Available online at www.sciencedirect.com
ScienceDirect
Expert Systems with Applications 34 (2008) 2754–2762
Expert Systems with Applications
www.elsevier.com/locate/eswa

Intelligent value-based customer segmentation method for campaign management: A case study of automobile retailer

Chu Chai Henry Chan *

E-Business Research Laboratory, Department of Industrial Engineering and Management, Chaoyang University of Technology, No. 168, Jifong East Road, Wufong Township, Taichung County, Taiwan, ROC

Abstract

Most marketers have difficulty in identifying the right customers to engage in successful campaigns. So far, customer segmentation is a popular method that is used for selecting appropriate customers for a launch campaign. Unfortunately, the link between customer segmentation and marketing campaign is missing. Another problem is that database marketers generally use different models to conduct customer segmentation and customer targeting. This study presents a novel approach that combines customer targeting and customer segmentation for campaign strategies. This investigation identifies customer behavior using a recency, frequency and monetary (RFM) model and then uses a customer life time value (LTV) model to evaluate proposed segmented customers. Additionally, this work proposes using generic algorithm (GA) to select more appropriate customers for each campaign strategy. To demonstrate the efficiency of the proposed method, this work performs an empirical study of a Nissan automobile retailer to segment over 4000 customers. The experimental results demonstrate that the proposed method can more effectively target valuable customers than random selection.

Keywords: Customer segmentation; Generic algorithm; Customer lifetime value; Campaign management

1. Introduction

For a successful business, engaging in an effective campaign is a key task for marketers. Traditionally, marketers must first identify market segmentation using a mathematical mode and then implement an efficient campaign plan to target profitable customers (Fraley & Thearting, 1999). This process confronts considerable problems. First, most previous studies used various mathematical models to segment customers without considering the correlation between customer segmentation and a campaign. Previously, the link between customer segmentation and campaign activities was most manual or missing (Fraley & Thearting, 1999). From an academic perspective, the processes of customer segmentation should consider the constraints or dependent variables of campaign activities in attempting to increase the relevancy of both processes. For marketing researchers, segmentation should not the end in itself, but rather a means to an end (Jonker, Piersma, & Poel, 2004). Following the notion proposed by Jonker, this work presents a conceptual model by counting the significant campaign dependent variables of customer targeting in customer segmentation. In this way, the processes of customer segmentation and targeting thus can be linked and solved together. The outcomes of customer segmentation of this study are more meaningful and useful for marketers than the others.

Second, in most previous studies, the quality of a segmentation methodology is measured based on within-segment and inter-segment heterogeneity (Wedel & Kamakura, 2000). Realistically, marketers are concerned with and interested in maximizing the net value of targeted customers, rather than caring about within-segment homogeneity or targeting rate (Jonker et al., 2004; Kim, Street, Russell, & Menczer, 2005). To solve the core problem of marketers facing, this investigation applies a customer life time value

* Tel.: +886 423323000x4251; fax: +86 4 23742327.
E-mail address: ccchan@cyut.edu.tw

0957-4174/$ - see front matter © 2007 Published by Elsevier Ltd.
doi:10.1016/j.eswa.2007.05.043

model to assess the fitness between targeted customer groups and marketing strategies, rather than measuring the within-segment homogeneity.

To integrate customer segmentation and customer targeting, this work uses the generic algorithm (GA) to determine the optimized marketing strategy (Jonker et al., 2004; Kim & Street, 2004; Kim et al., 2005; Tsai & Chiu, 2004).

2. Research background

In traditional markets, customer segmentation is one of the most significant methods used in studies of marketing. This study classifies existing customer segmentation methods into methodology-oriented and application-oriented approaches. Most methodology-driven studies used mathematical methodologies, e.g. statistics, neural net, GA and Fuzzy set to identify the optimized segmented homogenous group (Hu & Sheub, 2003; Hwang, Jung, & Suh, 2004; Jiao & Zhang, 2005; Jonker et al., 2004; Kim, Jung, Suh, & Hwang, 2006; Kim & Street, 2004; Kim et al., 2005; Tsai & Chiu, 2004; Vellido, Lisboa, & Meehan, 1999).

On the other hand, application-oriented researches must search for the optimum method for solving segmentation problems in specific applications (Chan, 2005; Chung, Oh, Kim, & Han, 2004; Jones, Easley, & Koehler, 2006; Kuo, An, Wang, & Chung, 2006; Shin & Sohn, 2004; Woo, Bae, & Park, 2005). In such applications, studies sometimes combine multiple methods to solve the customer segmentation problem for specific individual applications (Chung et al., 2004; Kim & Street, 2004; Kim et al., 2005; Kuo et al., 2006; Shin & Sohn, 2004).

Each year numerous empirical researches are published dealing with this area. Table 1 summarizes recent customer segmentation research. Because too many methods are developed in conducting customer segmentation, it is quite difficult to make comparisons between all of them. Each study brings its own advantages and efforts to solve segmentation problems. Similarly, this work devises an approach for dealing with customer segmentation problems during a promotion campaign.

