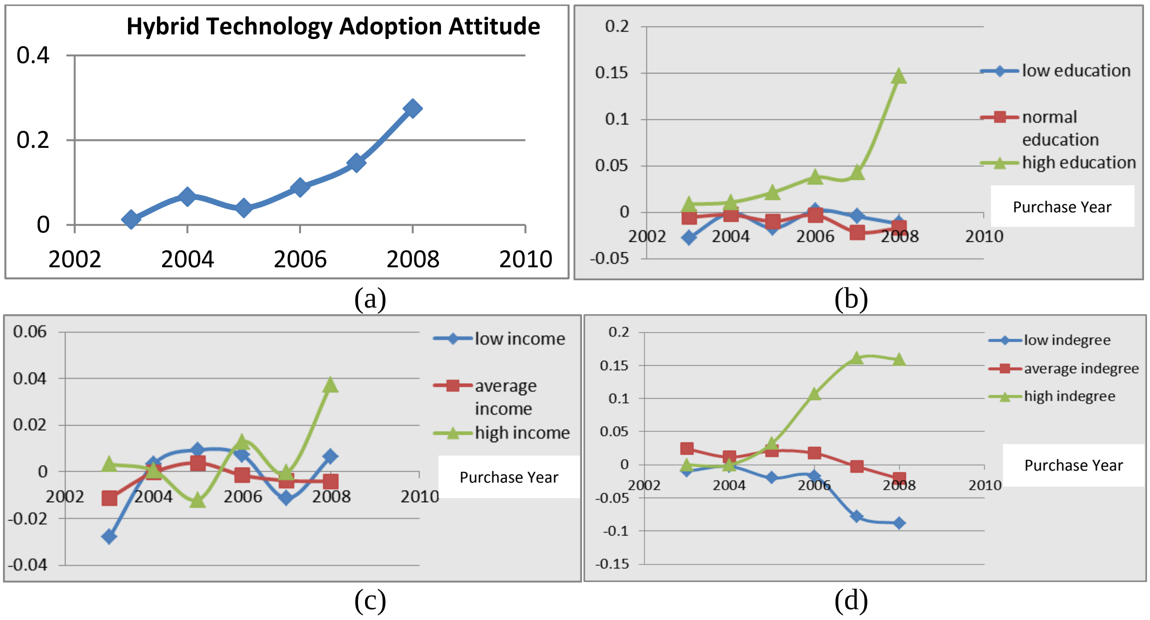

Figure 3. Hybrid Technology Attitudes from Year 2003 to 2008

Figure 4 provides a comparison of the choice predictions beyond year 2009 using the model with **N** and the model without **N**. Since demographic attributes, engineering attributes and usage context attributes are not time related, a choice model without social influence attributes cannot make time related predictions. As shown in Figure 4, the curve of the model without **N** remains to be relatively flat after the year of 2009. Social influence attributes, on the other hand, capture the time effect as each year's predicted number of consumers owning hybrid vehicle is increasing. In our prediction, we assume that customer's social influence is based on the effects from the previous year. One assumption for prediction is that the profile of consumers remains the same as the profile used for data analysis and model fitting. Comparing the real market share and the predictions confirms that the social influence attributes introduced in the choice model capture the time effect and play a critical role in future prediction for design.

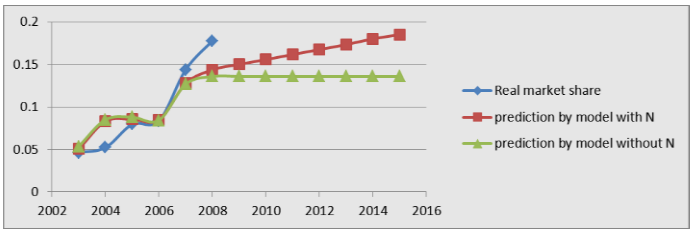

Figure 4. share prediction by model with N and without N

6 CONCLUSION AND FUTURE WORK

The primary research contribution of this work is the development of a more comprehensive methodology for integrating social influence into the Discrete Choice Analysis modeling for choice predictions. In the previous research by He and Chen (2012), social influence attribute was included in the choice modeling framework, but the simulation was based on insufficient consumer information. This research utilizes multiple demographic attributes and usage context attributes as social profile information to construct social network for simulating consumers' behavior. The critical social profile attributes are identified through data analytic techniques. Social network is constructed by the social distance method, and the social influence attributes are evaluated accordingly. The proposed choice model predicts customers' purchase behavior affected by social influence. It also helps designer create better engineering designs that are geared toward customer needs. An HEV choice model example using NHTS dataset is introduced to demonstrate the proposed methodology and to study the social influence on customers' attitude towards hybrid vehicle technology. Based on the result in the case study, we observe that the concept of hybrid vehicle technology has become better accepted throughout the past years because of the growing social influence. Hence, we conclude that the social influence does have a great impact on adoption of hybrid electric vehicle technology, and government and vehicle producers ought to advocate the concept of hybrid technology to more people.

