Market Potential Analysis and Branch Network Planning: Application in a German Retail Bank

Stephan Schneider University of Cologne schneider@wiso.uni-koeln.de Florian Seifert MOONROC Advisory Partners <u>f.seifert@moonroc.de</u> Ali Sunyaev University of Cologne sunyaev@wiso.uni-koeln.de

Abstract

Location problems are an integral part of strategic planning in many kinds of industries. Optimizing an organization's branch network requires considering multiple criteria such as location characteristics, branch performance, and competitors' locations. There is a need for concepts that support decision makers in solving these complex location problems. This paper presents a process for market potential analysis and branch network planning in retail banking. The process meets industry-specific challenges, allows considering multiple criteria for decision analysis, and incorporates aspects, which are currently neglected in the literature. We implement this process within a decision support system and apply the process to the branch network of a German retail bank.

1. Introduction

As a result of the late 2000s financial crisis, the banking industry's reputation suffered severely [1]. Credit institutions are facing a challenge to regain their customers' trust. Therefore, they focus on transparent and comprehensible products, but particularly on intensive personal contact with their customers [1, 2]. In addition, customers search for a more intense relationship to their consultants, especially for complex financial products [1]. Retail banks in Germany have recognized these trends and are currently reconfiguring their branch networks [3]. Since location decisions are crucial for a branch's performance and consequently influence a company's success, one of the key problems in strategic branch network planning is identifying profitable locations [4, 5]. However, estimating the profitability of potential locations requires decision makers to account for a considerable amount of criteria from multiple data sources, which demands for decision supportive tools that enable decision makers to reach well informed choices.

The objective of this paper is to develop a process for market potential evaluation and branch network

planning, which meets industry-specific challenges in retail banking, and enables decision makers to evaluate potential sites for new branches by considering multiple criteria for their decisions. Based on this process, we develop a model for branch network optimization and implement these two components within a decision support system called BankMAP-DSS (Market Analysis and Planning in Retail Banking) and demonstrate its applicability in a case of a German retail bank.

The remainder of this paper is organized as follows: section 2 provides background on retail banking and branch network planning. In section 3, we present BankMAP process and its implementation. To show the applicability of the developed process, we apply it to a branch network of a German retail bank in section 4. Section 5 provides a discussion and conclusions.

2. Background

2.1. Retail banking

In recent years, customers' sensitivity to prices and their willingness to switch credit institutions have increased significantly [1, 2]. Furthermore, direct banks are increasing competition in the retail banking market. Since these banks communicate with their customers via telephone and Internet, without maintaining expensive branch networks, direct banks can offer low-price products and high interest rates. In order to regain and strengthen their customers' confidence, in 2010, three quarters of all credit institutions in Germany focused on intensifying customer relationship management and developing a trustworthy consulting [1]. Bank managers think of a customer-orientated strategy as an answer to the intensifying competition in the market. According to a recent survey on the future of branch operations in retail banking, branches will continue to remain the most important distribution channel for banks, particularly, advising private and business customers in branches [2].

2.2. Branch network planning

It is widely agreed that the location of a bank branch has a significant impact on its performance [4, 5]. Whether the objective of a location problem is consolidation of branches or the expansion of a branch network, in both cases, there is a need for concepts that support decision makers in solving this complex problem. Bank branch performance is multidimensional [5] and it is necessary to evaluate multiple criteria of performance separately. For example, a branch might be in a favorable region to attract deposits, but in an unfavorable region to generate loan business [5]. Moreover, branch performance is influenced by external factors arising from the branch's local conditions and internal factors such as management performance and employee motivation.

2.2.1. Branch location evaluation. When planning a branch network, it is useful to split the location problem into two sub problems: the problem of allocating customers to (potential) branch locations and the problem of selecting locations for opening or closing branches [6].

Modeling customers' branch choosing behavior is an important aspect of location analysis. Since customer decisions are unknown for the planner, reasonable assumptions on the customers' spatial behavior should be met, for instance, by delineating a branch trading area. There are two predominant methods in the literature to define such a trading area: the analog model and the gravity model [7]. Objective of both models is delineating a geographical region containing the probable customers of the branch. The literature on defining a trading area often uses the characteristics of the branch as the determining factor for the trading areas' coverage range (e.g., [8]). But a trading area is defined to model customers' spatial behavior and therefore should rather be based on the populations' characteristics than on the characteristics of the branch. Modeling this assumption is not very complex (cf. [9]), but estimating or surveying customers' preferences requires extensive research.

In order select locations for opening or closing branches, it is crucial to identify criteria, which enable a reasonable differentiation and description of potential branch locations. The selection of those criteria depends on the business case as well as the availability and characteristics of the underlying data [4]. As a guideline for selecting suitable attributes, we refer to criteria for market segmentation, that is, identifiability, substantiality, accessibility, stability, responsiveness, and actionability [10]. Some frequently used location characteristics include socio-demographic attributes (e.g., population and household density, population growth rate, household size, population by age, household income) and characteristics describing the market in an area (e.g., number of retailers, number of competitor banks' branches, number of own branches, market shares) [7, 11].