3. Framework for value-based customer segmentation

In most marketing studies, customer segmentation is designed to increase customer value or profitability through careful customer targeting. (Chan, 2005; Chung et al., 2004; Hwang et al., 2004; Jones et al., 2006; Kim & Street, 2004; Kim et al., 2005; Kuo et al., 2006; Shin & Sohn, 2004; Woo et al., 2005). To achieve such a goal, the CRM research team of IBM corporation proposes 2W (What, Whom) and 1H (How) as three key factors in delivering customer value, as illustrated in Fig. 1 (Liu, 2001). First, it is important to consider what value should be delivered to customers. Second, it is important to consider which customers value should be delivered to. Finally, we will ask for how to identify and contact suitable consumers. Consequently, the objective of customer segmentation is to find customers that would be suitable for a marketing campaign. Customer segmentation must be linked to delivery of customer value and an effective campaign action.

The main problem in customer value creation is that most existing studies cannot link customer segmentation methods with campaign activities. To integrate these two processes, this study proposes linking the significant variables of campaign activities to customer segmentation (Jonker et al., 2004). To realize customer life time value in both processes, this investigation evaluates customers using two main factors; current value and potential value (Hwang et al., 2004; Kim et al., 2006). Current value represents historic customer purchase behavior. Meanwhile, potential value denotes the possibility of up-selling and cross-selling in the future (Hwang et al., 2004). Conducting a campaign requires first determining series of sequential marketing plans. The second step is collecting related customer information. As the data are collected, customer data must be transformed into the input format of the

Table 1
Recent customer segmentation research summary

Major method	Focus	Application	Literature
Chi-square automatic interaction (CHAID)	Market segmentation	Hotel guest room customers	Chung et al. (2004)
FUZZY	Cluster customers	Logistical distribution operations mobile phones	Hu and Sheub (2003), Jiao and Zhang (2005)
Fuzzy K-means cluster	Customer segmentation	Stock market	Shin and Sohn (2004)
Genetic algorithm	Markets segmentation	Retail store mailings	Tsai and Chiu (2004), Jonker et al. (2004)
K-means and SOM	Market segmentation	Fright transport industry	Kuo et al. (2006)
LTV model	Customer segment and strategy development	Wireless telecommunication	Hwang et al. (2004), Kim et al. (2006)
Neural network	Customer segmentation	Online market	Vellido et al. (1999), Chan (2005)
Neural networks (Anns) and genetic algorithms (Gas)	Customer targeting	Insurance for a recreational vehicle	Kim and Street (2004), Kim et al. (2005)
Rule-based approach	Multiple market segments	Combinatorial auction	Jones et al. (2006)
Visualization	Customer targeting	Credit card company	Woo et al. (2005)

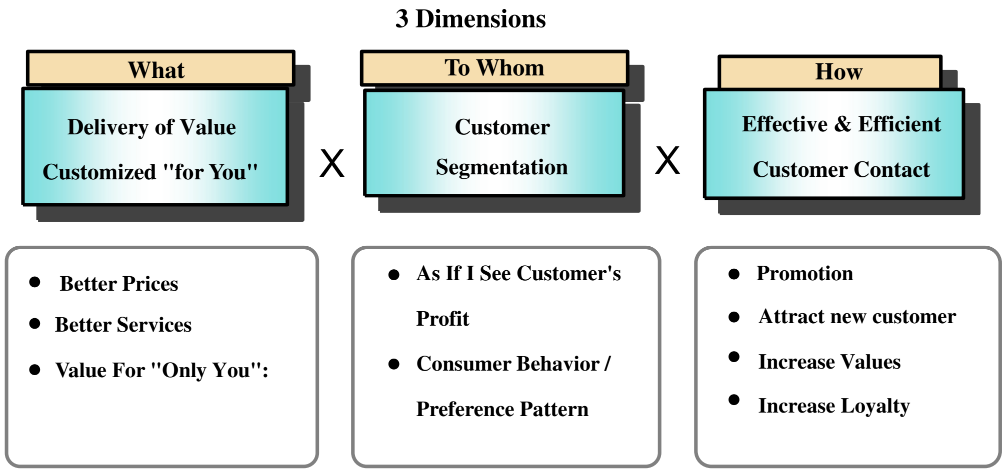


Fig. 1. Customer value creation concept defined by IBM (Liu, 2001).

customer targeting method. To search for the most suitable customer group, data-mining are used to analyze information and identify valuable customers. Following the marketing analysis, marketers should determine the targeted customers. It is necessary to identify the most profitable groups of customers for each campaign plan. The next step is to implement effective campaign management. Fig. 2 shows the phases used for targeted customer segmentation.

Fig. 3 illustrates a framework that joins customer segmentation and customer targeting via six phases. First, companies must plan and develop a marketing strategy for promotion campaigns this year. Second, marketers must gather customer data to establish customer profile and devise associated campaign information. This study uses a RFM model to represent customer behavior. Customer data are encoded using a RFM model and transformed into a binary string as the input format of genetic algorithm (GA). Conversely, this study collects and calculates customer time values as the fitness values of GA. The proposed LTV model considers the correlation between campaign strategy and customer value. The fourth step is segmenting customers into several homogenous groups using GA. Meanwhile, the fifth step involves targeting and matching segmented customers with the developed campaign strategies and programs. The final step involves classifying customers and turning a campaign plan into action.

Because one of the major concerns of marketers is net profits and customer values, this study develops an LTV model as the fitness function of GA to evaluate and assess the maximum customer life time value. Additionally, this study includes dependent variables of campaigns into the LTV model that connects customer behavior and campaign programs.

