American Scientific Research Journal for Engineering, Technology, and Sciences (ASRJETS)

ISSN (Print) 2313-4410, ISSN (Online) 2313-4402

http://asrjetsjournal.org/

A Probabilistic Approach to Maximize Cross-Selling Revenues of Financial Products

Yasin Altun[a], Ahmet Yucekaya[b*]

[a,b]Industrial Engineering Department, Kadir Has University, Istanbul, Turkey

[a]Email: ahmety@khas.edu.tr

[b]Email: yasinaltun@yahoo.com

Abstract

Customer oriented approach and developing analysis for customers have become more important as the competition became a global issue, especially after technological advancements. Companies aim to sell more products to new customers and also to their current customers while keeping them in the portfolio and making sure that they are happy. Cross-selling of products and services to their customers is almost as important as gaining new customers. In this paper, a probabilistic and integrated method of cross-selling financial products is proposed. The proposed method first segments the customers based on the selected criteria and then calculates the probability of buying each product using product and customer relationship matrixes. Then, the expected yield for each group of customers and offer is calculated, and the best cross-selling strategy is determined. The proposed methodology is applied to a Turkish bank that aims to sell financial products through cross-selling. The results show that the methodology successfully determines the product order to be used in cross-selling in an effort to increase the success rate in the selling process and expected revenue.

Keywords: Cross-selling; Financial products; Banking; Simulation; Integer programming.

1. Introduction

The fierce competition in the market and the increased availability of communication tools make it difficult for companies to keep their customers happy and loyal. On the other hand, the companies aim to sell more products to customers to maximize their profit and help customers to benefit more.

---

* Corresponding author.

The data for the customer is carefully recorded in databases in an effort to manage the service process efficiently. It is obvious that the main rationale for this effort is to create additional revenue and remain competitive in the market. The companies have limited resources, and their objective is to get maximum revenues while using their resources effectively. One of the important parts of this process is to preserve the current customers, add new customers to the portfolio, and increase profit per customer. Then, companies aim to sell new products to their current customers who have some of the products already. This cross-selling process aims to increase profit per customer and customer satisfaction [1]. On the other hand, if the customer is offered a product that he/she is not interested in, or is bothered many times, then it is likely that he/she will react negatively. It is worth mentioning that the marketing process brings extra cost in addition to the product itself. Customer Relationship Management (CRM) has been widely used since the 1990s and provided many insights about how companies should interact with customers. CRM aims to build a relationship with customers based on trust, customer price, place, promotion, and sales to provide the best product. It also aims to add value to customers to gain their loyalty in the long term to have a sustainable relationship. However, CRM needs to be supported with new methodologies in order to know the customer better and offer the right product, and approach him properly [2]. Traditional marketing methods are not as effective as before because of technological advancements and increasing communication. Hence, they need to be renovated and innovative. The competition requires companies to be more data oriented in order to keep their customers on hand, to reduce their cost, and increase their profitability. Cross-selling of products and services to their customers is almost as important as gaining new customers in this process. However, the sale process has a cost. Research shows that the cost of selling a product to a new customer is 6 times more than selling the product to existing customers on average. It is observed that, in some sectors and businesses, the cost reaches up even more. Cross-selling is used in especially service sectors such as financial services, insurance products, and online shopping. It is clear that using the revenue potential of current customers is very important for overall profitability. On the other hand, the customer data should be well analyzed to understand the trends, habits, and needs so as to provide demanded solutions, to have a lasting bond, increase loyalty, and be able to sell more products. Such efforts that include customer segmentation, product and customer matching, and demand analysis increase the success of cross-selling and provide the company with an opportunity to sell its products at a minimal cost and increase its profitability. There are some studies that analyze the cross-selling process from different perspectives. Li and his colleagues use the structural multivariate probit model to analyze how demand for multiple products in consumer banking evolves over time [3]. Kamakura and his colleagues propose a mixed data factor analyzer for data augmentation and prediction that combines information from a survey with data from the customer database on service usage [4]. Then, they make probabilistic predictions of ownership of services with the service provider and competitors. Knott and his colleagues propose next- product- to- buy models for cross-selling activities in an effort to increase profitability and decrease the required time for cross-selling activities [5]. Kamakura and his colleagues develop a latent trait analysis to estimate the likelihood that a customer will purchase additional services. The methodology then provides an opportunity for targeting customers for cross-selling [6]. Kamakura and his colleagues propose a model use timing of the past purchase of multiple products and produces estimates of each customer's propensity of ever purchasing a product as well as the timing of the purchase [7]. Netessine and his colleagues model the cross-selling problem as a stochastic dynamic program blended with combinatorial optimization for cross-selling products or services in the e-commerce setting [8]. Li and his colleagues propose a customer-response model that identifies the evolvement of customer demand for other products as well as the role of opportunities for promotion and advertising in cross-selling [9]. Peltier and his colleagues analyze the use of interactive psychographics to develop cross-selling strategies in the banking industry in an effort to match the psychological and purchasing needs of each customer [10]. Harrison and Ansell propose a survival analysis to predict cross-selling opportunities in the insurance industry based on randomly selected customer data [11]. There are other studies that discuss the impact of cross-selling such as [12,13,14,15,16,17,18,19] that present work on cross-selling considerations in operations. Although the researchers present different approaches to the problem, the customer segmentation, the product, and customer matching and relationship, and a sequential approach to measuring the buying behavior of each customer are not analyzed together to the best knowledge of the authors. In this paper, as a contribution to the literature, we propose an integrated method for cross-selling financial products. The proposed method first segments the customer, based on the selected criteria; and then, calculates the probability of buying each product using product and customer relationship matrixes. Using probabilities and segment information, the second algorithm calculates the expected yield of each customer group and offers types that can be possible considering the customers with the same characteristics as the groups. The decision maker will then be able to select the best strategy based on the expected yield from the ordered products. Product profitability and the number of customers who have the products are used as inputs to the model. The remainder of this paper is organized as follows. Section 2 provides a description of the data and the methodology as well as the proposed solution algorithm. Section 3 provides a case study for a bank with real data in an effort to validate the proposed methodology. Finally, in Section 4, the concluding remarks are provided.