The literature on location analysis in banking focuses on selecting variables for location evaluation (e.g., [7]), delineating trading areas (e.g., [6]), or optimizing branch networks (cf. section 2.2.2). All these studies focus on a-priori selected sub-markets (e.g., a state, municipality, or city). But the literature lacks in studies on identifying profitable sub-markets. Particularly, in large markets like Germany it is reasonable to preselect a sub-market for detailed planning. Identifying such a sub-market is closely linked to the detailed branch network planning in this sub-market. It is therefore reasonable to address these two aspects together.

2.2.2. Branch network optimization. A wide variety of location problems are discussed in the literature [12]. One of the frequently discussed problems is the Maximal Coverage Location Problem (MCLP). This problem seeks to place a given number of facilities at eligible locations and maximize the covered demand. A demand is considered as "covered" if at least one facility is sited within a specified service distance (i.e., the trading area). The MCLP was introduced 1974 by Chruch and ReVelle [13] and has since then been applied to various practical situations like siting emergency facilities, retail stores, and bank branches (e.g., [8, 9]). In order to extend its applicability, researchers developed extensions of the basic MCLP in various settings. For example, Church and Roberts [14] extend the binary coverage assumption (a demand point is either fully covered or not covered at all) by introducing a partial coverage function with multiple coverage levels and different coverage radii. Further extensions of the MCLP consider capacitated facilities [15], uncertainty in demand [16], full and partial coverage [9], and negative weights for discouraged locations [17]. Confer [18] for an overview of recent developments of covering models. Despite the magnitude of MCLP extensions, most of the branch network optimization studies lack of the ability to consider an existing branch network. Wang et al. [19] present one of the few studies considering the existing branch network of a bank. Other models regarding existing branch networks are scenarios for branch closures (e.g., [11]). The remainder of the reviewed literature on branch network optimization only aims at placing branches at optimal locations in a given region and ignore an eventually existing branch network.

3. BankMAP process development

BankMAP attempts to provide a practice-oriented process to support branch network planning operations of retail banks. The objective of this process is to identify regions with high market potential for branch network development and to identify potential sites for new branches. Figure 1 outlines the phases of the BankMAP process.

Phase 1	Market potential evaluation Consideration of the entire market			
$\overline{}$				
Phase 2	Sub-market evaluation · Selection of a sub-market			
Z Z				
Phase 3	Branch network planning · Detailed branch network planning			
Figure 1. Quilling of the three phase presses				

Figure 1. Outline of the three-phase process

3.1. Phase 1: Market potential evaluation

The first phase presents an approach for market potential evaluation. The objective of this phase is to determine market potential for each region of the market (e.g., zip code or metropolitan statistical area). The market potential helps decision makers to evaluate regions by aggregating and weighting multiple criteria from varying sources such as socio-demographic (e.g., population density), market (e.g., estimated savings of all citizens), competitor (e.g., competitor density), and the bank's data (e.g., number of loan customers).

The evaluation of the market potential is based on the assumption that a similar market penetration is possible in similar regions. This assumption is derived from fundamental ideas of market segmentation that can be described as follows [20]: If a market consists of a variety of consumers, characterized by different needs, it is possible to classify the market by certain consumer characteristics in internally homogeneous sub-markets. Furthermore, it is assumed that persons living in adjacent or similar neighborhoods, are likely to exhibit a similar social status and life style as well as a similar buying pattern. This phase consists of three steps, which are described in the following paragraphs.

Step 1: Define KPIs. Literature on retail banking applies different key performance indicators (KPIs), for instance based on volume of deposits or loans, number of (new) accounts, or number of existing customers (for cross-selling potential). These KPIs are evaluated either by branch, product (e.g., savings, sight, and time deposits), or region (e.g., zip code area) [5, 7, 11]. Similar to location characteristics, the choice of KPIs depends on the business case and the availability and characteristics of the underlying data set [4]. To consider multiple criteria in the decision-

making process, we use a product-based approach evaluating regions based on the volume of deposits. However, the regions could be evaluated likewise with KPIs based on number of accounts or customers.

Let P be the set of products used for performance evaluation (e.g., checking accounts, saving accounts, loans). Let G be the set of regions considered for evaluation and let v_p^g be the volume of deposits or loans of customers for product p ($p \in P$) in region g ($g \in G$). Additionally, for each product p, a profit margin q_p is defined, which expresses the annual profit generated by each Euro deposited or lent by a customer of product p. We define the KPIs for each product as the sum of the product's annual profit in all regions.