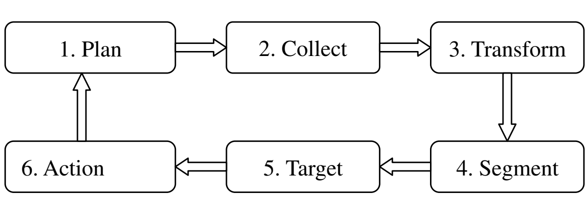


Fig. 2. Phases of targeted customer segmentation.

Fig. 4 shows the information flow of targeted customer segmentation. Customer transaction data and demographic data are gathered to establish a basic customer profile. The RFM model retrieves and transforms customer profile into a binary string which can be recognized by the generic algorithm. The LTV model calculates current customer value and predicts potential customer value. Finally, this work applies GA to select the optimum of customer segmentation for each marketing strategy.

4. RFM encoding scheme

To identify customer behavior, the well known method called recency, frequency and monetary (RFM) model is used to represent customer behavior characteristics (Chan, 2005; Hsieh, 2004). This approach models three dimensions of customer transactional data, namely recency, frequency and monetary, to classify customer behavior (Yao, Li, & Chew, 2000). The first dimension is recency, which indicates the length of time since the start of a transaction. Meanwhile, the second dimension is Frequency, which indicates how frequently a customer purchases products during a particular period. Finally, monetary value measures the amount of money that customer spending during a period (Jonker et al., 2004).

The basic assumption of using the RFM model is that future patterns of consumer trading resemble past and current patterns. The calculated RFM values are summarized to clarify customer behavior patterns. This study proposes usingthe following RFM variables (Chan, 2005):

- Recency (R): the latest purchase amount.
- Frequency (F): the total number of purchases during a specific period.
- Monetary (M): monetary value spent during one specific period.

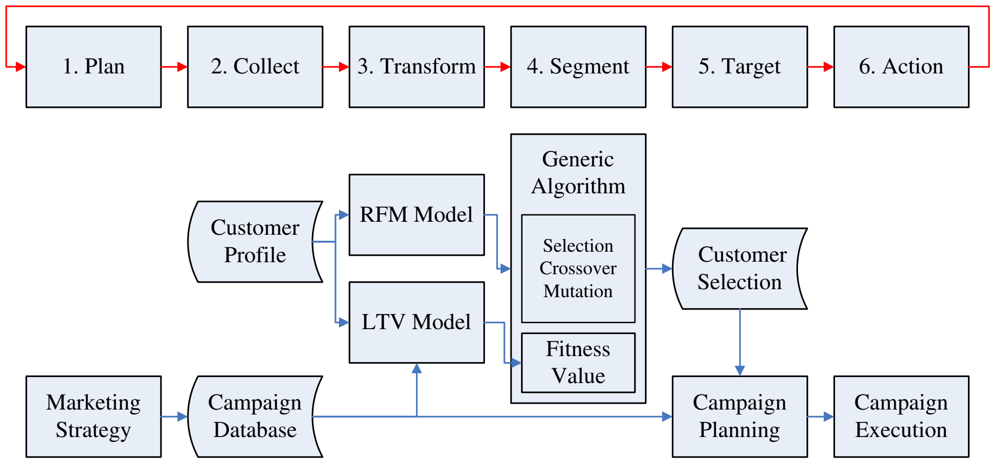


Fig. 3. The framework of customer segmentation.

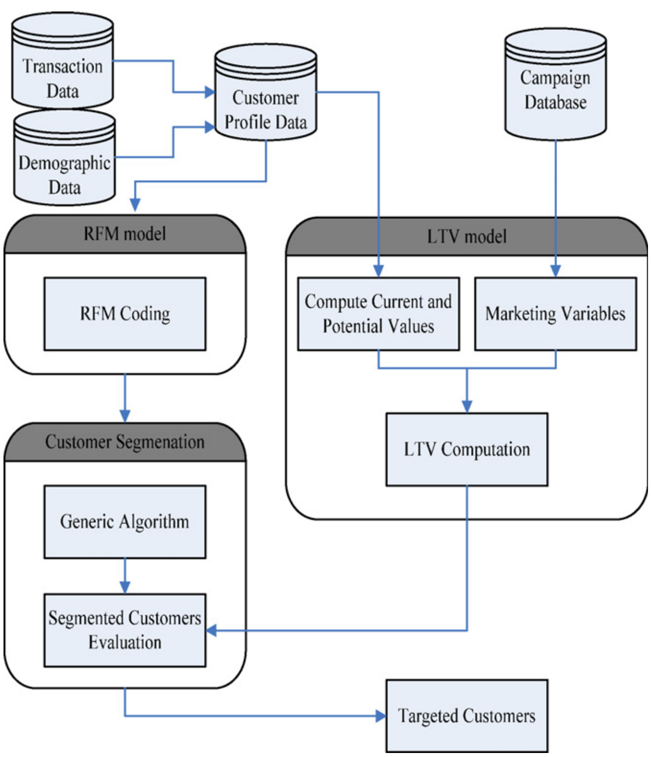


Fig. 4. Information flow of value-based customer segmentation.

After using the RFM model to represent customer behavior, this study encodes data into a binary string by dividing this values of recency, frequency and monetary into five sections. If the value lies between 80% and 100% the binary code is set to 5. Similarly, if the value is between 80% and 60% the binary code is 4. Table 2 lists the mapping relationship between the input data and binary codes.