2. Description of the Data and Methodology

Competition has always been an issue for banks, and it increased after technological advancements. The banks need to keep their customers in their portfolio, aim to add more customers to their customer database and sell more products to current and incoming customers. They follow a strategy to focus on profitability in a competitive environment and to differentiate themselves from their competitors positively. Almost all banks use CRM tools and keep their customer database updated. However, the cross-selling strategy to be followed, and proposing the right product to the right customer will make the difference. We consider a bank that aims to be competitive in the market and needs to develop a cross-selling strategy to increase its success rate. The bank uses data mining and clustering to analyze the behaviors of the customers, and they have all the related information for their customers to be used for the analyses. A customer has at least one product and can have more than one. Each product has an expected cost and yield for the bank. Assuming that a customer opens an account for at least one product, it means that he/she needs this particular product; and he/she opens the account for this purpose. In order to sell another product to this customer, the bank needs to make sure that the customer might show interest in this product. The bank can make a return from this sale as there is a cost for the product and a cost for the sale effort. Not each customer has the same revenue; so, each customer has to be analyzed separately. The bank will reach the customer using different communication channels; and not each customer will be happy with this communication. Thus, the rationale of the bank for this call should be solid.

2.1 The model development for cross-selling

The main objective of the cross-selling process is to determine the products to be offered to each customer, assuming that the customer already has one or more products. As expected, each product has a different yield, possible cost, and demand probability. Hence, not all products have the same value and importance. Cost is incurred as a source is reserved for the marketing of a product. It is rational to sell the products with higher yields first, and offer the next product with lower yields in a sequential manner. It is possible to calculate the probability of selling a product to a customer given that the customer already has another product. It is assumed that the bank has a certain number of customers with different revenue streams and product preferences. The bank needs to analyze the customer data, develop a model, and find the right product to offer to each customer. Now, the notation that is used is presented in Table 1.

