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DECISION MODEL OF RETURNS LOGISTICS UNDER MULTINOMIAL LOGIT MODEL CONSIDERING THE CUSTOMER BEHAVIOR

Wenjuan Wang

School of Management Science and Engineering
Dongbei University of Finance and Economics
No. 217, Jianshan St., Shahekou District, Dalian 116025, P. R. China
Wangwenjuan.cn@163.com

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Abstract. *In this paper a model is presented that locates the decision method. We consider a decision optimization problem where a logistics enterprise chooses whether to accept the returns logistics requirement of the customer. This model will support future decision making protocols. Random utility theory assigns utility to each returns activity of the system with the waiting time of the customer and the extra time of the logistics vehicle. The paper presents a methodology to determine the most suitable period to accept the customer's demand. At last, a case study is given. This will provide reference for decision-making when they improve the quality of work in Systems Engineering.*
Keywords: Returns logistics, Customer behavior, Random utility theory, Multinomial Logit Model, E-commerce

1. **Introduction.** E-commerce in China is estimated to exceed 5000 billion RMB in 2015. With 243 million of e-shoppers and an annual increase of 30 million new users, China E-commerce is taking more and more share in the global e-commerce market. China is a rapidly growing consumer market and more and more companies throughout the world are looking for ways to develop marketing, branding and communication that are relevant to Chinese consumers. There is a paradox when it comes to technology in China. On the one hand, the country excels in consumer-oriented tech services and products, and it boasts the world's largest e-commerce market and a very vibrant Internet and social-media ecosystem. On the other hand, it has been a laggard in applying business technology in an effective way. Especially, one challenge is to be able to deliver products to the entire country. Delivery is not easy work to do, all the companies in the field are fighting over prices, and profits are low. With an average 3-4 yuan margin in this sector (according to the Association of Logistics China) it remains a challenge for many companies.

Reverse logistics refers to the sequence of activities required to collect the used product from the customers for the purpose of either reuse or repair or re-manufacture or recycle or disposal of it. Perusal of the literature shows that research in the field of reverse logistics is in evolving phase and issues pertaining to adoption and implementation, forecasting product returns, outsourcing. The research on reverse logistics has evolved over the years and authors have defined reverse logistics in different ways. Earliest definition of reverse logistics was found to be given by Murphy and Poist mentioning about the reverse flow of goods [1]. Later on Carter and Ellram introduced the term "environment" in the definition of reverse logistics [2]. Rogers and Tibben-Lembke stressed on the purpose of the reverse logistics and established the most widely accepted definition as "reverse logistics is the process of planning, implementing, and controlling the efficient, cost effective flow of raw materials, in process inventory, finished goods and related information from the point of consumption to the point of origin for the purpose of recapturing value or proper disposal"

[3]. Stock and Srivastava have also defined reverse logistics from different perspectives [4,5]. Definition of reverse logistics has been changing over time and widening its scope with the interest of researchers. Reverse logistics has recently received growing importance and more firms are adopting it as a strategic tool for economic benefits and corporate social image [6]. Firms have also realized that a better understanding of product returns and efficient reverse logistics can provide a competitive advantage [7]. The multinomial logit model is the most frequently used model in regression analysis for un-ordered multi-category responses of competing products and determines their prices to maximize the total expected profit subject to a capacity constraint. Customers' purchase behavior follows the multinomial logit choice model with general utility functions [7,8].

Reverse logistics is paid more attention to by the governments, enterprises and customers with the development of the E-commerce. Returns logistics (RL) is an important part of the reverse logistics in E-commerce. It especially refers to the part of the reverse process of the production without any effect on sale again in this paper. And we pay more attention to the efficient operations of the returns logistics.

The rest of this paper is organized as follows. Section 2 reviews the related research. Section 3 describes our model in detail. A case study is presented in Section 4. We conclude the paper in Section 5.

2. **Literature Review.**

2.1. **Returns logistics.**

Returns management or reverse logistics is an important area for retailers in E-commerce. It can make or break customer satisfaction and loyalty, as well as the bottom line. Returns will always be a part of business, but be sure you are not limiting them to being a cost of business. A good returns logistics process can bring great value and improve customer loyalty to your bottom line. End users and consumers appreciate companies that work in their favor, and implementing a smooth returns system benefits them while boosting your performance. Reverse logistics can make the returns process easy for your customers and help you replace or refund their purchases quickly. Better manage and re-integrate your returned materials for streamlined practices, reduced waste, and continuing profits from your existing products. And it can ensure compliance by controlling speed and cost of inbound shipments [9-11].