This proposed encoding scheme transforms the points of the parameter space into a binary string representation. For instance, a point (3, 2, 5) in a three-dimensional parameter space can be represented as a concatenated binary string (Jang, Sun, & Mizutani, 1997).

Table 2
Transformation between input data and binary code

Value	Binary code
$80\% < X \leq 100\%$	5
$60\% < X \leq 80\%$	4
$40\% < X \leq 60\%$	3
$20\% < X \leq 40\%$	2
$X \leq 20\%$	1

<u>0011</u> <u>0010</u> <u>0101</u>
3 2 5

Each coordinate value is encoded as a gene composed of four binary bits using binary code. Customer behavior is represented by RFM and encoded using a three-dimensional binary code.

5. Marketing strategy for campaign activities

The challenge of a campaign lies in identifying what program is delivered to whom and predicting campaign effectiveness. The cycle of customer lifetime comprises

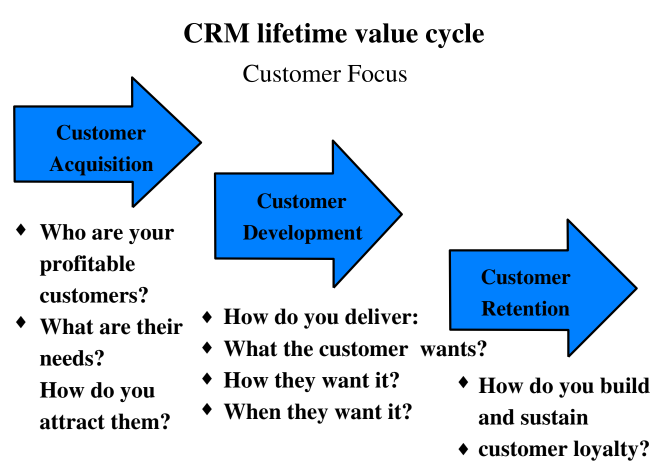


Fig. 5. Customer lifetime value defined by IBM (Liu, 2001).

Table 3
Marketing strategies for campaign programs

Marketing strategy	Purpose	Campaign plan
Acquisition	Recruit new customers	Free trial, DIY classroom, gift for consumer
Growing	Growing customers to be higher-valued by up-selling or cross-selling	Bonus and gift for credit card, free exam
Retention	Retaining the customers who are possible to leave or turn to other competitors	Free mileage tow, 6510 extended warrant
Relationship management	Target profitable or potential customers to increase values	High-value homecoming, free maintain for life time

customer acquisition, customer development and customer retention, as displayed in Fig. 5 (Liu, 2001). In the stage of customer acquisition, most sellers consider three issues: the identity of their profitable customers, their needs, and how to attract them. The second step is customer cultivation. Marketers have to consider issues in this step: matching customer wants and, delivery method. The final step is customer retention. The key issue is "How to establish and sustain customer loyalty?" IBM Corp. used three above steps to design a system for performing customer relationship management.

Numerous companies have adapted the customer relationship management (CRM) approach to improve profitability by retaining high potential customers This study assumes that a promotion campaign can increase customer value. Generally, campaigns are designed to include cross-selling, up-selling, retention, recovery, statutory operational communication, market research communication, data enrichment and customer acquisition (Doyle, 2005).

To maintain good customer relationships and enhance customer value, Nissan Corporation developed a list of campaign programs annually. This study classifies the campaign programs designed by Nissan into four major marketing strategies: acquisition strategy, growing strategy, retention strategy and relationship management. The acquisition strategy aims to attract new customers. The growing strategy is designed to increase customer values delivered by a campaign promotion program. Meanwhile, growing strategy customer acquisition is intended to augment the possibilities for further growing high-value customers by cross-selling and up-selling. The retention strategy is designed to retain customers as long as possible. This strategy is designed to raise customer loyalty. Meanwhile, the relationship management strategy is intended to target profitable customers or those with good potential. This study only discusses growing, retention, and relationship management strategies, because this research proposes an approach for enhancing the value of existing customers rather than finding new customers. Acquiring new customers are not a concern of this study. Table 3 details the campaign plans developed by Nissan.

6. Customer value model for campaign

To assess each generation of customer segmentation proposed by GA, this investigation develops a life time value (LTV) model as the fitness function of GA. Normally, customer life time value must consider both past profit contribution and future expected profitability (Hwang et al., 2004). This study proposed that the life time value of customers should comprise two key values: current value and potential value. The sum of these two values could be used as an index to determine customer life time value. Traditionally, the LTV model is shown as (Hwang et al., 2004):

$$\text{LTV} = \text{Current value} + \text{Potential value} \tag{1}$$

$$\text{Current value} = \sum_{t_i=0}^{N_i} \pi_{\text{p}}(t_i)(1+d)^{N_i - t_i} \tag{2}$$

where t_i is the service period index of customer i, N_i is the total service period of customer i, d is the interest rate and $\pi_{\text{p}}(t_i)$ is the past profit contribution of customer i at period t_i.

$$\text{Potential value}_i = \sum_{j=1}^{N} \text{Prob}_{ij} \times \text{Profit}_{ij} \tag{3}$$

$$\text{Customer Loyalty} = 1 - \text{Churn rate} \tag{4}$$

Previously LTV models could not link campaign activities. The main problem of most existing researches that the correlation between customer values and campaign activities is not considered in the LTV model. To cope with this difficulty, this study proposes a new model for calculating customer value based on a serial number of campaigned projects, as follows (see Fig. 6):

$$\text{Potential Value} = \sum_{j=1}^{N} \text{Prob}_{ij} \times \text{Profit}_{ij} \times M_{ij} \tag{5}$$

where Prob_{ij} is the probability of using marketing strategy j for segmented customer i, M_{ij} is the contribution factor of increasing monetary value by using strategy i for segmented customer i and N is the expected year of customer loyalty.

$$\text{Customer Loyalty}_i = \sum_{j=1}^{M} L_{ij} \times (1 - \text{Churn rate}) \tag{6}$$

where L_{ij} is the contribution factor of increasing loyalty by adapting strategy j for customer i and M is the total number of marketing strategy.