Step 2: Classify regions. We classify the regions using multivariate cluster analysis. These methods aim to classify a set of objects (regions) into a certain number of subsets (classes) so that the subsets are internally as homogeneous as possible (according to the attributes of the containing objects) and among each other as heterogeneous as possible [21].

Let M be the set of attributes identified to characterize each region (e.g., population density, household income, competitor branches). For each region g (g \in G) the vertex m^g (m^g $\in \mathbb{R}^{|M|}$) is defined, containing the attribute values of region g. As distance measure to determine the similarity between two regions, we use the squared Euclidean distance between their attribute values. Thus, the distance between two regions g and g' (g, g' \in G) can be formulated as

$$d(g,g') = \sum_{i=1}^{|M|} (m^{g}_{i} - m^{g'}_{i})^{2}.$$
 (1)

Let K be the set of classes to be calculated and G^k be the set of regions in class k (k \in K). Moreover let μ^k_i be the average value of attribute i of the regions in class k. The classification of regions into classes can then be formulated as an optimization problem, which aims to minimize the sum of squared errors within the classes:

$$Min \ z = \sum_{k \in K} \sum_{g \in G^k} \sum_{i=1}^{|M|} \left(m^g_i - \mu^k_i \right)^2.$$
 (2)

This problem can be solved by several clustering algorithms, which are provided in numerous software packages (e.g., IBM SPSS Statistics).

Step 3: Define benchmark. After classifying the regions into |K| regional classes, the benchmark $\tilde{\phi}_p^k$ is defined for each product and regional class, indicating

the achievable market penetration of product p in regional class k. Let e^g be the number of residents in region g and let c_p^g the number of the bank's customers in region g obtaining product p. The market penetration of product p in region g accounts

$$\phi_p^g = \frac{c_p^g}{e^g}.\tag{3}$$

Following the basic assumption of this approach (in similar regions a similar market penetration is possible), the regions with the highest market penetration within a class define the benchmark (e.g., the average market penetration in the most profitable regions of a class).

Step 4: Calculate market potential. The actual performance l_{ACT}^{g} describes the annual profit on all products of all customers in region g and is defined as

$$l_{ACT}^g = \sum_{p \in P} v_p^g * q_p \,. \tag{4}$$

Based on the market penetration benchmark of the regional class k, the target performance l_{TAR}^{g} of a region g (g \in G^k) can be calculated:

$$l_{TAR}^{g} = \sum_{p \in P} \frac{v_p^g}{c_p^g} * \widetilde{\varphi}_p^k * e^g * q_p.$$
 (5)

Thus, the target performance of a region g describes the potential annual profit on all products of all customers in the region, when the market penetration benchmark is achieved. The market potential of a region g is then defined as

$$l_{POT}^{g} = MAX(0, l_{TAR}^{g} - l_{ACT}^{g}).$$
 (6)

In this first phase, we calculated actual performance, target performance, and market potential for each region in the market. These values are incorporated (together with other attributes of the regions) in the next phase.

3.2. Phase 2: Sub-market evaluation

The second phase presents an approach for identifying sub-markets (e.g., states, cities, municipalities) with high market potential. The objective of this phase is to support the branch network planner in selecting a sub-market for detailed branch network planning. Step 1: Generate grid. Since the individual regions are different in size, a direct comparison is difficult. To overcome this problem, the entire market is divided into hexagonal grid cells (so that the entire market can be tessellated in equally sized and nearly circular cells). These grid cells are evaluated with the attributable market potential of the intersected regions. The grid cell shown in Figure 2 is therefore valued with a market potential of 195,000 \in .

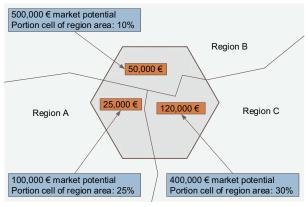


Figure 2. Market potential in a grid cell

Step 2: Evaluate sub-markets. We define submarkets as a distinct consolidation of several regions. Every region of the market is within exactly one submarket (e.g., a grouping of zip code areas by the first three digits of the zip code or a grouping of municipalities by districts). Due to the limited trading area of a branch, it is important to identify regions with high market potential in a confined space. To develop a measure for this concentrated market potential, a threshold t is defined. If the market potential in a grid cell i (i \in I) exceeds the threshold t ($a_i \ge t$), this cell is considered as hot spot. The set of hot spots in a region g is defined as H^g ($H^g \subseteq I$) and consists of all grid cells within the region that have a greater market potential than the threshold t. Consequently, the number of hot spots in a region accounts [H^g]. Since each region is located exactly within one sub-market, the number of hot spots in the sub-market $G'(G' \subseteq G)$ adds up to $\sum_{g \in G'} |H^g|$ and the sum of market potential within the hot spots of the sub-market G' adds up to $\sum_{g \in G'} \sum_{i \in H^g} a_i$. Both the number of hot spots and the sum of market potential within the hot spots are provided to serve as additional decision support criteria for selecting a relevant sub-market.