2.2. **Multinomial Logit Model (MNL).**

The multinomial logit model is the most frequently used model in regression analysis for un-ordered multi-category responses. A multinomial logit discrete choice model for multiple answers is presented (with data that is not defined in an ordered scale). Spatial multinomial logit models can be found in the literature applied to residential location and accessibility or for the location choice of residential spaces (for example, homes with only one working or several working residents, or owner occupiers) [12-15]. Other authors have applied discrete choice models in the field of transport planning [16]. The final aim of the results of this research is to include them in a special decision making system which would mainly be used in evacuations due to emergency situations [15].

Perhaps the simplest approach to multinomial data is to nominate one of the response categories as a baseline or reference cell, calculate log-odds for all other categories relative to the baseline, and then let the log-odds be a linear function of the predictors.

Typically we pick the last category as a baseline and calculate the odds that a member of group i falls in category j as opposed to the baseline as π_{i1}/π_{ij}. In our example we could look at the odds of being sterilized rather than using no method, and the odds of using another method rather than no method. For women aged 45-49 these odds are 91 : 183 (or roughly 1 to 2) and 10 : 183 (or 1 to 18).

The discrete choice models are based on Random Utility Theory which postulates that each individual, in this case each railway safety expert, associates an stochastic type of utility to each stop alternative, choosing the one which maximizes its utility [17,18]. The utility function of each canton is defined in the following expression:

$$U_i = \mu_i + \varepsilon_i \tag{1}$$

In this equation μ_i is the deterministic part of the utility. ε_i are random, corresponding to that the idiosyncrasies among customers toward deferent alternative i are random. A number of approaches have been proposed in the literature to overcome computational difficulties both in standard multinomial logit model and multinomial logit mixed effects model. Breslow and Clayton advocated penalized quasi-likelihood estimation approach to avoid the complex form of multinomial likelihood in 1993 [19]. Chen and Kuo used the fact that the multinomial distribution can be derived from a set of Poisson random variables conditionally on their total being fixed and suggested transforming the multinomial problem to Poisson log-linear or non-linear model [20]. Because normalization needs to be enforced for each distinct covariate pattern, the Poisson log-linear transformation is restricted to discrete covariates [15].

3. **Model Specification.** Let us consider the following choice model where there are 1 enterprise providing logistics service, E-commerce sellers and m customers $M = \{1, \cdots, m\}$ in the returns logistics system. And we assume that they are the same across all customers. The enterprise manages the returns logistics. There are n alternatives $N = \{1, \cdots, n\}$. It is assumed that each customer has a random utility on each alternative m, $U_i = \mu_i + \varepsilon_i$ where U_i is the deterministic part of the utility. μ_i could be of form $a_i - b_i C$ where a_i is the feature of the service provided by the logistics enterprise and C is the cost of time. It consists of the waiting time about customers and the extra time about the logistics vehicle completed request of customers. C is of form $\alpha_i t + \beta_i \tau$.

a_i represents the feature of the service provided by the logistics enterprise.

b_i represents the cost-sensitive factor of the customers i.

C represents the cost of time.

α_i represents the parameters which will be estimated by the model and calibrates the perception of the waiting time about customers i.

β_i represents the parameters which will be estimated by the model and calibrates the perception of extra time about the logistics vehicle completed request of customers i.

t represents the waiting time of the customer.

τ represents the extra time of the logistics vehicle.

ε_i are random, corresponding to that the idiosyncrasies among customers toward deferent alternative i are random. We assume that the distribution of $\varepsilon_i = (\varepsilon_1, \cdots, \varepsilon_m)$ is known in the random utility model, each customer picks the alternative with the highest utility, i.e., a customer will pick alternative i if and only if $U_i > U_j,\ \ \forall j \neq i$. What is the probability a customer will pick alternative i? (Assume to be absolutely continuous distribution) The random utility model is:

$$q_i(\mu) = \mathrm{P}\left(i = \arg\max_{K \in N}(\mu_k + \varepsilon_k)\right) \tag{2}$$

In the model, we choose ε's to be i.i.d. Gumbel distributions with scale parameter η. The CDF of Gumbel distribution is:

$$F(x) = e^{-e^{-(x/\eta+\gamma)}} \tag{3}$$

where $\gamma = 0.5772$ is the Euler's constant (to ensure zero mean). We can compute the choice probability:

$$q_i(\mu) = \mathrm{P}\left(U_i > U_j,\ \ \forall j \neq i\right) = \frac{\exp\left(\mu_i/\eta\right)}{\sum_{k \in N} \exp\left(\mu_k/\eta\right)} \tag{4}$$

In the MNL model, notice that this demand function does capture substitution effects among products. If the utility of one product increases, the probability of choosing other products will decrease. We can conclude the time threshold that the logistics can accept the returns request of the customer.

