ADVANTAGES AND LIMITATIONS IN IMPLEMENTATION OF BUSINESS INTELLIGENCE SYSTEM IN MONTENEGRO: CASE STUDY TELENOR MONTENEGRO

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ABSTRACT

Data warehouse is the main technology which integrates data from company operations. Business Intelligence with DW at its center, enables the company to extract very important information for making business decisions from these data. Implementation of these systems is a very expensive and long lasting process. These systems are used a lot and they bring great benefits to companies in developed economies. However, their implementation has a great number of limitations, especially in our conditions of operations. In this paper we have recognized the advantages and limitations of implementation of the BI systems in poor conditions of operations and on a small market such as the one in Montenegro, as well as the methods for overcoming some of those limitations. We have also done the case study research which shows that the implementation of these systems is possible even under such circumstances.

Keywords: business intelligence, data warehouse, OLAP, data mining, integration dirty data, Telenor Montenegro, Teradata Warehouse Miner, CRISP DM

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1. INTRODUCTION

Data Warehouse (DW) is subject oriented, integrated, time-variant and relatively non-volatile collection of data in support of business decision making (Inmon 2006). Business intelligence (BI) is a term closely connected with DW. Business intelligence is consisted of DW, OLAP (On Line Analytical Processing) and data mining (Balaban 2006). OLAP systems enable ad hoc flexible business queries over data warehouse. They enable business analysts to analyze the business facts from the aspect of several dimensions and levels of aggregation. Data mining systems automatically detect hidden dependencies and trends existing in the data stored in DW. These systems use intelligent algorithms based on machine learning. With methods of data mining we can accurately segment the market, discover the profile of typical customer for specific type of product and his preference for purchase, discover potential frauds on sales locations, detect stolen credit cards, anticipate trends of phenomena etc. (Klepac 2006).

It is not disputable that these systems are very important and useful. A great number of companies in the world use these systems and thanks to them they are having higher revenues and they manage to save even up to several million euros on an annual level. For example, the Royal bank in Canada, by implementing the BI system in the process of discovering credit cards abuse, managed to elimi-

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nate losses worth millions of dollars which it suffered every year (Vuksanović 2006).

However, implementation of these systems is very demanding, both financially and in terms of time. Their price can be even up to one million euros, and its completion sometimes takes several years.

In this paper we will discuss the advantages and limitations in the implementation of the BI system in our conditions of operations, as well as the methods for overcoming some of the limitations. The goal of this paper is to show that these systems can be cost effective even in our conditions and that they can bring a series of advantages to the company. The case study research which was conducted in this paper shows that the implementation and use of this system is possible and useful even here.

Unfortunately, some empirical research on the subject of efficiency indicators of the system on the Montenegro market is not possible, due to a very low number of companies using the BI systems (only few telecommunication companies). Such research within some other 'small markets', with more BI users, could motivate our companies to start with the implementation of these systems.

2. ADVANTAGES IN IMPLEMENTATION OF BI SYSTEM

There are many advantages which the company might have with the use of these systems. The first thing that the company management thinks of when they decide on the implementation of the BI system is whether and to what extent it will increase the income. The BI systems provide useful knowledge regarding the users of products and services and the market on the micro and macro level. When it understands its clients, the company can proactively take the initiative on market segments. This implies targeted marketing and increase in client's loyalty which can significantly increase the income. The company can significantly increase the income from sales to the population of existing customers by selling the products which the BI system recognized as possible products and services which the customers want to buy (cross selling). Big losses can occur in case of losing the clients and the BI systems can predict such trends (churn prediction) and help the company discover the causes on time and react in an appropriate way.

These systems can also have a very important role in the detection of deviations of some key indicators of operations. They can warn the company on time about the occurrence of some problem and thus prevent its consequences. For example, the data mining system can detect when the company is going into a financial crisis, i.e. the occurrence of loss and liquidity curtailment (Kašćelan & Bečejski-Vujaklija 2005).

Another very important advantage is achieving higher operational efficiency. A good example is the system discovering the abuse of credit cards. Manual authorization is almost impossible, because it implies a very fast analysis of a great number of relevant data. The BI systems on the basis of rigid rules determine quickly and efficiently whether the transaction should be approved or not. They can also timely detect the abuse with the help of neural networks which recognize the transactions that stand out of the normal purchase patterns of the card user.

There are many advantages of the BI systems; the most of the leading companies in the world have recognized them and use these systems successfully.

3. LIMITATIONS IN IMPLEMENTATION OF THE BI SYSTEMS

In poor conditions of operations and on a small market, such is the one in Montenegro, these systems are rarely used. There is a large number of reasons for that, and we will mention some of them as follows.