Table 1: Notations used for the analysis

$i,k \in I,K$	Product indexes
j	Customer index
t	Order index
I,K	Total number of products
J	Total number of customers
T	Total number of trials
$o \in O$	Offer group
$g \in G$	Customer group
$s \in S$	Customer segment
$V_{s,i}$	The average yield of product *i* in segment *s*
$GV_{t,g}$	Expected yield of group *g* in trial *t*
$OV_{o,g,t}$	Offer value for offer *o* in group *g* in trial *t*
$P_{i,k,t}$	Probability of selling product *k* in trial *t* assuming customer already has product *i*
R_k	Average revenue of product *k*
$R_{k,t}$	Average revenue of product *k* in trial *t*
$C_{k,t}$	The average cost of product *k* in trial *t*
B_i	Number of customers who has product i
$A_{i,k}$	Number of customers who has product *i* and *k*
$x_{j,i}$	1 If customer *j* already has product *i* 0 Otherwise
$Y_{j,k,t}$	1 If customer *j* buys product *k* in trial *t* 0 Otherwise

The problem can be formulated to maximize revenues from cross-selling. Eq. 1 presents the objective function of the problem. The problem is a linear integer model, and the parameters can be updated in each iteration.

$$Max \sum_{t=1}^{T,T\leq I} \sum_{j=1}^{J} \sum_{i=1}^{I} \sum_{k=1,i\neq k}^{K} P_{i,k,t} R_k (1 - x_{i,j}) Y_{j,k,t} \quad (1)$$

The objective function calculates the total expected yield and revenue from the cross-selling. The probability of selling product k in the t given that the customer already has product i, $P_{i,k,t}$, is the most important part of the formulation. As cross-selling deals with millions of customers, it is not likely to ask questions or do a survey on all customers. Various criteria could be added for minimum error probability in this approach. The segmentation of the customers is frequently used for such big data. The customers are segmented to s segments based on attributes such as their asset size, credit opening amounts, and loans. A customer j has one or more products of i, and it is possible that customer j might be interested in buying other products that were not sold before. However, the preference level of the customer should be determined as not all the products are preferred at the same level. The preference levels for products change in each segment. The customer j is assigned as a member of each s. As the data gets larger, it is possible to have a probability value that is very close to reality. The data provides the number of customers who have a product i and $k\neq i$. One can find the number of customers with both products i and k, $A_{i,k}$, then this number can be used to calculate the $P_{i,k,t}$, as given below.

$$P_{i,k,t} = \sum_{t=1}^{T} \sum_{i=1}^{I} \frac{A_{i,k}}{B_i} \qquad for\ \forall\ k \in K \quad (2)$$

The model is assumed to find the right product to offer to each customer in the portfolio. The model forces the decision variable to have at least one value by selling one product at each iteration. Note that the number of iterations is limited with the number of available products, and this is also limited with the model formulation.

$$\sum_{t=1}^{T,T\leq K} \sum_{k=1}^{K} Y_{j,k,t} \geq 1 \qquad for\ \forall\ j \in J \quad (3)$$

It is important that the sell offers be presented without bothering the customer. Otherwise, there could be an atmosphere resulting in a loss of customers. The cost of second or subsequent offers will not have the same effect and tolerability as the first sell offer. Multiple offers can be presented to a customer. However, the success rate is expected to decrease, and a success factor should be defined manually. For example, the success rate for the first offer can be defined as α; for the second offer 0.5α; and in the third offer, this ratio can be defined manually as 0.25α. Then, the following constraint is imposed on the real revenue of a product.