Step 3: Select a sub-market. The last step of this phase consists of the decision makers' analysis of submarkets and the selection of one sub-market for detailed branch network planning in phase 3. The implementation of BankMAP (cf. section 4) supports the decision maker with data visualization and display of available criteria for each region and sub-market.

3.3. Phase 3: Branch network planning

The third phase applies a model for branch network optimization on the selected sub-market. The objective of this phase is to identify potential sites for new branches. As in phase 2, we divide the sub-market into grid cells. Since we reduced the problem size by focusing on a sub-market, we can apply a much finer grid than in phase 2. Demand is defined with market potential on the grid cells (cf. formula (6), Figure 2). Each grid cell can be set as potential location for a branch. Distances between grid cells are calculated using the Euclidean distance between the cell centers.

This model is based on the generalized MCLP by Church and Roberts [14] with multiple coverage radii and a stepwise decreasing coverage function. In order to consider the populations' characteristics in the locations' trading areas (cf. section 2.2.1), we extend the definition of the maximal service distance by a customer-based maximal service distance. That means, instead of defining an overall maximal service distance or a maximal service distance based on branch characteristics, we define a maximal service distance for each demand point, based on its populations' characteristics. In order to be able to represent an existing branch network (cf. section 2.2.2), we define a set of fixed sites. To formulate the problem, the following notations are defined:

- Set of demand points, I =
- = Set of potential sites, J
- Set of sites to ensure location of a branch: F = $F \subseteq J, |F| \leq b,$
- R = Set of steps in the coverage function,
- b = Number of branches to be located,
- Demand at demand point i, ai =
- = Distance between demand point i and site j, dii
- = Coverage rate: Proportion of covered demand Wr in coverage step r ($r \in R, w_r = [0, 1]$),
- s_ir = Maximal distance from demand point i to a branch, so that demand a_i is covered with coverage rate w_r,
- N_i^r = Set of sites being able to cover demand point i with coverage rate w_r : $\{j \in J \mid d_{ij} \le s_i^r\}$.

Decision variables:

- $\begin{cases} 1 , & \text{if a branch is located at site j,} \\ 0 , & \text{otherwise,} \end{cases}$ =
- $y_i^r = \begin{cases} 1, & \text{if demand point i is covered} \\ & \text{with coverage rate } w_r, \\ 0, & \text{otherwise.} \end{cases}$

The stepwise decreasing coverage function is represented by the sets N_i^r ($i \in I, r \in R$) and the coverage rates wr. The purpose of the parameters for maximal service distances s_i^r is only to calculate the sets N^r_i. The maximal service distance of a demand point is customer-based. That is, a consumer who lives in grid cell i, is with probability wr willing to travel a distance of s_i^r to a branch in order to obtain a service. The coverage function needs to be a function, which monotonically decreases with increasing distance. Thus, the following constraint applies for the coverage rates and service distances: $s_i^q < s_i^r \Leftrightarrow w_q > w_r \forall i \in$ I; q, r \in R: q \neq r. The problem can be formally stated as follows:

Max
$$z = \sum_{i \in I} \sum_{r \in R} w_r a_i y_i^r$$
 (7)

$$\sum_{j \in N_i^r} x_j \ge y_i^r \qquad \forall i \in I, r \in R,$$
(8)

$$\sum_{\substack{\mathbf{r}\in\mathbf{R}\\ \nabla}} \mathbf{y}_{i}^{\mathbf{r}} \leq 1 \qquad \forall i \in \mathbf{I},$$
(9)

$$\sum_{i \in I} x_i = b, \tag{10}$$

$$\mathbf{x}_{j} = 1 \qquad \forall j \in \mathbf{F}, \tag{11}$$

$$\forall j \in J,$$
 (12)
 $\forall f \in J,$ (12)

∀i∈l,r∈R. (13)

A demand point i is considered as covered with coverage rate w_r , if the distance to the closest branch j is less or equal to s_i^r ($d_{ij} \le s_i^r$). A demand point is considered as not covered, if the distance to the next branch j is greater than the maximal service distance of grid cell i ($d_{ij} > s_i^r \forall r \in R$).