First of all, we need to point out the initial price of the BI system which can reach even one million euros for big companies. Data mining tools use very sophisticated algorithms and they require additional training of personnel using them, so they could work interactively with those tools and understand the meaning of outputs. This usually requires hiring external consultants, which further increases the costs of implementation.

The time of implementation can take from 6 months to several years for a complete system. All of this can look discouraging, especially to companies with limited financial assets.

Uncertainty in the success of implementation is not a problem just in our conditions of operations. The research of Gartner Group shows that out of 2,000 data warehouse projects, only 20% of them are successfully implemented to the end.

One of the biggest problems of our companies is obsolescence of standard information systems which usually produce inaccurate data in an inappropriate format, the so called dirty data. Databases have an outdated design, they are usually without supporting documentation, they are not flexible and have limited possibilities for access to data. The majority of the information systems do not allow the integration of the BI system due to the lack of the integration option. A poor quality of source data is responsible for the majority of time and cost overruns during the implementation of the BI systems.

However, we can say that the main limitations here are the lack of experience of the personnel in use of these systems, as well as the misconceptions regarding their possibilities. The misconceptions usually refer to unrealistic expectations in the sense of functionality of these systems, as well as the potential effects such as improvement of operations efficiency and profit. The data mining analysis usually gives results which are not completely defined in business terms i.e. they are not provided in form of simple if-then rules or decision tree. DM systems do not usually use the original names of attributes but rather symbolic titles used in internal code of the program. Such results can be very confusing and incomprehensible for a user without additional post processing, usually with appropriate visualization. For example, the results of data mining obtained by neural network are not expressed explicitly. There is a series of papers in this field dealing exactly with the extraction of rules. There is an interesting example of extraction of decision table on the basis of results of neural network for evaluation of credit risk (Baesens et al. 2003).

Most data mining analyses are interactive, i.e. they require an active participation of a user in the process of research and data analysis. In order for a user to interactively participate in this process, he must posess some knowledge of the algorithm on which the process is based. We already emphasized that these are very complex algorithms based on techniques of artificial intelligence i.e. machine learning. Some of these techniques, such as induction of classification rules, decision tree, neural network and genetic algorithms are described in Kascelan & Bečejski-Vujaklija (2003). Statistical techniques are also frequently used in business applications and they are usually in the form of linear regression.

One of the key problems is also selection of an appropriate data mining technique for the business problem being solved. This depends on the number and type of independent variables as well as on the size of the set of examples analyzed by the system. Linear regression is a better choice if we have mainly continuous independent variables or just one categorical variable, while in case of several categorical variables neural networks would give better results (Kim 2008). Business analyst must posess the knowledge and experience regarding the technique and problem being solved.

It is very important that the analyst who uses data mining systems is aware of the issues related to the activity for which the analysis has been made. Specifically, data mining systems can sometime spot some important links and trends existing between the data. Also, these systems can generate some relations which are insignificant and meaningless. Business analyst has to be able to recognize valid outputs of data mining.

A large number of significant data in the company is located within the unstructured data. Structured data are stacks located within a relational database. Unstructured data are located in textual documents, usually within e-mail messages. Companies receive millions of e-mail messages every year which contain very important data and information. There are attempts to integrate unstructured data into relational databases (Mansuri et al. 2006) but data mining systems for the research of such data are still in their initial development stage. We can say that this is one of the limitations in achieving full effectiveness of these systems in discovering knowledge in a company.

4. CASE STUDY: TELENOR MONTENEGRO

Telecommunication companies are forced to constantly change and increase their production, i.e. services in order to survive on the market, and stay competitive. With the development of new technologies and increasing requests of consumers, the companies in this field are in a constant race to adopt new services and methods on how to keep their customers and win the new ones.

By facing everyday problems, such as churn (cancellation of services by customers) or declining the profit rate, companies realize that the need for the analysis of customers' behavior is becoming a priority in this field. Kim et al. (2006) described churn as 'the number or percentage of regular customers who abandon a relationship with a service provider'.

The main goals which the companies in such cases have are the expansion of customers' base, i.e. getting the new customers, as well as keeping the existing ones (which is especially relevant on the Montenegro telecommunications market in conditions when the market penetration is almost 200%). By using the business intelligence, companies are "smarter" in targeting potential customers as well as the current users of their services who want to abandon them. This leads to the optimal distribution of assets available to marketing, as opposed to the conditions when the marketing campaign covers the entire market regardless of the needs of narrow segments.

Besides the fact that the market conditions force companies to apply a more serious approach to the analysis of customers and their behavior, challenges before these companies mean that they have to be more proactive. Being proactive, in light of business intelligence, is defined not only by the analysis of past events and behavior of customers, but also by predicting such facts.