We often assume there is an outside option for the consumer, denoted by 0, such that $U_0 = \mu_0 + \varepsilon_0$ where ε_0 also satisfies the Gumbel distribution with the same parameter.

4. **Case Study.** Numerical experiments are conducted to evaluate the validity of the proposed model. Real data of the customers are collected from Dalian YT logistic in China. We select some data to test in order to verify the validity of the model one day in May 2015. H is the current position of the logistics vehicle. There are 6 customers sending the request of returns of the products. They are point A, B, C, I, J, F in Figure 1.

The distance between any two points is presented in Table 1. The longest waiting time of the customer is in Table 2.

According to the vehicle routing, we can test the model by some data that they are randomly generated in Table 3. $\tau_1 = 15$, $\tau_2 = 34$, $\tau_3 = 36$, $\tau_4 = 28$, $\tau_5 = 90$, $\tau_6 = 55$. We draw the conclusion the demand of the customer I and J will be met.

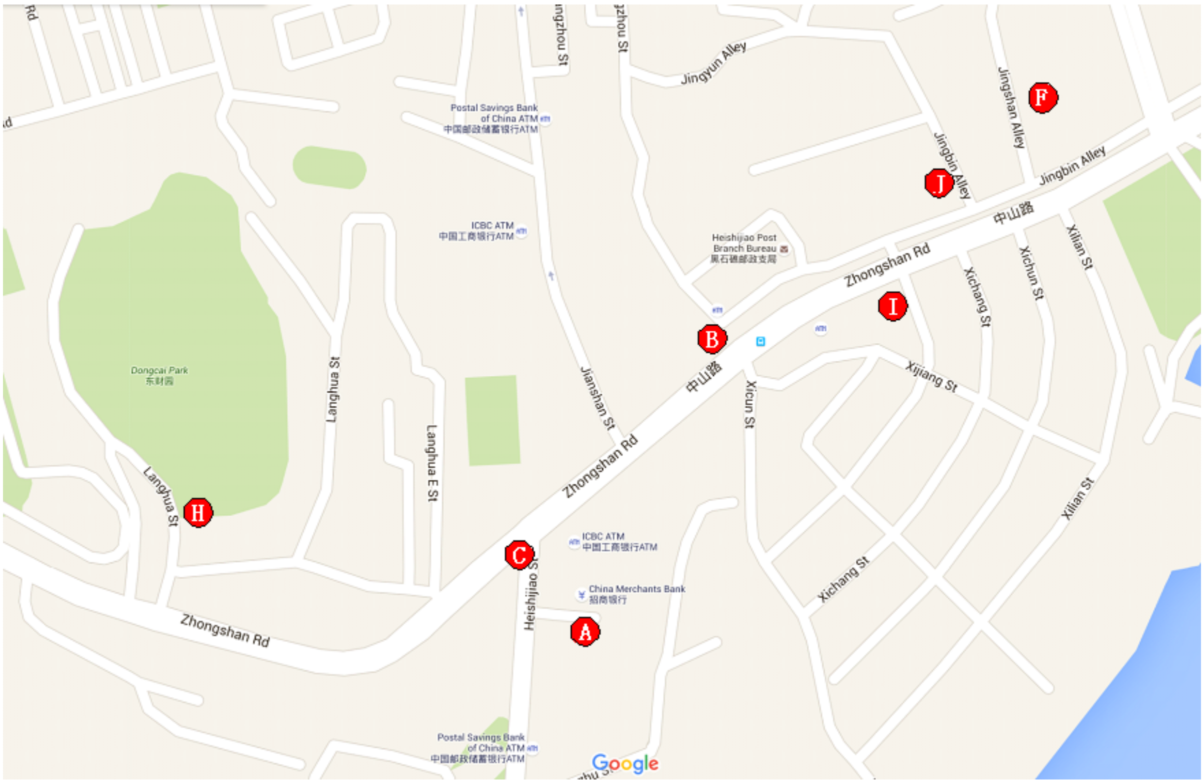

FIGURE 1. Customers request of returns

TABLE 1. The distance between any two points (min)

	H	A	B	C	I	J	F
H	0	20	45	15	60	75	80
A	20	0	15	5	20	35	40
B	45	15	0	12	8	20	25
C	15	5	12	0	23	40	45
I	60	20	8	23	0	13	22
J	75	35	20	40	13	0	5
F	80	40	25	45	22	5	0

TABLE 2. The longest waiting time of the customer (min)

Customer	A	B	C	I	J	F
Waiting time t_i	10	25	25	30	120	60

TABLE 3. The relevant parameters

	H	A	B	C	I	J	F
a_i	0.3	0.6	0.7	0.8	0.5	0.5	0.6
b_i	0.9	0.4	0.5	0.6	0.2	0.3	0.7
α_i	0.29	0.15	0.83	0.12	0.8	0.20	0.25
β_i	0.77	0.64	0.38	0.25	0.23	0.49	0.82

5. **Conclusions and Limitations.** Although this is preliminary work, we have provided some useful contributions to both research and practice: the customer returns behavior is an important problem in E-commerce. It is directly related to the quality of logistics service. And the waiting time of the customer is the important factor in our decision model. A reasonable method is provided in this paper.

