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# Intelligent Decision Support System in the Choice-Based Network Revenue Management

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**Abstract:** During recent years, independent demand assumption in traditional revenue management models has been faced with serious doubts and has been replaced with choice-based models. More accurate modeling of individual's decisions is a key factor in these models. Although multinomial logit model (MNL) is the most well-known choice model, it has a limitation which causes the ratio of choice probabilities of two distinct alternatives to be independent from the attributes of any other alternatives and is called independence of irrelevant alternative (IIA). Nested logit model can be replaced with MNL for relaxing this restriction. Empirical results indicate inadequacy of MNL for itinerary share prediction. Simulation outputs indicate that sole concentration on the statistical tests for selecting choice model, would increase problem complexity without significant increasing of firm's revenue. Therefore, the key issue is deciding about instantaneous changing choice model to the more complex one, based on statistical tests results solely. In this paper, general architecture of intelligent decision support system is proposed for choosing the most appropriate choice model during booking horizon. Main component of this system is knowledge acquisition subsystem with a rule bank. The simulation tool is applied for extracting the required rule and choice-based deterministic linear programming model is used in optimization module. The simulation is considered for predicting improvement percent obtained by using more accurate choice model. This prediction will be compared with threshold value for making final decision. This threshold value is determined by the firm and indicates the importance of obtained decisions. These results show that scarce capacity and high correlation will lead to emphasize the process of choosing the most appropriate choice model. Different strategies for selecting suitable choice model is analyzed in the computational experiment and it is shown that proposed architecture leads to decrease time complexity of problem with preserving firm's revenue.

**Key words:** Independent demand, Multinomial Logit model (MNL), independence of irrelevant alternatives (IIA), Nested Logit model, intelligent decision support system, simulation, extracting, rule bank

## INTRODUCTION

Nowadays, choice-based network revenue management models are widely used instead of traditional models. The independent demand assumption is the most limitative assumption of traditional models (for a further details about traditional models, refer to Talluri & van Ryzin (2004b). Importing individual's decisions in previous RM models relaxes this restriction.

In the literature, choice-based revenue management models are developed according to general structure of choice models. Anderson (1998) and algers and Beser (2001) used empirical data on Scandinavian Airline System (SAS) for estimating the recapture and buy-up using stated and revealed preferences data. Belobaba and Hopperstad (1999) studied a consumers' purchase behavior by simulation for considering the impact of airline schedule, path and fare on passengers' preferences. Zhang and Cooper (2005) formulated seat-inventory control of a set of parallel flights under customer choice using Markov decision processes. Virtual nesting control strategy is studied in a quantity-based network revenue management problem with substitutable products (2008).

The concept of preference orders, which is stated list of customer's preferred products is studied in the choice-based network revenue management (Chen, L. and T. Homem-de-Mello, 2010). An efficient sets concept for single leg revenue management model is introduced by Talluri & van Ryzin (2004). Gallego *et al*. (2004) proposed choice-based deterministic linear programming model. Their model does not allow any kind of segmentation. Liu & van Ryzin (2008) extended previous work by allowing market segmentation by disjoint consideration sets of products. They extended the efficient sets concept to network and showed that as demand and capacity are scaled up asymptotically, only efficient sets are used in an optimal policy. Bront *et al*. (2009) extended work of Liu & van Ryzin (2008) by applying market segmentation which products could belong to

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overlapping segments. The heuristic for importing initial guess of bid price vector is considered by Meissner (2012) in the network revenue management.

We encounter with two main challenges during applying a choice-based network revenue management which are modeling customer's choice behavior and importing it to the optimization model. There are various types of discrete choice models which are derived from different assumptions on distribution of utility function's error term. Multinomial logit model is the most simple and popular choice model which is used widely. In spite of its advantages, this model has a one main limitation which is called independence of irrelevant alternatives (IIA). This restriction originates from the independent distribution assumption of the utility function's error across the alternatives. This property, states that the ratio of the choice probabilities is independent from the attributes of any other alternatives. The nested logit model is the next frequently used model in practice. This model incorporates more realistic substitution pattern by relaxing the independent assumption of utility function's error terms (Garrow, L.A., 2010).