Telenor Montenegro is the first company in the field of mobile communications in Montenegro. It has timely recognized the advantages of application of the BI systems and invested in their implementation.

This company did not build the data warehouse itself. With the help of vendor and a team comprised of IT and business experts, it has created a huge data warehouse, which is not located in the company due to its size and complexity. In conditions when the independent vendor built the DWH on the basis of business and technical inputs, the company has people who regularly supervise the technical processes connected to the loading of DWH and data quality, and on the other side there are users, i.e. business analysts who use these data. Telenor has employed young people, who recently graduated from college, who studied information technologies and who are ready to adopt new knowledge. With good training of these personnel they have managed to build a team which successfully works with the BI system.

Telenor uses the methodology of data mining which is most frequently used in the telecommunications industry. CRISP DM (Cross Industry Standard Process for Data Mining) method is developed by experts from NCR/Teradata, SPSS and DaimlerChrysler, and it is adjusted to the field of telecommunications. CRISP methodology uses Teradata Warehouse Miner (TWM) as a tool for data manipulation by business users. This tool is connected to the DWH, i.e. data mart defined for this purpose, and it can process huge amounts of data in a very short time interval.

MicroStrategy (MSTR) tool is used for OLAP. There is a possibility to connect the results obtained by data mining with MSTR reports with the help of TWM, so that users can connect the obtained results in tables with the data on customers.

For some years now, Telenor has been successfully using this data mining method for churn prediction (cancellation of company services by some customer, i.e. loss of customer loyalty) and identification of market micro-segments. OLAP multidimensional analyses are used for measuring company efficiency as well as for a series of other everyday activities on an executive level.

4.1 Churn prediction

In the telecommunications industry there is a definition of churn for customers who use the services without a contract (prepaid) and those with a contract (postpaid). Prepaid churner is a customer who does not use services of the company (does not make any traffic, calls, messages, does not receive calls or messages and does not make any top-ups to his account) in excess of 90 days, while postpaid churner is a customer who terminates the existing contract with the company.

The main reason for developing the churn prediction model is focusing on the customers who are least loyal and finding the way to keep them. Business users, i.e. decision makers, on the basis of information they get with this model, will be able to target in their campaigns on keeping only those customers who have medium or high probability for abandoning the services. Such approach is far better (efficient and certainly cheaper) than the creation of campaigns which would be focused also on those who do want to leave.

CRISP data mining implies several stages: problem understanding, data understanding, data preparation, modeling, evaluation and scoring.

Problem understanding implies identification of data which will serve as the basis of the analysis. When we talk about churn prediction, this stage implies providing the accurate definition of churn, what it is, and what it is not; data description should be used in analysis of customers who already churned so that on the basis of those customers we could make conclusions on potential churn compared to the customers still loyal to our company; what is the time period for which the prediction is done and what is "churn event" (point at time when the customer stopped using the services or when by definition he was deleted from the base).

In the data understanding stage, verification of data quality is performed. By using the TWM it is possible to perform a series of analytical actions, so that the process of data verification (value analysis, correlation matrix, statistical analysis, histogram, frequencies etc.) would be completed as fast and satisfactory as possible. They enable some of the basic verifications (verification of missing values, values equal to zero, the same values within one variable, maximum and minimum), as well as the verifications of numbers of observations, minimum, maximum, mean value, standard deviation, standard error, variance, sum of least squares and similar.

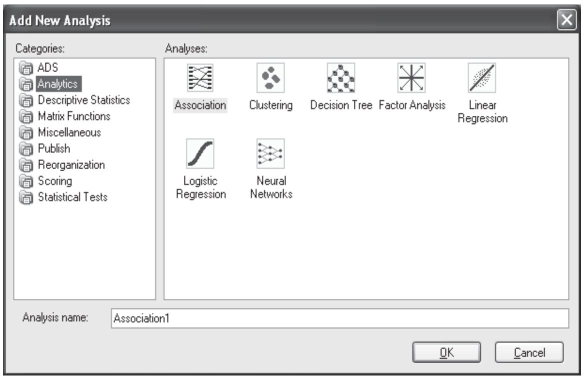

Figure 4.1. Analytical methods in the TWM

Data preparation implies all activities leading to the building of the final database on the basis of basic or raw base we have available such as: data cleansing, selection, transformation of variables etc. This stage is performed by technicians until the level of "bringing" data to the TWM (by using various tables from the DWH), while the process of data transformation and placing in the same table is continued by business users, i.e. data mining analysts. The table created in this stage is called ADS (Analytical Data Set) and it includes all attributes which can be significant for the understanding of churn.