$$R_{k,t} = R_k - tC_{k,t} \quad (4)$$

2.2 An integrated simulation approach for the cross-selling

It is also important to note that if a customer already has product i, this product should not be offered to the same customer again. We first develop a methodology that groups all the customers based on the product-customers and customer-products criteria. Once the analysis for the product offers is performed, a matrix of ixk is gained that shows the probabilities of selling product i, assuming that the customer already has product k. The solution approach should also include the data preparation as there are huge data and calculations involved. Figure 1 shows the pseudo code of the solution approach.

```
Start
Set t=1, i=1, j=1, k=1
For t=1 to T ≤ I do
  For j=1 to J do
    For i=1 to I do
      For k=1 and k≠i to K do
        Calculate P_{i,k,t}
        Assign i to s
        Calculate P_{i,k,t} x V_{s,i}
      End for
    End for
  End for
Assign customers with the same
  characteristics to group g
Assign offers with the same
  characteristics to offer id o
Update the list
End for
Return offers and groups
End
```

```
Start
Set t=1, i,k ∈ I,K
For t=1 to T ≤ I do
  For g=1 to G do
    For o=1 to O do
      Calculate OV_{o,g,t}
      Calculate GV_{g,t}
    End for
  End for
End for
Sort offers based on the GV_{g,t}
Update the list
End for
Determine Y_{j,k,t} that maximize
  the objective function
End
```

Figure 1: Pseudo code for the analysis

The methodology assigns each customer i to a segment s based on the predefined criteria. Once the probabilities are calculated for each product, the matrix can be used to calculate the expected value of the offer and the expected yield for all combinations. Assuming a data set of customers and offer types is reached, it is easier to group customers and offers with the same characteristics for calculations. Customers and offers with the same characteristics are assigned to a group g and offer id o, respectively. The first part of the algorithm returns the customer groups and offers to be used in the next analysis. The offer value for o in group g and expected yield of group g in trial t are calculated for each group. The decision maker aims to determine the offers with the highest expected yield; hence, all offers are sorted based on the expected yield of the offers. The offers that maximize the expected revenue are reported to be used in the cross-selling as an output. Note that the methodology presents the results of the first replication. After the first trial of cross-selling, the customer database can be updated; and the same methodology can be repeated to find the second products to be offered that are viable to the decision maker.

3. A cross-selling application for a Turkish national bank

We develop a case study for a private bank, which is one of the top 10 retail banks in the Turkish banking industry with the objective of selling products using cross-selling strategy. The bank sets an annual target rate for cross-selling to increase customer loyalty and profitability of the bank. Then, the regions and branches work to achieve this target using their customer portfolio. It is believed that an effective strategy will differentiate the bank from its peer banks, and will have a positive impact on its profitability. Hence, they are eager to have new strategies and use models to determine the sequential offers that need to be offered to customers. The bank updates its cross-selling information each month. The data includes information for 9 million customers and their transactions on over 70 products. The data shows the activity status of each customer including the products that each customer has, their usage frequency, and the products that the customers do not have. As the objective of the bank is to sell new products, they are not interested in the products that the customers already owned. Hence, they represent the customers based on the product ownership as 1 and 0 where 1 shows that a customer j has a product i. It is expected that not all the customers would have the same income and capital ownership. The banks usually group their customers and develop products for each group such as high level, moderate level, and low-level income groups. The CRM team is responsible for the grouping of the customers and determining marketing strategies. They also work with a team of information technology specialists to do the analysis. Each customer is assigned to a segment according to the objective of the bank in an effort to create different products and services for each segment of customers. This assignment process is performed each month and updated regularly. We classify the customers as segment 1 customers, segment 2 customers, and segment 3 customers based on their activity and income levels where segment 1 represents the customers with the highest income. Figure 2 shows the distribution of the customers by groups.