Volcano *et al*. (2010) developed a maximum likelihood estimation algorithm for estimating discrete choice models parameters in airline revenue management. Competitive overview of discrete choice models and their applications are explained by different authors (Garrow, L.A., 2010; Ben-Akiva, M.E. and S.R. Lerman, 1985; Train, K.E., 2009; Carrier, E., 2007; Newman, J., *et al*., 2011).

Empirical results from different markets in the United States and Canada reveal that itinerary share models employing Multinomial Logit methodology are not adequate (Coldren, G.M., F.S. Koppelman, 2005a). These results show that itineraries sharing a common time period or carrier exhibit an intense competition among themselves (Garrow, L.A., 2010; Coldren, G.M., F.S. Koppelman, 2005a). Empirical results indicate that itineraries which are closer to each other by departure time exhibit greater covariance; therefore, there is a greater substitution or competition among them in comparison with the itineraries that do not have close departure times. (Coldren, G.M., F.S. Koppelman, 2005b).

The modeling process of airline passengers' choice of itineraries is initially represented using MNL models (Garrow, L.A., 2010). According to these, the main question is whether changing choice model from multinomial to nested logit during all conditions is reasonable? Does the sole concentration on the correlation among the products which leads to the instantaneous change of the primary choice model, increase firm's revenue necessarily? In this paper, the knowledge-based intelligent decision support system is proposed for answering these questions.

The process of selecting the most suitable choice model is affected by combination of factors such as modeler's intuition, statistical tests and interaction of choice models and optimization techniques. To date, there are various formal and informal statistical tests that are used during customers' behavior modeling process, but little attention has been placed on analyzing interaction of choice models and optimization techniques. This interaction is related to expected revenue improvement obtained by applying more complicated and accurate choice models. Two factors, which are expected revenue improvement and firm's preferences, influence choosing final choice model, according to the outputs of statistical tests. Firm's preference, indicates the importance of obtained results.

Decision support systems are computer-based tools for supporting decision-making activities by offering information and interpretations for different alternatives (Turban, E., 1990). After introducing DSS, researches have concentrated on integrating knowledge-base into decision support systems. There is vast literature about using knowledge-based decision support systems (Wen, W., *et al*., 2005; Pal, K., O. Palmer, 2000; Liao, S.-h., 2000; Ferreira, I.M.L., P.J.S. Gil, 2012). There are another researches which concentrate on developing intelligent decision support system for making decisions about financial problems (Wen, W., *et al*., 2005; Chan, S.W.K., J. Franklin, 2011; Tan, K.H., *et al*., 2006; Blue, J., F.K. Andoh-Baidoo, 2010; Cho, V., 2010).

In this paper, knowledge-based decision support system is proposed for deciding about the most suitable choice model which will be fed into optimization module. The simulation is done for predicting revenue improvement and extracting appropriate rules for making final decision. The details of optimization module and simulation will be described in the next sections.

The organization of this paper is as follows. In section two, a description of proposed knowledge-based model and its processes are described. In section three, the choice-based deterministic linear programming (CDLP) approach and the nested logit model are explained. At the beginning of section four, the column generation algorithm is described, then, a new subproblem, based on the nested logit model is proposed. In the rest of this section a new approach composed of heuristic and genetic algorithms is introduced to solve the problem, and its results are analyzed through two problems. In the next section, the network are modeled and solved by the aid of the proposed system, and the results are illustrated using the simulation of the customers' behavior. In the last section, the results are discussed, and some conclusions are made.

***Knowledge-Based Decision Support System:***

The general architecture of RM process flow includes different stages such as forecasting, optimization and setting booking limits. Core part of revenue management system is including demand forecasting and optimization. According to the RM flow, the outputs of the forecasting module are fed into the optimization module. This procedure reveals that during mentioned process, forecasting and optimization modules run independently. Reasoning module is involved in this process for analyzing these two modules interaction before making final decision for selecting appropriate choice model. The most important aspect of this interaction is expected percent of revenue improvement which could be obtained by applying more accurate choice model. Concentrating on the market data and statistical tests for selecting choice model would lead to increase time complexity of problem without significant increasing in the firm's revenue. Figure 1 shows the architecture of proposed KDSS.