Introducing social influence attributes in choice modeling may cause endogeneity, since unobserved environment and preferences may impact both the modeled decision maker and consumers , yielding correlation between social influence attributes and the error (Walker et al. 2011). Social influence may affect consumers differently for different products, which leads to a need of different social network construction tools. Therefore, more social network construction methods should be tested such as random graph method (Newman, Watts and Strogatz 2002) and agent-based simulation method (Chan, Son and Macal 2010). The current implementation of the social distance method for constructing a social network utilizes consumer profile information; its confounding with introducing demographic attributes as explanatory variables in a choice model needs to be carefully avoided. It should be pointed out that the influence of consumer profiles on the choice has different meanings from their influence on the social network formation. Therefore even if the same set is used at both places, there may not be any confounding. Another future extension of this work is to develop a methodology combining empirical studies of social network with network construction and simulation to eliminate the assumptions adopted in this work for social network simulation.

ACKNOWLEDGEMENT

Grant supports from National Science Foundation (DUE-0920047) and ISEN (Initiative for Sustainability and Energy at Northwestern) are greatly appreciated.

REFERENCE

Akerlof, G. A. (1997) Social distance and social decisions. *Econometrica*, Vol. 65, No. 5, pp. 1005-1027.

Brock, W. A. & S. N. Durlauf (2002) A multinomial-choice model of neighborhood effects, *American Economic Review*, Vol. 92, No. 2, pp. 298-303.

Case, A. (1992) Neighborhood Influence and Technological-Change, *Regional Science and Urban Economics*, Vol. 22, No. 3, pp. 491-508.

Chan, W. K. V., Son, Y., and Macal, C. M., (2010) Agent-based simulation tutorial - simulation of emergent behavior and differences between agent-based simulation and discrete-event simulation, In Johansson, S. J. B., Montoya-Torres, J., Hugan, J., and Yücesan, E., (eds) *2010 Winter Simulation Conference (WSC)*, Baltimore, MD.

Dugundji, E. R., Gulyas, L. (2003a) Empirical estimation and multi-agent based simulation of a discrete choice model with network interaction effects, In *8th International Conference on Computers in Urban Planning and Urban Management*, Sendai, Tohoku University .
Dugundji, E. R., Gulyas, L. (2003b) An exploration of the role of global versus local and social versus spatial networks in transportation mode choice behavior in the Netherlands, In *AGENT 2003: Challenges in Social Simulation*, , Chicago, Argonne National Laboratory.
Festinger, L. (1954) A Theory of Social Comparison Processes, *Human Relations*, Vol. 7, No. 2, pp. 117-140.
He, L. & W. Chen. (2011). Usage Context-Based Choice Modeling for Hybrid Electric Vehicles, In Culley, S.J.; Hicks, B.J.; McAloone, T.C.; Howard, T.J. & Dong, A. (eds) *11th International Conference on Engineering Design*, Copenhagen, The Technical University of Denmark .
He, L. and Chen, W. (2012) Incorporating Social Impact On New Product Adoption In Choice Modeling: A Case Study In Green Vehicles, In *2012 ASME International Design Engineering Technical Conferences & Computers and Information in Engineering Conference*, Chicago, the Design Society.
Hoyle, C., Chen, W., Wang, N., and Gomez-Levi, G., (2011) Understanding and modelling heterogeneity of human preferences for engineering design, *Journal of Engineering Design*, Vol. 22, No. 8, pp. 583-601.
Kelman, H. C. (1958) Compliance, Identification, and Internalization: Three Processes of Attitude Change, *Journal of Conflict Resolution*, Vol. 2, No. 1, pp. 51-60.
Kroes, E. P. & R. J. Sheldon (1988) Stated Preference Methods - an Introduction, *Journal of Transport Economics and Policy*, Vol. 22, No. 1, pp. 11-25.
Krugman, P. (1991) Increasing Returns and Economic-Geography, *Journal of Political Economy*, Vol. 99, No. 3, pp. 483-499.
Leenders, R. T. A. J. (1995) Models for Network Dynamics - a Markovian Framework, *Journal of Mathematical Sociology*, Vol. 20, No. 1, 1-21.
Leenders, R. T. A. J. (2002) Modeling social influence through network autocorrelation: constructing the weight matrix, *Social Networks*, Vol. 24, No. 1, pp. 21-47.
Lewis, K., W. Chen & L. Schmidt. (2006) *Decision Making in Engineering Design*, New York: ASME Press.
Manski, T. J. (1995) Gigantism and Somatostatin Neurons, *Journal of Neurosurgery*, Vol. 82, No. 6, pp. 1100-1101.
McFadden, D. (2010) Sociality, rationality, and the ecology of choices, In *Choice Modeling: The state-of-the-art and the state-of-practice*, UK: Emerald Group Publishing Ltd.
Michalek, J. J., Ceryan, O., and Papalambros, P. Y. (2006) Balancing marketing and manufacturing objectives in product line design, *Journal of Mechanical Design*, Vol. 128, No. 6, pp. 1196-1204.
Monge, P. R. & N. Contractor. (1988) Communication networks: Measurement techniques, In *A handbook for the study of human communication*, New Jersey: Ablex.
Monge, P. R. & N. S. Contractor. (2003) *Theories of Communication Networks*, New York: Oxford University Press.
Newman, M. E. J., D. J. Watts & S. H. Strogatz (2002) Random graph models of social networks, *Proceedings of the National Academy of Sciences of the United States of America* 99, Suppl 1, 2566-2572.
Paez, A., D. M. Scott & E. Volz (2008) A discrete-choice approach to modeling social influence on individual decision making, *Environment and Planning B-Planning & Design*, Vol. 35, No. 6, pp. 1055-1069.
Samuelson, P. A. (1948) Consumption Theory in Terms of Revealed Preference, *Economica-New Series*, Vol. 15, No. 60, pp. 243-253.
Snijders, T. A. B. (2001) The statistical evaluation of social network dynamics, *Sociological Methodology 2001*, Vol. 31, No. 1, pp. 361-395.
Steglich, C., T. A. B. Snijders & M. Pearson (2010) Dynamic Networks and Behavior: Separating Selection from Influence, *Sociological Methodology*, Vol. 40, No. 1, pp. 329-393.
Walker, J. L., E. Ehlers, I. Banerjee & E. R. Dugundji (2011) Correcting for endogeneity in behavioral choice models with social influence variables, *Transportation Research Part a-Policy and Practice*, Vol. 45, No. 4, pp. 362-374.