The major limitation of this paper lies in application of the case, which was selected randomly among the practices and therefore cannot be considered representative of the whole customers one day. Rather, we provide examples of advanced practices that are indeed applied in real cases. Although some limitations exist, opportunities for further research are also apparent. Future developments will surely allow researchers to evaluate a larger sample and will provide a better understanding of the decision model's various elements and their mutual relationships.

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REFERENCES

[1] P. R. Murphy and R. P. Poist, Managing of logistics retro movements: An empirical analysis of literature suggestions, *Transp. Res. Forum*, vol.29, no.1, pp.177-184, 1989.
[2] C. R. Carter and L. M. Ellram, Reverse logistics: A review of the literature and framework for future investigation, *J. Bus Logist.*, vol.19, no.1, pp.85-102, 1998.
[3] D. S. Rogers and R. Tibben-Lembke, *Going Backwards: Reverse Logistics Trends and Practices*, Reverse Logistics Executive Council, Reno, NV, 1999.
[4] J. R. Stock, *Development and Implementation of Reverse Logistics Program*, Council of Logistics Management, Oak Brook, IL, 1998.
[5] S. Srivastava, Network design for reverse logistics, *Omega*, vol.36, no.4, pp.535-548, 2008.
[6] G. Kannan, M. Palaniappan, Q. Zhu and D. Kannan, Analysis of third party reverse logistics provider using interpretive structural modeling, *Int. J. Prod. Res.*, vol.140, no.1, pp.204-211, 2012.
[7] S. Agrawal, R. K. Singh and Q. Murtaza, A literature review and perspectives in reverse logistics resources, *Conservation and Recycling*, vol.97, pp.76-92, 2015.
[8] C. W. Autry, Formalization of reverse logistics programs: A strategy for managing liberalized returns, *Industrial Marketing Management*, vol.34, no.7, pp.749-757, 2005.
[9] W. Wang and Q. Ding, Disruption measurement model based on behavior of passengers in ferry passenger system, *ICIC Express Letters*, vol.9, no.4, pp.1115-1119, 2015.
[10] Q. Ding, A model of disruption management with human behavior in logistics distribution, *ICIC Express Letters, Part B: Applications*, vol.4, no.4, pp.991-998, 2013.

[11] W. Wang, X. Hu, L. Wu et al., A simulation optimization approach to campus bus routing with diversion, *The 4th International Conference on Innovative Computing, Information and Control*, pp.713-716, 2009.

[12] P. Waddell, Accessibility and residential location: The interaction of workplace, residential mobility, tenure, and location choices, *The Lincoln Land Institute TRED Conference*, 1996.

[13] J. Guo and C. Bhat, Residential location choice modeling: Accommodating sociodemographic, *School Quality and Accessibility Effects University of Texas*, Austin, 2001.

[14] Á. Ibeas, R. Cordera, L. dell'Olio and P. Coppola, Modelling the spatial interactions between workplace and residential location, *Transportation Research Part A: Policy and Practice*, vol.49, pp.110-122, 2013.

[15] R. Sañdo, M. Bordagaray, L. dell'Olio and Á. Ibeas, Discrete choice models to determine high-speed passenger stop under emergency conditions, *Transportation Research Procedia*, vol.3, pp.234-240, 2014.

[16] A. Mohammadian and P. Kanaroglou, Applications of spatial multinomial logit model to transportation planning, *The 10th International Conference on Travel Behaviour Research*, Lucerne, 2003.

[17] T. A. Domencich and D. Mcfadden, *Urban Travel Demand: A Behavioral Analysis: A Charles River Associates Research Study*, North-Holland, Amsterdam, 1975.

[18] M. E. Ben-Akiva and S. R. Lerman, *Discrete Choice Analysis: Theory and Application to Travel Demand*, MIT Press, Cambridge, MA, 1985.

[19] N. E. Breslow and D. G. Clayton, Approximate inference in generalized linear mixed models, *Journal of the American Statistical Association*, vol.88, pp.9-25, 1993.

[20] Z. Chen and L. Kuo, A note on the estimation of multinomial logit models with random effects, *The American Statistician*, vol.55, pp.89-95, 2001.