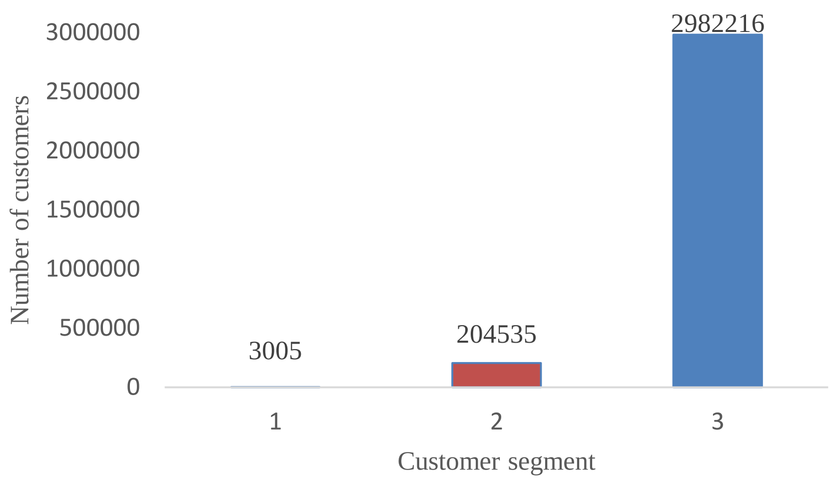

Figure 2: The distribution of the customers based on the segmentation

According to the bank rules, virtual or artificial branches are provided for the customers who have certain criteria. The customers who open accounts in private banking branches and making transactions on forex or derivative products in the relevant period are assigned as segment 1 customers. A segment 1 customer can be moved to segment 2 in the next periods based on a hierarchy. The customers with an asset size of £ 100,000 and above, a credit opening amounting to 100,000 TL and higher mortgage, loans or auto loans of over 75,000 TL, upper and middle-level public administrators, doctors, pilots, lawyers, notaries, and so on are assigned as segment 2 customers. These are the customers managed by an executive branch. If the customers are in retail banking with a non-active private banking record, they are assigned to segment 3. Such customers are the largest number of total customers. We adapt the routine for the analysis. After an analysis of the products used by about 9 million customers, totally 17 products are identified that are eligible for cross-selling. The data for the customers, the activity levels and the segments that the customers are assigned are determined. Table 2 shows the distribution of the customers and the average monthly yield of each product in the corresponding customer segment. As the bank information is confidential, the product names are represented with numbers.

Table 2: Customer segments and product relationship matrix

	Segment 1 customers		**Segment 2 customers**		**Segment 3 customers**	
PRODUCT	Number of customers	Average Yield (TL)	Number of customers	Average Yield (TL)	Number of customers	Average Yield (TL)
1	1198	495,93	58482	67,44	595984	11,14
2	550	649,29	5631	181,05	20225	21,74
3	153	23,48	90380	48,78	786179	22,81
4	2284	2004,3	27663	169,11	126267	21,76
5	786	2920,82	6909	266,36	10598	37,91
6	0	0	303	215,15	1211	29,67
7	0	0	149	160,7	3635	7,85
8	37	17566,32	4286	145,25	28235	12,76
9	1779	345,11	19712	37,32	106441	3,95
10	116	1082,54	397	109,45	258	32,59
11	129	7246,92	1455	595,95	5248	85,47
12	26	13966,31	0	0	0	0
13	0	0	21638	106,21	706517	31,46
14	0	0	14680	117,53	38847	28,92
15	0	0	1444	131,06	6913	27,32
16	0	0	30598	22,75	641714	6,37
17	0	0	0	0	1252	-123,22

Realize that it is essential to work on the customers who do not have the products yet, rather than the customers who already have the products and do not use the products. The customers with no activity on the products are removed, and the customers are rearranged by their product usage. The customers actively using a product are assigned 1 to the corresponding product, and the products which are eligible for cross-selling are labeled 0. Then, a clustering based on the product usage is performed on the customer data set and a total of 564 different customer groups are identified. Table 3 shows a general view of the customers. As the table has data of 9 million real customers, it is not possible to include all the information, so information for just 25 customers is provided.

One of the important parameters is to determine the probability of buying another product by a customer who already has at least one product, $P_{i,k,t}$. We use Eq (2) to determine the probability of selling another product to a customer given that he/she already purchased at least one. Table 4 shows a representative probability matrix. As we have 17x17 matrixes for each segment, we just include a representation of the real data for 3 segments.