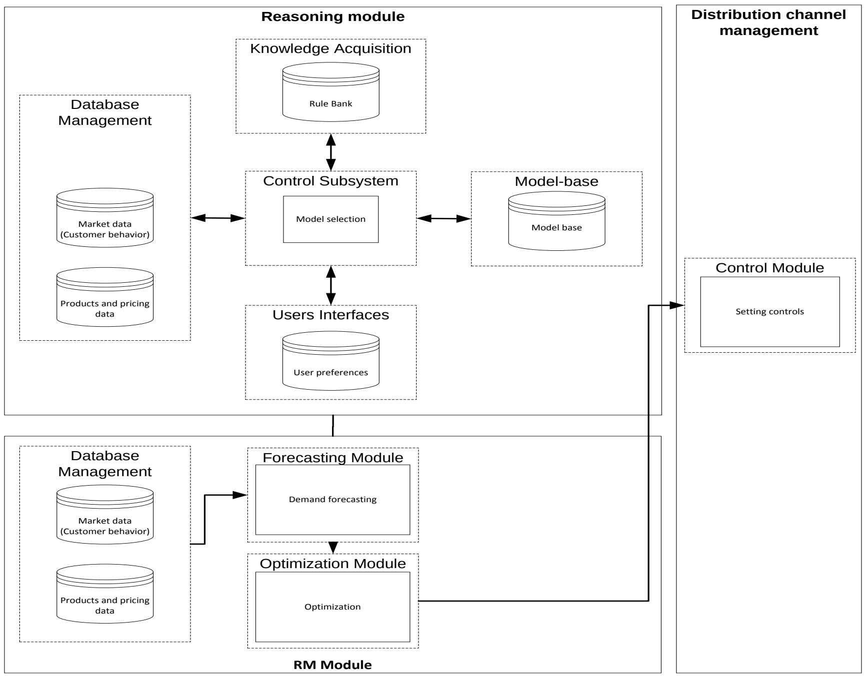


**Fig. 1:** Architecture of proposed intelligent decision support system

This system is composed of five main components as shown in figure 1. The database management system contains the relative databases including products data and market historical data. The user interface determines the importance of decisions which will be received from user. The model-base subsystem includes different statistical tools and discrete choice models. The main component of this system is knowledge acquisition module which has the rule bank. The simulation tool is used for extracting the appropriate rules. The details of the simulation mechanism for determining rules will be explained in the next section. Figure 2 explains the process flow of this system.

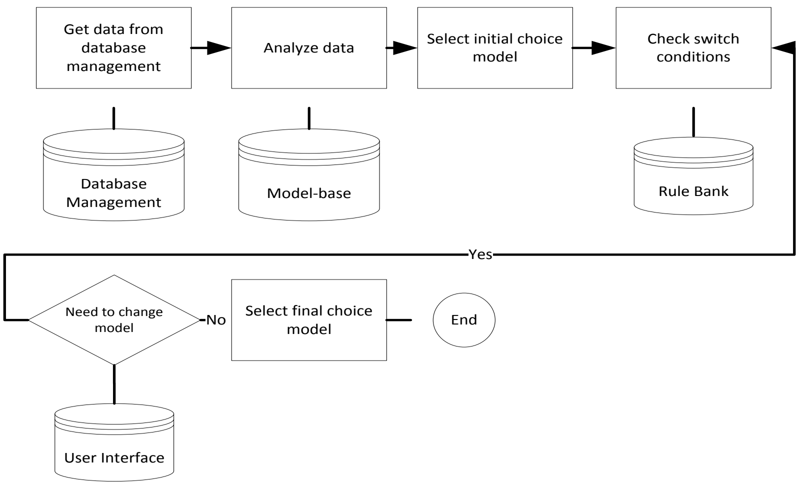


**Fig. 2:** The process flow of reasoning module

As shown in this figure, the process starts with gathering required data including available products information and customers' revealed preferences. Afterwards, system tries to fit the best choice model to the data by statistical tools. MNL is applies as the base model and observing correlation between products could lead system to promote that to the nested logit model. According to empirical results, MNL is inadequate model for itinerary share modeling. If the more accurate choice models are fitted to the data, the rule-bank is applied for deciding about changing base choice model to more accurate one. These results will be compared with decision importance which is determined by user and final decision will be obtained.