The objective function (7) maximizes the covered demand, consisting of the coverage rate w_r , the demand a_i and the decision variable y^r_i. If demand point i is covered with coverage rate w_r, the decision variable y_i^r equals 1 and the demand a_i adds (weighted by the coverage rate w_r) to the objective value. Constraints (8) ensure that a demand point i is only covered ($\sum_{r \in \mathbb{R}} y_i^r = 1$), if a branch is located ($x_i = 1$) at one of the potential sites $j \in N_i^r$. That is, at least one branch is located within a distance of s^r_i to demand point i. Constraints (9) ensure that coverage for each demand point is only calculated in one way. Suppose that demand point i is covered by two branches j and j'; with proportion w_1 by branch j and with proportion w_2 by branch j' $(w_1 > w_2)$. Constraints (8) allow y_i^1 as well as y_i^2 to equal 1, so that the demand a_i would be incorporated twice in the objective value. But constraints (9) allow only one of the decision variables $y_i^r (r \in R)$ to equal 1. Since $w_1 > w_2$, y_i^1 adds a

s.t.

greater contribution to the objective value than y_i^2 , so that $y_i^1 = 1$ und $y_i^2 = 0$. Constraint (10) guarantees that the number of branches to be located equals b. Constraints (11) ensure that a branch is located at all fixed locations while constraints (12) and (13) specify, that decision variables x_i und y_i^r can only equal 0 or 1.

3.4. BankMAP-DSS implementation

To perform spatial calculations and assist the planner in executing the process, we implemented the application BankMAP-DSS in the programming language Java. The graphical user interface (GUI) of BankMAP-DSS guides the user through phases 2 and 3 of the process. Phase 1 is calculated using spreadsheet software and imported to BankMAP-DSS. For cluster analysis, we use IBM SPSS Statistics with the K-Means algorithm. To solve the MCLP in phase 3, we integrate IBM ILOG CPLEX Optimizer via the Java API. Data preprocessing is executed in BankMAP-DSS and sent to CPLEX, then the optimization problem (7) to (13) is solved using CPLEX Optimizer. After that, BankMAP-DSS presents and exports the results. Results and statistics are presented within the GUI and can be exported in detail to spreadsheet software. Visualization of results is realized in a simplistic manner within the GUI. For advanced, sophisticated, and interactive visualizations, we integrated the Google Earth API, enabling us to draw multiple scenarios of the entire branch network, enriched with sociodemographic and market data for the regions, competitors branch networks, and performance indicators of the existing branch network. We present the user interface and features of BankMAP-DSS in the next section by a real-world application example.

4. BankMAP application

BankMAP has been applied in an actual banking environment on the branch network of a German commercial bank that we call ABC Bank. Our objective is to identify potential regions for branch network expansion and select potential locations for new branches. This case depicts a simplified scenario calculated for ABC Bank. In the real-world application of BankMAP at ABC Bank, we calculated multiple scenarios with different KPIs (including for instance deposit and loan volumes, new customer acquisitions, existing customers, etc.) and different combinations of location characteristics (including for instance competitor branches, high movement areas such as shopping centers, daytime population, etc.). Selection of KPIs and location characteristics is a challenging task that can be inhibited by availability of data or monetary restrictions, since buying socio-demographic data on granular levels is associated with high costs.

4.1. Phase 1: Market potential evaluation

Step 1: Define KPIs. In particular, the products that are complex and require close contact to customers (e.g., consumer loans, building loans, time deposits, savings bonds, etc.) are important KPIs for ABC Bank. Furthermore, KPIs are based on volumes of (new) deposits, number of (new) accounts, volume of (new) loans, and number of existing customers in each region. The different KPIs have different profit margins (e.g., profit margin for each new loan customer depends on the loan volume and needs to account for commissions and fees). In order to keep the example comprehensible, we only consider the volume of checking and savings accounts for performance evaluation. We split up checking accounts into liabilities (deposits) and assets (overdrafts), because these cases provide different profit margins. Table 1 presents deposit volumes (v_p) and profit margins (q_p) for ABC Bank's products as well as the number of customers using these products (c_p) . The data is extracted from the ABC Bank's internal databases, depicts aggregated data and is provided on zip code level. The data in this scenario does not include estimated growth rates since such data is not available to us. To represent the retail banking market, we only consider consumer deposits.

Table 1. ABC Bank's product-based data

Product	Deposits (Mio. €)	Customer s (Mio.)	Margin (%)
Checking liabilities	10,873	4.32	5,0
Checking assets	827	4.32	8,0
Savings	21,948	2.64	1,5

Step 2: Classify regions. After analyzing the available socio-demographic data, we select the following criteria for regional classification: private buying power per household (as indicator for wealth in a region) and inhabitants per square kilometer (as indicator for population density). We include an indicator for population density in order to model the assumption that people living in urban regions are willing to drive or walk shorter distances to the next bank branch than people living in rural regions. These two criteria were used in the real-world application as well. The number of classes is determined using the elbow-criteria [21]. We classify the regions in classes from 2 to 15 and calculate the sum of squared errors within these classes (cf. Figure 3). When changing from five to six and from eight to nine classes, the reduction of the sum of squared errors levels off. In

other words, by adding a further class, the sum of squared errors within the classes does not reduce significantly in comparison to the prior reduction.

We set the number of classes to eight, because it allows a more detailed description of the regions (cf. Figure 4). The regional classes may be described by their mean attribute values. For example, class 2 consists of regions with high private buying power per household and low population density, while class 8 contains regions with low buying power and high population density.