Table 3: Customer and product usage matrix for 1st group of customers

Customer group	Products																
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1
1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1
1	0	0	1	0	0	0	0	0	0	0	0	0	1	0	0	0	1
1	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0
1	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	1
1	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0
1	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	1
1	0	0	1	1	0	1	0	0	0	0	0	0	0	0	0	0	1
1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
1	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
1	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1
1	0	1	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0
1	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1
1	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0
1	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	1
1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1

As there are 564 different customer groups in 3 segments, possible offer combinations for all customers should be evaluated. The simulation evaluates each customer group based on the product they have and the other products that can be sold to the customers in the corresponding group. The number of customers in the group can be used to calculate the expected revenue of the scenario by multiplying the number of customers with the expected yield of the product that can be sold. The simulation returned more than 22200 offer combinations to each of 564 customer groups, and the expected yield for each offer is calculated. Table 5 provides just a part of the data for all the offers for selected combinations.

Table 4: Probabilities for buying the offered product for each segment

Customer segment (s)	Owned product (i)	Candidate product (k)	Probability of purchasing the candidate product ($P_{i,k,t}$)
1	1	2	0.279
1	1	3	0.068
1	1	4	0.878
1	1	5	0.310
1	1	8	0.023
1	1	9	0.795
1	1	10	0.045
1	1	11	0.096
1	1	12	0.022
2	1	2	0.052
2	1	3	0.381
2	1	4	0.212
2	1	5	0.029
2	1	6	0.000
2	1	7	0.000
2	1	8	0.044
2	1	9	0.217
3	1	2	0.014
3	1	3	0.254
3	1	4	0.065
3	1	5	0.003
3	1	6	0.000
3	1	7	0.002
3	1	8	0.015
3	1	9	0.082
...	...	...	...

Table 5: Representative data for all the offers table based on the simulation results

Offer ID	Group ID	Customer segment (s)	Owned product (i)	Candidate product (k)	Offer Value(TL)	Expected Yield (TL)
738	25	1	9	4	1.775,81	50.107,48
2212	62	2	16	14	26,56	4.701,04
4423	127	2	5	14	0,35	1.175,26
5160	147	2	2	14	4,47	10.694,87
5897	166	2	1	4	35,85	14.882,03
7371	198	2	9	16	2,18	58.530,60
8108	213	2	3	15	0,52	1.310,55
8845	227	2	4	13	4,25	2.230,31
11056	272	3	8	5	0,08	530,74
11793	298	3	16	14	0,81	51.822,85
12530	321	3	16	1	2,59	1.493,16
13267	341	3	11	9	0,17	86,83
14004	366	3	4	8	0,09	22.124,11
14741	385	3	4	11	0,51	940,17
15478	407	3	2	5	3,34	492,83
16215	428	3	3	5	0,04	24.527,77
16952	446	3	3	2	0,04	1.673,90
17689	464	3	1	2	0,30	693.104,54
18426	479	3	1	13	7,77	2.233,80
19163	498	3	1	15	0,06	655,75
19900	513	3	13	14	0,03	6.622,45
20637	530	3	2	5	3,34	417,01
21374	545	3	16	14	0,81	4.222,17
22111	560	3	3	13	8,97	1.352,87
...	...	...	...	...	...	...

All offers data includes the results of all possible scenarios including their expected yield. The offers that return the highest expected yield can be determined by the simulation results. The offers with the maximum yield expectancy are determined by all the offers; they can be sorted, and the best offers for the first trial can be determined. Table 6 provides a part of the best offers.

Once the products to be offered to each customer are determined, the expected yield can also be calculated and reported to the decision-makers. Results show that the customers in the first segment are on top of the list. Although their numbers are lower than other segments, their value is significantly higher as the expected yield is higher. These customers have higher portfolios, and high value for the banks; hence, the banks need to pay more attention to such customers. The proposed methodology can evaluate all scenarios for product offers. For the sake of clarity and easier presentation of such huge data, we just assume that the bank aims to offer at most three offers to customers. As mentioned, the success rate decreases as the number of marketing trials by the bank increases. Table 6 shows the number of products that are offered to each segment of customers in the first trial.