The appropriate rule should be determined for deciding about the suitable choice model. The equation $(\frac{Total\ remaining\ capacity}{Remaining\ time\ horizon} * logsum)$ is used for constituting required rule. Logsum in this equation refers to a measure of the degree of correlation and substitution among alternatives in the nests. Higher value of the logsum implies less correlation and vice versa. This equation indicates the importance of applying the most accurate choice model. Lower values of this equation imply more importance of choosing the most appropriate choice model.

During cycling through these processes at repeated intervals, reasoning module runs repeatedly, and it is possible to use different choice models within booking horizon. This decision result could change during booking horizon according to factors which are remaining capacity, remaining time periods and the relative importance of the resulting decisions.

***Computational Experiment:***

Mont Carlo simulation is used for simulating customer's choice behavior and extracting appropriate rules in reasoning module. For this purpose, it is assumed that the customers choose products based on nested logit model. In first scenario, the firm neglects the correlations in nests and apply multinomial logit model for deciding about offer sets and during next state, the firm use more accurate nested logit model for choosing offering products. We suppose that there are two times which the firm updates its offering products and we should decide about the most appropriate choice models in this times.

In order to determine the offer sets in each period, choice-based deterministic linear programming problem is solved, and the optimal offer sets and their related time periods to recommend them are determined. These sets are offered according to the lexicographic order of the indices of the LP variables. Since the variable $t(S)$ could be fractional, they are rounded to the nearest integer.

***4.1. A small airline network:***

Consider a network with 4 airports and 7 flight legs. This network is inspired from Bront *et al*. (2009). The capacities of the legs are $C = (200{,}300{,}300{,}300{,}300{,}160{,}160)$. The firm offers two high (H) and low (L) fares on each leg. Considering the local and connecting itineraries, customers can choose from 22 available products defined by itineraries and fare class combinations. This airline network is illustrated in Figure 3.

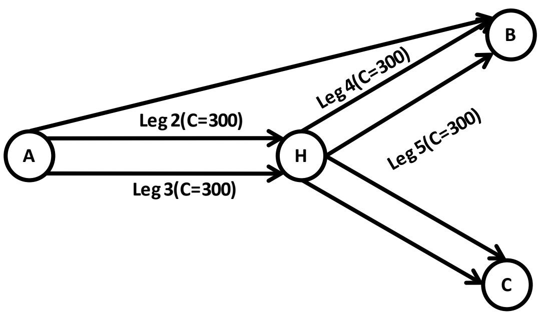


**Fig. 3:** A Small network airline

**Table 3:** Customer Segmentation in a small network problem

According to the customer's price and time sensitivities and also their origin and ultimate destination, 10 overlapping segments and 20 nests (two nests in each segment) are defined in this example. This segmentation is described in Table 5.

The probability of a customer's arrival for the corresponding segment is given in the last column. Columns 3, 4 &5 specify the nests, their consideration set, and the observed utility for the indicated products, respectively. The critical value for comparing with rule's equation in this network is supposed to be 0.6.

Table 4 represents obtained revenue according to different strategies for choosing choice model. First column of results indicate the correlation measures in the nests. Next column refers to the strategy which the firm prefers to use the base MNL choice model during all periods and the next column is related to condition which the firm decides switching to more accurate choice model always. Fourth column of results indicates the situation which proposed system is used for choosing the most appropriate choice model. Last column indicates the number of times which the firm prefers to switch more complicated choice model from base model in the decision support system.