The new model adds two contribution factor variables. The first variable is the probability of customer i adapting

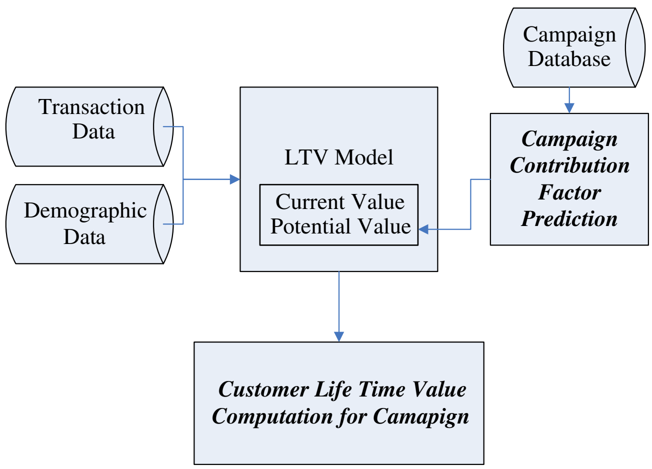


Fig. 6. Customer life time value computation.

strategy j. Meanwhile, the other factor is the contribution value when customer i uses strategy j. These variables link campaign programs and customer values.

7. GA for customer segmentation

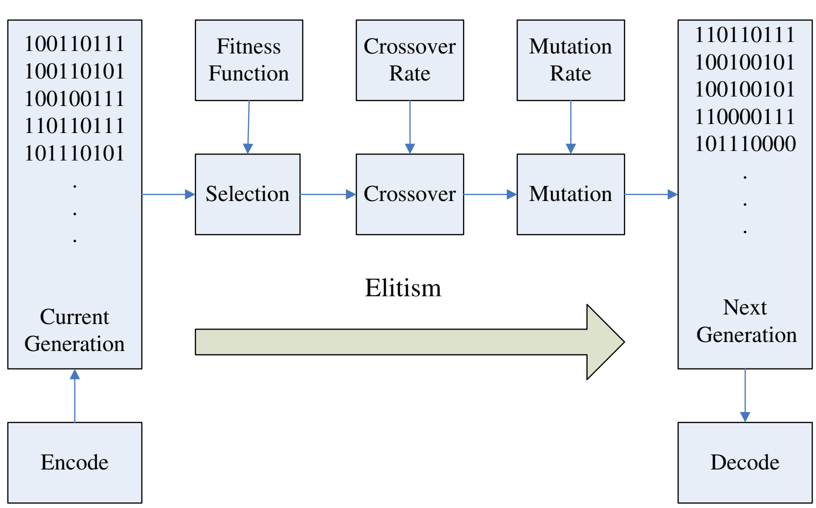
Since GA was introduced by Holland (1975), many studies have demonstrated good results in numerous different applications (Jonker et al., 2004; Kim & Street, 2004; Kim et al., 2005; Tsai & Chiu, 2004). GA is a derivative-free stochastic method based on natural selection and evolutionary processes. GA has the following characteristics (Jang et al., 1997):

- GA is applicable to both continuous and discrete optimization problems.
- GA is stochastic and unlikely to get trapped in local minima.
- The flexibility of GA facilitated both structure and identification in the complex model.

To apply GA in customer segmentation, this study requires encoding input data into a binary bit string called a chromosome. Rather than a single point, GA usually takes a set of points as a population and repeatedly evaluates fitness value to determine better values (Jang et al., 1997). In each generation, GA creates a new population using genetic operators such as crossover and mutation. Ultimately, only the generated members with higher fitness value can survive. GA is referred to as a population-based optimization method that improves performance by upgrading the entire population rather than individual members (Jang et al., 1997). GA is composed of encoding scheme, selection, crossover, mutation, and the decoding shown in Fig. 7. This study selects simple GA to segment customers.

Fig. 8 shows the system flow (Kwang, 2006). At first, the input parameters must be setup and customer data encoded as a binary string. Second, GA initializes the chromosome randomly. Third, each chromosome is evaluated. Fourth, higher fitness value members are selected as parents for the next generation. Fifth, crossover is used to generate new chromosomes with provable crossover rate that we hope to preserve good genes from parents. Sixth, mutation is used to flip a bit with the probability of fixed mutation rate. This step can generate new chromosomes to prevent the entire population from converging on trapped local optima. Seventh, a new generation is produced. Meanwhile, the eighth step is evaluating a new generation to measure the stop criteria. If the stop criteria remain unsatisfied, the processes will repeat. If the criteria are satisfied, the evolution will stop. Finally, the best chromosomes are chosen and decoded as the final solutions.