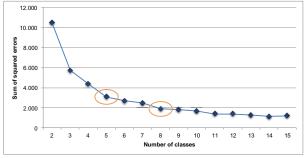


Figure 3. Sum of within-class squared errors

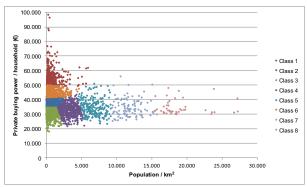


Figure 4. Results of the cluster analysis

Step 3: Define benchmark. Market penetration in each region is calculated with formula (3). We define the market performance benchmark $(\widetilde{\Phi}_{p}^{k})$ of each class (and thereby the benchmark for all regions in a class) as the 0.9-quantile of a product's market penetration within the regions of a class. Meaning that 90% of the regions within a class are performing below the benchmark and accordingly have potential for improvement.

Step 4: Calculate market potential. Based on the previously calculated data, we calculate actual performance using formula (4), target performance using formula (5), and market potential using formula (6) for each zip code area. Table 2 depicts the market potential for ABC Bank in Germany. 50% of the previously calculated market potential is distributed to only 20% of the area in Germany. Our objective is to

identify the regions, where the market potential is concentrated on a confined space.

Table 2. Market potential by product		
Product	Amount	
Checking liabilities	354 Mio. €	
Checking assets	49 Mio. €	
Savings	199 Mio. €	
Total	602 Mio. €	

2 Market notential by product

4.2. Phase 2: Sub-market evaluation

Step 1: Generate grid. We set the width of the grid cells to five kilometers and evaluate each cell with the previously calculated market potential.

Step 2: Evaluate sub-markets. The generated grid consists of 16,513 cells with an average market potential of 36,475 € per grid cell. 53 of these cells exhibit a market potential of over one million Euros. We use the districts in Germany as sub-markets. In order to identify concentrated market potential, we define the grid cells with more than one million Euros of market potential as hot spots. Further statistics on the distribution of market potential in the grid cells is shown in Figure 5.

Step 3: Select a sub-market. After calculating the number of hot spots and the sum of market potential in the hot spots, BankMAP-DSS shows a screen to support the user in analyzing the sub-markets (cf. Figure 6). The user is now able to analyze each sub market. BankMAP-DSS presents a list of all submarkets (1). The combo box (2) lets the user select different attributes (e.g. market potential, actual performance, population) to sort the list (1). On the right part of the screen (3) all attributes of the currently selected sub-market are presented. The screen center (4) presents the location of the selected sub-market and the geographical distribution of the selected attribute (2) in the sub-market.

We select the sub-market with the highest average market potential per hot spot, a small district in Midwestern Germany. Within this district, there is a hot spot with 1.5 million Euros of market potential. There are 330 thousand inhabitants and 170 thousand households on an area of 260 km². ABC Bank manages 32 million Euros of checking and 89 million Euros of saving deposits of 11 thousand customers with checking and 9 thousand customers with savings accounts. Table 3 shows the performance and market potential in the selected sub-market.

A grid cells counts as hot spot, if its market potential exceeds		Market potential		Percentiles	
the defined threshold.		Sum.	602,066,598	1	879
			36,475	5	2,619
		Avg.		10	3,812
		Min.	0	25	7,576
		Max.	2,117,110	50	15,467
Sub-markets defined by	Districts			75	28,896
Sub markets defined by				90	60,045
Hot spot threshold	1000000	#Grid cells	16,513	95	103,048
		a Grid Certs	10,515	99	506,779
	Identify hot spots		Save als xls		

Figure 5. BankMAP-DSS: Phase 2, Step 2

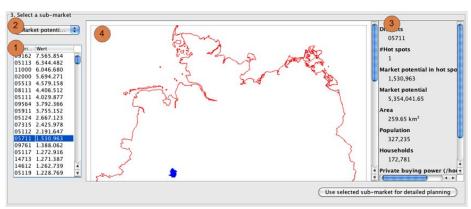


Figure 6: BankMAP-DSS: Phase 2, Step 3

Table 3. Performance and market potential in					
the selected sub-market (in Mio. €)					
	C			1.	TF (1

	Savings	Checking	Total
Actual performance	1.8	1.3	3.2
Target performance	5.7	2.8	8.5
Market potential	3.9	1.5	5.4

4.3. Phase 3: Branch network planning

We define a grid width of 200 meters and value each grid cell with the market potential calculated in phase 1. We do not fix any branches, because we already considered the actual branch network in phase 1: Market potential is calculated by formula (6) and consists of the difference between target and actual performance. The actual performance represents the market potential gathered by the current branch network. Fixing the existing branches in the model would take the existing branch network into account twice. Therefore, we defined the set of potential sites J, the set of demand points I, the set of fixed branches F, and the demand a_i. In order to define the parameters for the coverage function (R, w_r, s_i^r, N_i^r) , we use planning parameters surveyed by the ABC Bank, which are depicted in Table 4.