Table 6: Example data for all the offers table based on the simulation results

Offer ID	Group ID	Customer segment (s)	Owned product (i)	Candidate product (k)	Offer value(TL)	Expected yield(TL)
4	2	1	9	4	1.775.809	116.249.342
5	2	1	9	5	800.304	169.407.502
10	2	1	9	11	471.050	420.321.476
1137	34	1	5	11	1.188.495	326.111.490
1111	34	1	1	11	695.705	326.111.490
1150	34	1	9	11	471.050	326.111.490
1371	39	1	9	4	1.775.809	60.128.970
1332	39	1	1	4	1.759.775	60.128.970
7640	204	2	4	5	26.636	9.056.070
7634	204	2	3	13	14.019	3.610.970
7656	204	2	8	9	13.508	1.268.710
5081	145	2	5	4	67.984	9.639.498
5095	145	2	11	4	61.896	9.639.498
5093	145	2	11	1	48.217	3.843.909
10582	260	2	2	11	122.170	53.039.461
10608	260	2	5	11	41.716	53.039.461
12969	332	3	13	3	7.230	7.731.912
12983	332	3	14	3	3.923	7.731.912
12981	332	3	14	1	3.889	3.777.477
17203	452	3	9	13	9.690	818.012
17191	452	3	3	13	8.967	818.012
17179	452	3	1	13	7.771	818.012
18483	480	3	11	2	15.109	543.475
18478	480	3	3	13	8.967	786.550

Table 6: Offered products and number of offers

Segment 1		Segment 2		Segment 3	
Product	Total offers	Product	Total offers	Product	Total offers
1	2	1	110	1	109
2	2	2	36	2	24
4	28	3	67	3	210
5	33	4	152	4	45
8	3	5	121	5	19
9	3	6	4	7	1
11	47	7	1	9	1
12	20	9	3	11	85
		11	67	13	355
		13	57	14	4
		14	30	16	41
		16	3		

Note that these products are determined as the ones that will be offered in the first trial. The methodology is run again with the updated list, and the products that can be offered to customers in the second round can be determined. As the size of the data is huge, we just provide the results of the first round. The results show that products 10, 15, and 17 were not chosen for the offered products within the best three products. Relatively fewer customers already owned these products before; and it was not appealing for customers to buy products 10, 15, and 17 as their return was lower. The demand for these products decreases rapidly. Products 1, 2, 4, 5, 9, and 11 are preferred by each segment as they are attractive products. On the other hand, products that are related to credits, credit cards, and term deposit accounts are on top of the offered product list. The results show that the density of customers and yields of these products are better than others, which also shows the general trend of the customers. The proposed methodology increased the success rate for selling 20% in the first trial comparing with previous efforts. It is also interesting to see that only 8 products appear in the best 3 products list for the first segment of customers. The results also show that 12 products can be offered to second segment customers, and 11 products can be offered to third segment customers.

4. Conclusion

The marketing strategies are important for the banks in order to be competitive and to maximize their profit. CRM tools, data mining methods, and analysis are required, and useful, but they should be supported with efficient algorithms. The number of customers in the system is usually very high in a bank that requires a careful classification of each customer based on the determined characteristics. The bank needs to sell the products to the right customers who already own some of the other products that the bank offered. The cross-selling effort requires calling the customer for marketing purposes; and if the right customer is not chosen, that might annoy the customer and lead to extra cost. That requires a methodology to determine the right customer for each product type and prioritization of the products to be offered to each customer. In this paper, we propose a data processing and simulation methodology that determines the order of each product to be offered to each customer to maximize the expected profit. The customers are segmented first based on the income and activity levels. Then, the product ownership matrix for each customer group is determined; and the proposed methodology successfully determined the order of each product to be used in the cross-selling strategy. Given that the product and offering process have a cost, the proposed model is also expected to increase the revenue/cost ratio. The proposed methodology can be used in periodic campaigns or to reach target customers for the new cross-selling strategies. On the other hand, the needs of the customers will be determined before the customer search for a solution; and the loss of a customer to a competitor will be prevented. The periodic events such as tax payments, fiscal periods and education calendar might impact the product demand; hence, they can be included in the simulation methodology in an effort to increase the accuracy. The improved customer segmentation, the inclusion of the calendar of events, and better classification of the products can take the proposed model one step ahead in future studies.