In the modeling stage, the models which correspond to the problem are applied, parameters are calculated and their optimal values are "set up" depending on the knowledge from business practice and data behavior. Modeling implies: creating training and test samples, results evaluation or just creation of models and decisions regarding the fact which variables (attributes) are important for behavior of a dependent variable, i.e. churn.

During modeling we use the training sample, whereas the test sample is used only for testing the model. The first step is to determine a dependent variable, and then the method to be used in modeling. A dependent variable is, in this case, churn probability, and in the TWM the modeling methods which are available are presented in Figure 4.1. Selection of the best method for churn prediction is the subject of research in many scientific papers in this field. Neslin et al. (2006) analyzed the results of various data mining methods used for churn prediction and concluded that good results are obtained from logistic regression and decision tree. If we select logistic regression for the creation of model, it is necessary to define a dependent variable and give guidelines to the model in terms of where the independent variables are. In this case a dependent variable is the probability of churn for individual customers, and the independent ones are located in the entire ADS. The model chooses itself which independent variables it will take into consideration, and it also chooses the order of their taking, i.e. the first independent variable is as a rule the strongest initiator of churn. Logistic regression has to be verified on the basis of parameters obtained as an output, which is shown in Table 4.1.

Verification of results is observed first through the evaluation of the B coefficient – it should be checked if the direction of movement is logical, i.e. is it justified from the business standpoint that the B coefficient has a positive or negative sign. The higher the B coefficient is, the stronger influence is of the specific independent variable on the movement of the dependable one. The values for standard error of variable and T – standard error of parameter depend on the selected trust interval, while P statistics for every independent variable should be equal to zero.

Table 4.1. Parameters of logistic regression

McFadden's Pseudo R-Squared

0,4813

Column Name	B Coefficient	Standard Error	Wald Statistic	T Statistic	P-Value	Odds Ratio	Lower	Upper	Partial R
(Constant)	3,4379	0,0671	2627,105	51,2553	0	N/A	N/A	N/A	N/A
subscr_equip_dur_cnt_6M	-0,1041	0,0026	1632,6845	-40,4065	0	0,9012	0,8966	0,9057	-0,2425
subscr_cust_age_cnt	-0,0008	0	352,1159	-18,7648	0	0,9992	0,9991	0,9993	-0,1124
call_in_onnet_top10_cnt_r_3M	-0,5538	0,0773	51,3715	-7,1674	0	0,5748	0,494	0,6687	-0,0422
subscr_react_cnt_6M	1,119	0,0896	156,0062	12,4902	0	3,0619	2,5688	3,6496	0,0745
subscr_tariff_chs_cnt_6M	-0,4478	0,042	113,6051	-10,6586	0	0,639	0,5885	0,6939	-0,0634
rechrg_amt_dist_cnt_6M	-0,6962	0,07	99,0069	-9,9502	0	0,4985	0,4346	0,5717	-0,0592
subscr_spend_amt_dev_6M	0,0385	0,004	90,508	9,5136	0	1,0392	1,031	1,0475	0,0565
call_out_offnet_top10_cnt_r_1M	0,3825	0,0737	26,9149	5,188	0	1,4659	1,2687	1,6937	0,03
call_in_dist_cnt_1M	-0,009	0,0011	71,3215	-8,4452	0	0,9911	0,989	0,9931	-0,05
rechrg_day_cnt_avg_6M	-0,0048	0,0009	25,4218	-5,042	0	0,9952	0,9934	0,9971	-0,0291
rechrg_call_z_bal_cnt_avg_6M	0,0013	0,0003	13,8628	3,7233	0,0002	1,0013	1,0006	1,002	0,0207
call_out_qty_bdi_3M	0,17	0,0413	16,9237	4,1138	0	1,1853	1,0931	1,2854	0,0232

For evaluation whether the model is good or not we also use the Lift graph. Figure 4.2 presents an example of this graph. If the graph, as a result of the model, shows a straight line, the model is not good, if it looks like an exponential curve, the model is good.

In this example, Lift in first decile (the first tenth of data) is 30%, which means that in one tenth of the customers we have identified 30% churners, and in the second decile Lift is 50%. This means that if the campaign is to target 10% of the population of customers, not taking into account the results of the model, the campaign would “impact“ 10% of churners. By using the findings of the model and targeting those customers who are prone to churn, we will “impact“ all 30% of the churners and therefore efficiently spend the funds foreseen for the campaign. The basic task of the evaluation is to check if something important has been overlooked and not included in the ADS, amend it if possible, and the entire model, proven to be accurate after statistical and logical evaluations, examined in sense of its purpose.