Table 4. Coverage function parameters					
Population density		Coverage rate at			
		dist	ance [k	[m]	
Type	Inhabitants per km ²	100%	80%	60%	
А	< 200	4.50	6.00	7.5	
В	201 - 500	2.70	3.60	4.5	
С	501 - 1800	1.20	1.60	2.0	
D	1801 - 3500	0.90	1.20	1.5	
Е	> 3500	0.60	0.80	1.0	

These service distances state that, for example, 60% of the customers living in a type B region are willing to travel at the maximum 4.5 km to a branch in order to obtain a service. The parameter b (number of branches to locate) can be set manually by the user or determined by BankMAP-DSS. In order to determine parameter b automatically, a minimum profit per branch needs to be specified. The ABC Bank calculates with a minimum profit of 400,000 Euros per year for a new branch. This minimum profit threshold is based on internal calculations of ABC Bank (considers costs for rent, workforce, marketing, etc.). BankMAP-DSS solves the model starting with one branch and adding another one if the additionally gathered market potential exceeds 400,000 Euros. Using these parameters, the optimization problem is solved by CPLEX Optimizer. The optimal solution for the submarket is reached with two branches. The additionally gathered market potential amounts to 801,917 Euros.

4.4. Interpretation of results

Currently, the ABC Bank operates three branches in the selected sub-market and gathers a market potential of 3.2 million Euros. By adding two more branches, the estimated market potential gathered increases by 25% and reaches 4 million Euros.

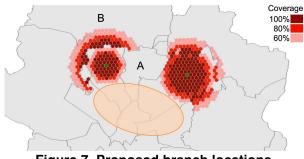


Figure 7. Proposed branch locations

Figure 7 shows the process results. The green grid cells are the proposed locations for the two new branches. The orange shaded area depicts the region, where currently existing branches of the ABC Bank are located. Figure 7 also visualizes the effect of customerbased service distances. The zip code area A has a higher population density (3,751 inhabitants per km²) than zip code area B (655 inhabitants per km²). Therefore, demand points in zip code area A have a shorter service distance (1 km) than demand points in zip code area B (2 km) (cf. Table 4 for service distances by population density). For this reason, the coverage area of the left branch reaches further into the rural region B than into the urban region A.

5. Discussion and conclusion

We developed a process for market potential evaluation and branch network planning in retail banking. BankMAP supports retail banks' decision makers in branch network planning and addresses specific challenges in retail banking: the multidimensional performance of banks is taken into account by incorporating multiple criteria for market potential evaluation in phase 1. Phase 2 assists by identifying relevant sub-markets for detailed planning. The problem of allocating customers to branches is implemented by a customer-based definition of trading areas in phase 3. In addition, the existing branch network is considered implicitly in the way market potential is calculated. By fixing certain sites in the optimization model (parameter F), the existing branch network is considered explicitly.

As with any research, this paper has its limitations. The monetary market potential measure has the advantage that it is intuitively understandable by decision makers and provides a benchmark for the achievable profit in a region. However, this approach also has drawbacks. First, the target performance benchmark is an internal benchmark, which is determined by historical performance of the bank in similar areas. The market potential is thus limited by this historical performance. Second, this indicator requires the existence of branches in similar areas. A bank, operating only in a few regions, could face the problem of lacking necessary data. Third, we want to stress, that the additional market potential cannot just be gained by simply opening more branches. The results rather provide an implication of possible revenues that could be generated by new branches. ABC Bank is currently using BankMAP to reconfigure its branch network. Thus, we cannot evaluate accuracy of market potential estimation or managerial implications from using BankMAP and leave the evaluation open for future research.

BankMAP has also limitations in its assumptions that limit generalizability. First, for each product, we assume one single profit margin for all regions. However, some products (e.g., loans) have higher risk in particular regions. In order to account for such region-based risk factors that limit profits in particular regions, the parameter q_p needs to be determined for each region (q_p^g) . However, such granular data was not available at ABC Bank. Second, we classify customers by the regions they live in. While this is a legitimate assumption for their buying behavior [10], the customers' spatial behavior in the context of banking may be influenced by other factors as well (e.g., region of employment). In the real-world application, we accounted for daytime population in the evaluation of regions, but did not determine the customer-based trading areas by place of employment, since such data was not available and is expensive to gather.

In the application example, we did not consider competitors branch networks. In the real-world application, the competitor networks were for instance incorporated in the visualizations in Google Earth. BankMAP DSS helps decision makers in branch network planning by simplifying the complex location problem, gathering multiple criteria from diverse data sources, and visualizing potential branch network scenarios. Thus, competitors' branch networks were considered by supporting the decision maker in the visualizations with detailed information on competitor branches as well as other retail outlets (e.g., shopping centers). Including competitors branch networks in the actual market potential evaluation is possible by adding criteria to the location characteristics (e.g., competitor branch density) and applying negative weights, thus reducing market potential in areas, where the competitor branch networks are dense.