References

[1]. Akçura, M. T., & Srinivasan, K. (2005). Research note: customer intimacy and cross-selling strategy. Management Science, 51(6), 1007-1012.

[2]. Jarrar, Y. F., & Neely, A. (2002). Cross-selling in the financial sector: customer profitability is key. Journal of Targeting, Measurement and Analysis for Marketing, 10(3), 282-296.

[3]. Li, S., Sun, B., & Wilcox, R. T. (2005). Cross-selling sequentially ordered products: An application to consumer banking services. Journal of Marketing Research, 42(2), 233-239.

[4]. Kamakura, W. A., Wedel, M., De Rosa, F., & Mazzon, J. A. (2003). Cross-selling through database marketing: a mixed data factor analyzer for data augmentation and prediction. International Journal of Research in marketing, 20(1), 45-65.

[5]. Knott, A., Hayes, A., & Neslin, S. A. (2002). Next- product- to- buy models for cross- selling applications. Journal of interactive Marketing, 16(3), 59-75.

[6]. Kamakura, W. A., Ramaswami, S. N., & Srivastava, R. K. (1991). Applying latent trait analysis in the evaluation of prospects for cross-selling of financial services. international Journal of Research in Marketing, 8(4), 329-349.

[7]. Kamakura, W. A., Kossar, B. S., & Wedel, M. (2004). Identifying innovators for the cross-selling of new products. Management Science, 50(8), 1120-1133.

[8]. Netessine, S., Savin, S., & Xiao, W. (2006). Revenue management through dynamic cross selling in e-commerce retailing. Operations Research, 54(5), 893-913.

[9]. Li, S., Sun, B., & Montgomery, A. L. (2011). Cross-selling the right product to the right customer at the right time. Journal of Marketing Research, 48(4), 683-700.

[10]. Peltier, J. W., Schibrowsky, J. A., Schultz, D. E., & Davis, J. (2002). Interactive psychographics: Cross-selling in the banking industry. Journal of Advertising Research, 42(2), 7-22.

[11]. Harrison, T., & Ansell, J. (2002). Customer retention in the insurance industry: using survival analysisto predict cross-selling opportunities. Journal of Financial Services Marketing, 6(3), 229-239.

[12]. Wong, R. C. W., Fu, A. W. C., & Wang, K. (2005). Data mining for inventory item selection with cross-selling considerations. Data mining and knowledge discovery, 11(1), 81-112.

[13]. Liu-Thompkins, Y., & Tam, L. (2013). Not all repeat customers are the same: Designing effective cross-selling promotion on the basis of attitudinal loyalty and habit. Journal of Marketing, 77(5), 21-36.

[14]. Lee, D., Park, S. H., & Moon, S. (2013). Utility-based association rule mining: A marketing solution for cross-selling. Expert Systems with applications, 40(7), 2715-2725.

[15]. Zhang, R. Q., Kaku, I., & Xiao, Y. Y. (2011). Deterministic EOQ with partial backordering and correlated demand caused by cross-selling. European Journal of Operational Research, 210(3), 537-551.

[16]. Wong, R. C. W., Fu, A. W. C., & Wang, K. (2003, November). MPIS: Maximal-profit item selection with cross-selling considerations. In Third IEEE International Conference on Data Mining (pp. 371-378). IEEE.

[17]. Armony, M., & Gurvich, I. (2010). When promotions meet operations: Cross-selling and its effect on Call center performance. Manufacturing & Service Operations Management, 12(3), 470-488.

[18]. Nash, D., & Sterna-Karwat, A. (1996). An application of DEA to measure branch cross selling efficiency. Computers & operations research, 23(4), 385-392.

[19]. Schmitz, C., Lee, Y. C., & Lilien, G. L. (2014). Cross-selling performance in complex selling contexts: an examination of supervisory-and compensation-based controls. Journal of Marketing, 78(3), 1-19.