The method of segmentation in this study is defined by variable breakpoints (Jonker et al., 2004). The number of segmentations increases rapidly whenever the number of breakpoints increases. For example, if each RFM variable



Source: Jang, et al., 1997

Fig. 7. Producing a better generation by GA.

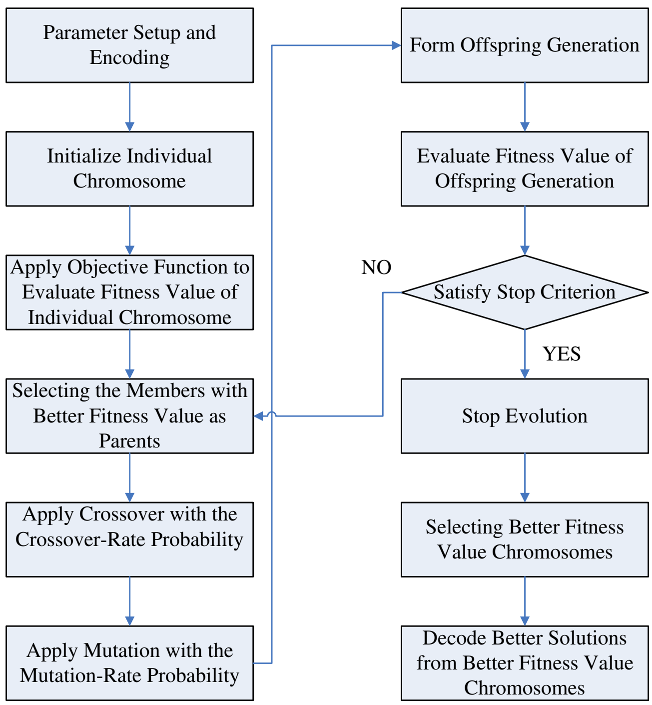


Fig. 8. System flowchart of GA.

has one breakpoint, there are 8 (=2^3) segmentations and this number increases to 27 as the number of each variable is increased to three. Various reasons exist for limiting the number of breakpoints. An excessively large number of segments will make the space too large to search. Simultaneously, if the number of customers in each segmented group becomes too small, analysis becomes too difficult and the results become meaningless.

8. Case study

To enhance campaign effectiveness, Empower company (a Nissan dealer) spent one and half a years conducting a project for customer relationship management. This project collected and sampled over 40,000 customers. The present study sampled 4659 customers. The detail of customer segmentation is represented and discussed in this section.

8.1. Data preparation

To segment customer data, Empower Corporation provided 4659 pieces of historical customer data from January 1995 to April 2005. Table 4 lists the customer distribution of the nine car models. The most popular car models include SENTRA M1, MARCH, CEFIRO, ALL NEW SENTRA, NEW CEFIRO and X-TRAIL. If car models are classified according to size, SENTRA M1, MARCH, ALL NEW SENTRA were classified as small and medium size vehicles. Meanwhile, CEFIRO and NEW CEFIRO are classified as luxury size vehicles. X-TRAIL is compact SUVs.

Table 4
The customer distribution of car model

Model	The number of customer	Percentage (%)
SENTRA M1	1261	27.1
MARCH	705	15.1
CEFIRO	630	13.5
ALL NEW SENTRA	589	12.6
NEW CEFIRO	555	11.9
X-TRAIL	468	10.0
QRV	151	3.2
TEANA	43	0.9
QUEST	22	0.5
Others	235	5.2
Total	4659	100.0

8.2. Customer current value analysis

Before analyzing customer life time value, it is important to know current customer value. Table 5 lists the distribution of current customer value. Almost 30.3% customers spent less than 1000 NT dollars annually; 49.4% of customers spent between 5000 NT dollars and 1000 NT dollars; 13.6% of customers spent between 10,000 NT dollars and 5000 NT dollars, and 4.5% pent between 15,000 NT dollars and 10,000 NT dollars. From the above summary, 90% of customers spent less than 10,000 NT annually.

8.3. Customer segmentation by GA

The generic algorithm is applied to segment customers with the parameters shown in Table 6. This study divides customers using one breakpoint per variable. This study sets the crossover rate to 0.9 and the mutation rate to 0.1. The total number of generations is limited to 50.

To understand the outcomes of 50 generations, this study selects the best 10 solutions listed in Table 7. The best ten solutions obtain the same fitness value (930869133.41 NT), so the final result converges to an optimized value. This study uses the 50th generation as the final outcome of customer segmentation. The optimum solution segmented 4659 customers into eight groups. The numbers of customers in each group was shown in Table 8. Table 9

Table 5
The distribution of customer current value

Current value (1000 NT/Unit)	The number of customer	Percentage (%)
1	1414	30.3
5	2303	49.4
10	633	13.6
15	208	4.5
20	66	1.4
25	22	0.5
30	7	0.2
35	4	0.1
50	1	0.0
55	1	0.0
Total	4659	100.0

Table 6
Input parameters of GA

Parameter	Value
Population size	100
Crossover rate	0.9
Mutation rate	0.1
Generations	50
Best fitness unchanged generations	20