Wassenaar, H. J. & W. Chen (2003) An approach to decision-based design with discrete choice analysis for demand modeling, *Journal of Mechanical Design*, Vol. 125, No. 3, pp. 490-497.

APPENDIX

Appendix A. List of Attributes in Choice Mode

Consumer-desired product attributes A			**Customer demographic attributes S**		
A_1	Price	MSRP	S_1	Income	Household income
A_2	Length	Length of vehicle	S_2	Children	Children in the family
A_3	Width	Width of vehicle	S_3	Education	Education level of respondent
A_4	Rlr	Rear leg room	S_4	Location	Respondent resident location in zip code
A_5	Fhdr	Front head room	S_5	Race	Race of respondent
A_6	Torque	Torque of vehicle	S_6	Age	Age of respondent
A_7	MPG	Miles per gallon	S_7	Gender	Gender of respondent
A_8	Hybrid	Hybrid electric vehicle indicator	**Usage context attributes U**		
A_9	Height	Height of vehicle	U_1	Mile driven	Miles driven each year
Social influence attributes N (simulated)					
N_1	Indegree	the number of times a person *n* is connected in the network inwards $N_{n,t}^{Indegree} = y_{n,t}\sum_{m=1}^{N} w_{nm}^{r}$	N_2	Alter	defined by the behavior percentage of people who are connected to person *n* $N_{n,t}^{AverageAlter} = y_{n,t}(\sum_{m=1}^{N} w_{nm}^{r} y_{m,t-1}) / (\sum_{m=1}^{N} w_{nm}^{r})$

Appendix B. Results of Choice Model Coefficients

Models	MNL with social influence N		MNL without social influence N	
Attributes	Coefficient	Standard error	Coefficient	Standard Coefficient
Length (A_2)	-0.000124	0.0019672	-0.0001099	0.0019648
Rear leg room (A_4)	-0.0334703	0.0058437	-0.0339144	0.0058358
Hybrid (A_8)	-0.2738703	0.1270668	0.4941757	0.0855812
Width(A_3)	0.0938653	0.0088165	0.0936654	0.0088008
Torque(A_6)	0.0003605	0.000468	0.0003277	0.0004674
Front head room (A_5)	0.1145566	0.0187383	0.1124856	0.0187048
MPG (A_7)	0.1753132	0.0060163	0.1752264	0.0059673
Height(A_9)	0.0201609	0.0041548	0.0205884	0.0041372
Price/income ($A_{1/}$ S_1)	-0.0000594	0.0000147	-0.0000595	0.0000147
Hybrid*miledriven(A_8* E_1)	-0.0000465	5.01E-06	-0.0000434	4.86E-06
Children*length (S_2* A_2)	0.0088762	0.0010461	0.0087915	0.0010471
Hybrid*indegree (A_8* N_1)	0.126358	0.0547837	N/A	N/A
Hybrid*alter (A_8* N_2)	0.2275542	0.036971	N/A	N/A