**Table 4:** Firm's obtained revenue according to different strategies for choosing choice model

| Initial Capacity | Correlation | Mulnomial Logit | Nested Logit | DSS | No. of switch |
|---|---|---|---|---|---|
| [120,180,180,180,180,96,96] | 0.4 | 417153 | 422493 | 422280 | 2 |
| | 0.6 | 409932 | 420047 | 419896 | 2 |
| | 0.8 | 377209 | 415616 | 415954 | 2 |
| [160,240,240,240,240,128,128] | 0.4 | 517511 | 518906 | 517391 | 0 |
| | 0.6 | 504693 | 510283 | 510032 | 2 |
| | 0.8 | 469113 | 484492 | 484009 | 2 |
| [200,300,300,300,300,160,160] | 0.4 | 550523 | 550095 | 550349 | 0 |
| | 0.6 | 538365 | 540045 | 539747 | 1 |
| | 0.8 | 503605 | 523203 | 523189 | 2 |

Table 5 shows the 95 percent confidence interval for improvement percent while applying different strategies.

**Table 5:** 95% confidence interval for revenue change percent during different choice model selection strategies

| Initial Capacity | Correlation | NLM-MNL | NLM-DSS |
|---|---|---|---|
| [120,180,180,180,180,96,96] | 0.4 | (0.716, 1.909) | (-0.633,0.398) |
| | 0.6 | (1.834, 3.196) | (-0.597,0.693) |
| | 0.8 | (9.424, 11.072) | (-0.276,0.469) |
| [160,240,240,240,240,128,128] | 0.4 | (-0.303, 0.897) | (-0.476,0.654) |
| | 0.6 | (0.440, 1.874) | (-0.349,0.798) |
| | 0.8 | (2.637, 3.991) | (-0.764,0.387) |
| [200,300,300,300,300,160,160] | 0.4 | (-0.679, 0.598) | (-0.507, 0.794) |
| | 0.6 | (-0.312, 1.014) | (-0.527, 0.694) |
| | 0.8 | (3.205, 4.669) | (-0.391,0.288) |

It can be seen that scarce capacity and high correlation will lead to mattering the process of choosing the most accurate choice model. It can be observed that if we concentrate on statistical tests solely for choosing final choice model, it will increase the complexity of problem without significant increasing in the firm's revenue and insisting to use MNL during all conditions will lead to lose considerable revenue. Table 5 indicates that although demonstrating correlation by statistical tests, decision of proposed system to use the base simple choice model, preserves the firm's revenue with decreasing the complexity of problem.

These results reveal that increasing the nest's correlation will lead to increase total number of switching to more complicate choice model. They show that high correlation among products and scarce capacity will lead to applying the more accurate choice model during all updating times.

***Conclusion:***

This article concentrates on the designing specific framework for analyzing effects of different choice models on firm's revenue and choosing the most appropriate one. Multinomial logit model is the most simple and popular choice model that is used widely. In spite of its simplicity, it has a main limitation which is independence of irrelevant alternatives. Empirical results exhibit competition between itineraries based on their departure time and carriers and inadequacy of this model in itinerary share prediction. More accurate and complicate choice models such as nested logit model can relax this limitation. Switching base choice model (MNL) to more complicate ones such as nested logit model will increase the complexity of the problem. The main question that this paper tries to answer is about necessity of switching to more accurate choice models according to results of statistical tests on market data.

In this paper, intelligent decision support system has been added to the revenue management base flow. This system analyzes interaction between discrete choice and optimization models based on expected revenue improvement obtained by using more accurate choice model. Rule-based reasoning module is applied for this analysis. The simulation tool is used for extracting the appropriate rules. The well-known choice-based deterministic linear programming is employed for deciding about products' offer sets. Simulation study is done under two different scenarios for computing expected improvement obtained by using more accurate choice model. These results are used in order to constitute appropriate rules for deciding about choice models.

Computations results reveal that in spite of fitting market data to nested logit model, it is not necessary to switch from the simple multinomial choice model to more complex nested logit during all conditions. The results indicate that reasoning module leads to decreasing complexity of problem by applying simpler choice models simultaneously with preserving firm's revenue. These results show that when there is scarce capacity and high correlation, specifying more accurate choice model is so important. This process will be updated at repeated intervals and the selected choice model could change during booking horizon.

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