We used socio-demographic data on zip code basis and assumed that market potential is evenly spread across regions. The larger the zip code area, the more error-prone the calculation. We chose this approach because the most granular available geometric shapes and socio-demographic data were based on zip codes. However, the model is capable of handling more granular data. Future extensions could incorporate open geographical data to identify non-populated areas, for example by parsing data from openstreetmap.org.

This paper contributes to the knowledge base on branch network and location planning in the retail sector, as it may be applied in various settings in the retail industry, such as location of fast food restaurants. However, research needs to be conducted to ensure BankMAP's applicability in other settings. Besides identifying sub-markets with high market potential, the process is also applicable to identify sub-markets with low market potential for market retraction.

6. References

[1] Spath, D., Praeg, C.-P., Vocke, C., and Engstler, M., Trendstudie Bank & Zukunft 2010, Die Wiederentdeckung Der Kunden, Frauenhofer IRB, Stuttgart, 2010.

[2] Köhler, M., and Lang, G., Trends Im Retail-Banking: Die Bankfiliale Der Zukunft, Zentrum für Europäische Wirtschaftsforschung, 2008.

[3] Deutsche Bundesbank, Bankenstatistik Februar 2011 -Statistisches Beiheft Zum Monatsbericht 1, 2011.

[4] Dick, A.A., "Demand Estimation and Consumer Welfare in the Banking Industry", Journal of Banking & Finance, 32(8), 2008, pp. 1661-1676.

[5] Doyle, P., Fenwick, I., and Savage, G.P., "A Model for Evaluating Branch Location and Performance", Journal of Bank Research, 12(2), 1981, pp. 90-95.

[6] Hopmans, A.C.M., "A Spatial Interaction Model for Branch Bank Accounts", European Journal of Operational Research, 27(2), 1986, pp. 242-250.

[7] Boufounou, P.V., "Evaluating Bank Branch Location and Performance: A Case Study", European Journal of Operational Research, 87(2), 1995, pp. 389-402.

[8] Xia, L., Yin, W.J., Dong, J., Wu, T., Xie, M., and Zhao, Y.J., "A Hybrid Nested Partitions Algorithm for Banking

Facility Location Problems", Ieee Transactions on Automation Science and Engineering, 7(3), 2010, pp. 654-658.

[9] Alexandris, G., and Giannikos, I., "A New Model for Maximal Coverage Exploiting Gis Capabilities", European Journal of Operational Research, 202(2), 2010, pp. 328-338.

[10] Wedel, M., and Kamakura, A., Market Segmentation: Conceptual and Methodological Foundations, Kluwer Acad. Publ., Boston, 2000.

[11] Ioannou, G., and Mavri, M., "Performance-Net: A Decision Support System for Reconfiguring a Bank's Branch Network", Omega, 35(2), 2007, pp. 190-201.

[12] Brandeau, M.L., and Chiu, S.S., "An Overview of Representative Problems in Location Research", Management Science, 35(6), 1989, pp. 645-674.

[13] Church, R., and Revelle, C., "The Maximal Covering Location Problem", Papers of the Regional Science Association, 32, 1974, pp. 101-118.

[14] Church, R., and Roberts, K.L., "Generalized Coverage Models and Public Facility Location", Papers of the Regional Science Association, 53, 1983, pp. 117-135.

[15] Pirkul, H., and Schilling, D.A., "The Maximal Covering Location Problem with Capacities on Total Workload", Management Science, 37(2), 1991, pp. 233-248.

[16] Berman, O., Krass, D., and Wang, J.M., "The Probabilistic Gradual Covering Location Problem on a Network with Discrete Random Demand Weights", Computers & Operations Research, 38(11), 2011, pp. 1493-1500.

[17] Berman, O., Drezner, Z., and Wesolowsky, G.O., "The Maximal Covering Problem with Some Negative Weights", Geographical Analysis, 41(1), 2009, pp. 30–42.

[18] Berman, O., Drezner, Z., and Krass, D., "Generalized Coverage: New Developments in Covering Location Models", Computers & Operations Research, 37(10), 2010, pp. 1675–1687.

[19] Wang, Q., Batta, R., Bhadury, J., and Rump, C.M., "Budget Constrained Location Problem with Opening and Closing of Facilities", Computers & Operations Research, 30(13), 2003, pp. 2047-2069.

[20] Meffert, H., Burmann, C., and Kirchgeorg, M., Marketing, Gabler, 10th edn, Wiesbaden, 2008.

[21] Backhaus, K., Erichson, B., Plinke, W., and Weiber, R., Multivariate Analysemethoden, Springer, 13th edn, Berlin, 2011.