Table 7
Best 10 solutions from 50 generation

	R	*F*	*M*
Solution 1	4.43	3.81	3.62
Solution 2	4.43	3.79898	3.62
Solution 3	4.416549	3.79898	3.62
Solution 4	4.43	3.81	3.599451
Solution 5	4.43	3.787961	3.62
Solution 6	4.416549	3.81	3.599451
Solution 7	4.416549	3.787961	3.62
Solution 8	4.403098	3.81	3.62
Solution 9	4.416549	3.79898	3.599451
Solution 10	4.43	3.787961	3.599451

Table 8
Customer segmentation

Group no.	The number of customer	Percentage (%)
1	2002	43.0
2	464	10.0
3	491	10.5
4	761	16.3
5	481	10.3
6	144	3.1
7	112	2.4
8	204	4.4
Total	4659	100.0

shows the values and variables from generations 1 to 50. All initial values of the RFM variables are set to 1, and the total custom life time value (fitness value) is evaluated as 689332704.175 NT dollars. After 50 generations, the three RFM variables become 4.43, 3.787961 and 3.599451 and the fitness values is increases to 930869133.41 NT dollars.

Using the proposed method to segment customers could increase the potential value, loyalty and life time value. Fig. 9 illustrates that the potential values of the segmented group are increased with the proposed method. Specially, the potential values of groups 1, 3 and 4 are increased by more than 100%. Fig. 10 shows a similar effect for loyalty.

Table 9
Fitness value and RFM variables from generation 1 to generation 50

R	*F*	*M*	Fitness value (NT)
Generation 1			
1	1	1	689332704.175252
Generation 50			
4.43	3.787961	3.599451	930869133.41

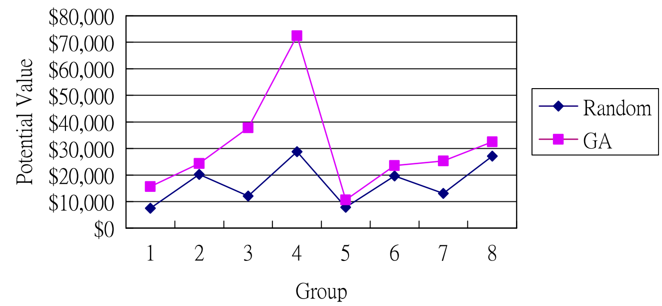


Fig. 9. The potential value by using GA and random selection.

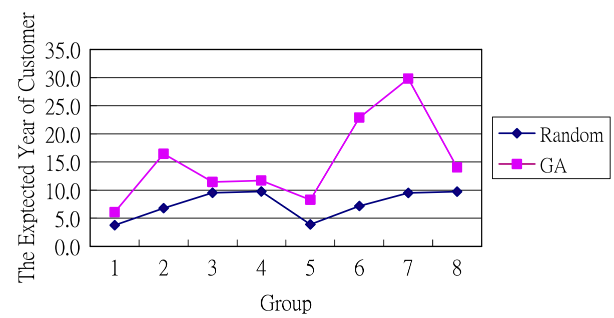


Fig. 10. The expected year of loyalty by using GA and random selection.

Groups 6 and 7 display an increase in loyalty exceeding 200%. Fig. 11 shows that the life time values of customers calculated using the proposed segmentation method are much better than those calculated using random selection. Fig. 12 shows the fitness values from generations 1 to 50. The fitness value increases rapidly after generation 13. The fitness value converges to a stable value after 22 generations. This result shows that the proposed approach is effective for promotion campaigns and can increase customer value.

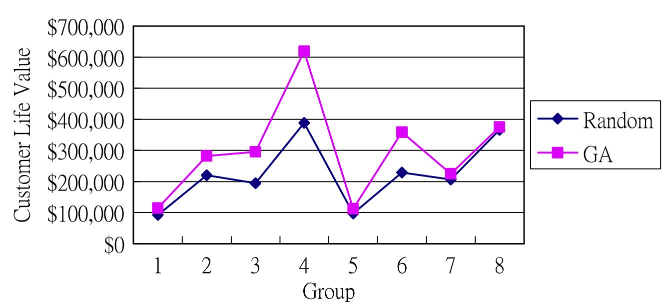


Fig. 11. Customer life time value by using GA and random selection.

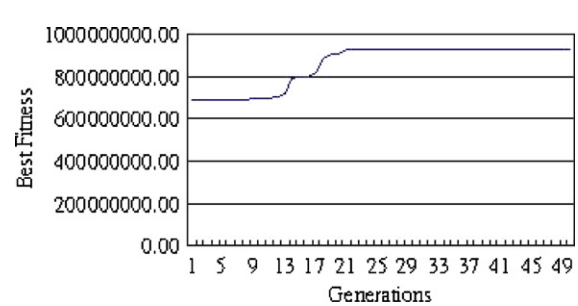


Fig. 12. The fitness values for different generations.

9. Conclusions

Most previous studies classified RFM and LTV models as two different methods of segmenting customers. Generally, RFM models represent customer dynamic behavior. On the other hand, LTV models normally evaluate customer value or contribution. Identifying the behavior of high-value customers is a key task in customer segmentation research. This study proposes an intelligent model that uses GA to select customer RFM behavior using a LTV evaluation model. Customer life time value is taken as the fitness value of GA. If the proposed methodology is applied, high-value customers can be identified for campaign programs. Anther advantage of the proposed methodology is that it considers the correlation between customer values and campaigns. Valuable customers thus can be identified for a campaign program. This case study examines over 4000 customers of a Nissan automobile retailer. The final results demonstrate that the proposed approach can increase potential value, customer loyalty and customer life time value.

However, this study still suffers from a couple of limitations. First, this proposed method requires numerous customer data. In this study, a Nissan dealer spent half a year to collect 10 years of customer data. Implementing this method thus is a burdensome job for a company. Second, only one breakpoint is used for each variable. In the future, more breakpoints can be investigated to determine the optimal numbers of breakpoints for customer segmentation. Third, too many methods can be used for segmentation, and it is difficult to compare all of them. This paper can only propose a suitable method for campaigns. In the future, we wish to develop an experiment for comparing the advantages and disadvantages between existing segmentation methodologies. Finally, customer acquisition is not included in this study, because it only considers segmenting existing customers instead of attracting new customers. Our future studies will explore the possibility of targeting and finding new customers.

Acknowledgements

The authors would like to thank the Empower company (a Nissan dealer) for financially supporting this research under Contract No. UT93-DPTD5-O-004 and his graduate student, Yun-Chiang Kwang, for preparing data for this study.

References

Chan, Chu-Chai Henry (2005). Online auction customer segmentation using a neural network model. *International Journal of Applied Science and Engineering, 3*(2), 101–109.

Chung, Kyoo Yup, Oh, Seok Youn, Kim, Seong Seop, & Han, Seung Youb (2004). Three representative market segmentation methodologies for hotel guest room customers. *Tourism Management, 25*, 429–441.

Doyle, Shaun (2005). Software review business requirements for campaign management – A sample framework. *Database Marketing & Customer Strategy Management, 12*(2), 177–192.

Fraley, Andrew, & Thearting, Kurt (1999). Increasing customer value by integrating data mining and campaign management software. *Data Management*, 49–53.

Holland, J. H. (1975). *Adaptation in natural and artificial systems*. Ann Arbor: University of Michigan Press.

Hsieh, Nan-Chen (2004). An integrated data mining and behavioral scoring model for analyzing bank customers. *Expert Systems with Applications, 27*, 623–633.

Hu, Tung-Lai, & Sheub, Jiuh-Biing (2003). A fuzzy-based customer classification method for demand-responsive logistical distribution operations. *Fuzzy Sets and Systems, 139*, 431–450.

Hwang, Hyunseok, Jung, Taesoo, & Suh, Euiho (2004). An LTV model and customer segmentation based on customer value: A case study on the wireless telecommunication industry. *Expert Systems with Applications, 26*, 181–188.

Jang, J.-S. R., Sun, C. T., & Mizutani, E. (1997). *Neuro-fuzzy and soft computing*. USA: Prentice Hall Inc.

Jiao, Jianxin, & Zhang, Yiyang (2005). Product portfolio identification based on association rule mining. *Computer-Aided Design, 37*, 149–172.

Jones, Joni L., Easley, Robert F., & Koehler, Gary J. (2006). Market segmentation within consolidated E-markets: A generalized combinatorial auction approach. *Journal of Management Information Systems, 23*(1), 161–182.

Jonker, Jedid-Jah, Piersma, Nanda, & Poel, Dirk Van den (2004). Joint optimization of customer segmentation and marketing policy to maximize long-term profitability. *Expert Systems with Applications, 27*, 159–168.

Kim, Su-Yeon, Jung, Tae-Soo, Suh, Eui-Ho, & Hwang, Hyun-Seok (2006). Customer segmentation and strategy development based on customer life time value: A case study. *Expert Systems with Applications, 31*, 101–107.

Kim, Yong Seog, & Street, W. Nick (2004). An intelligent system for customer targeting: A data mining approach. *Decision Support Systems, 37*, 215–228.

Kim, Yong Seog, Street, W. Nick, Russell, Gary J., & Menczer, Filippo (2005). Customer Targeting: A Neural Network Approach Guided by Genetic Algorithms. *Management Science, 51*(2), 264–276.

Kuo, R. J., An, Y. L., Wang, H. S., & Chung, W. J. (2006). Integration of self-organizing feature maps neural net work and genetic *K*-means algorithm for market segmentation. *Expert Systems with Applications, 30*, 313–324.

Kwang, Yun-Chiang (2006). Integrate genetic algorithm and clustering technique to formulate the appropriate campaign strategies – A case study of automobile dealership. Master thesis, Chaoyang University of Technology.

Liu, Emmy (2001). CRM in e-business era. In *CRM conference*.

Shin, H. W., & Sohn, S. Y. (2004). Segmentation of stock trading customers according to potential value. *Expert Systems with Applications, 27*, 27–33.

Tsai, C.-Y., & Chiu, C.-C. (2004). A purchase-based market segmentation methodology. *Expert Systems with Applications, 27*, 265–276.

Vellido, A., Lisboa, P. J. G., & Meehan, K. (1999). Segmentation of the on-line shopping market using neural net works. *Expert Systems with Applications, 17*, 303–314.

Wedel, M., & Kamakura, W. A. (2000). *Market segmentation: Conceptual and methodological foundations* (2nd ed.). Dordrecht: Kluwer.

Woo, Ji Young, Bae, Sung Min, & Park, Sang Chan (2005). Visualization method for customer targeting using customer map. *Expert Systems with Applications, 28*, 763–772.

Yao, Jingtao, Li, Yili, & Chew, Lim Tan (2000). Option price forecasting using neural networks. *The International Journal of Management Science, 28*, 455–466.