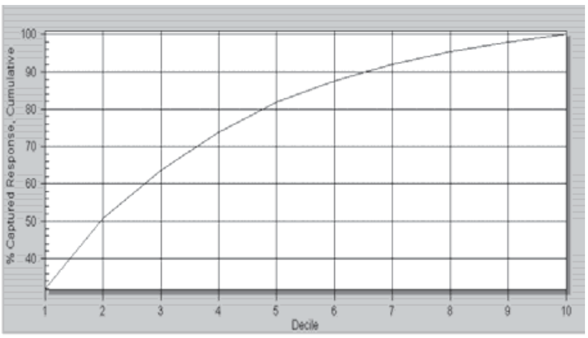

Figure 4.2. Lift graph

As a result of the model, we can get that the churners are customers who: spend less than average, rarely top-up their account, have a small share of long calls in the total number of calls, have a low share of calls during holidays, low share of sent MMSs and GPRS connections. In the evaluation stage, we should check if all these items (independent variables) can be influenced, i.e. to have the churn decreased.

In the last stage of the process, we have a base from which our “perfect“ model draws data to give us prediction of who will be a churner in the coming period and what is the probability of that. Also, the variables are defined with the biggest influence (either positive or negative) on the probability of churn. This stage implies the copying of the model on all active customers at the moment of scoring. As a result, customers will be evaluated with the probability of churn, on a scale of zero to one.

Development or scoring is done every month. With inclusion of all active customers in the processing, business analysts apply the acquired logistics equation. The table containing the probability of churn can also be added to MSTR in the form of new metrics, enabling business users to see it and connect it with the data on customers (phone number, name etc.), and to create reports.

Churn prevention is one of the main goals of this analysis. Researches on influence of cross selling on prevention of churn (Lariviere & Van den Poel, 2004) point to possible activities which can be undertaken for those purposes. Namely, discovering the products even the churners would probably like to get, allows some of them to be preserved.

4.2 Identification of market micro-segments

In conditions of growing competition in the field of telecommunications and a large number of users of these services, every serious company has to face the fact that every customer is not the same, but that there are groups of customers with similar needs. Micro-segments represent specific numbers of customers with similar behavior in respect of the usage of services and spending.

In Telenor Montenegro micro-segments are defined in four categories, as follows:

- average lifecycle income per customer,
- consumption of basic or advanced services,
- customer lifecycle,
- customer churn score.

Micro-segments are dynamic categories – changing from month to month because the behavior of a customer can also change. Depending on the income from a customer, how he spends by services, what is his lifecycle and probability that he will stop using the services, we can place him within a specific segment (e.g. he gives a very high income, uses only basic services, he is a new user and has a low churn score).

The final report which sorts all the customers in one of the micro-segments will have:

Attributes:

- customer's phone number (card),
- date of initial activation,
- average lifecycle income from customer,
- month,
- tariff plan,
- type of contract (prepaid vs. postpaid),
- status of customer (according to system).

Prompts:

- selection of segment by category of income (we can observe only those customers with a very low average lifecycle income or all, by all categories),
- selection of segments by use of basic or advanced services,
- selection of customers by lifecycle,
- selection of customers by churn score,
- selection of month to which the report relates.

Depending on the current goals of the company, by means of this report, we can find customers who are very risky in respect of churn, and who, at the same time, make large profit (those are most precious to every company), regardless to their lifecycle (in prompt on lifecycle we shall include all five categories). Iin order to know what to offer them, we shall observe their usage of basic or advanced services. Such creation of campaign and focusing only on the specific segment reduces costs and makes the campaign more efficient.

For example, with segmenting the customers to the basic and active ones, decision makers in the company decided to make new tariff plans for prepaid customers. The features of tariff plans are defined in the way that one is suitable for active customers (who frequently use SMS, MMS or GPRS, and few calls), and the other for basic customers (who call frequently). With direct marketing communication each segment is informed about the new tariff plan.

One month after marketing communication and notification about the new tariff plans, market research was done and it confirmed that exactly the highest number of basic customers is using the basic plan, while active customers are using the plan adjusted to their needs.

Before the DWH and the micro-segmentation model implemented in it, all plans were offered to the entire base of customers. On the one side that was creating really high costs of marketing communication, and on the other we would come to a situation that customers do not know what is better for them: Thus, they select the tariff plan which is not suitable for them (new products did not “impact“ its target group very well).

4.3 Some of the practical examples

We will also mention some of the practical examples how the decisions on the executive level made on the basis of business intelligence contributed to the improvement of operations of this company.

Table 4.2. Report from the monitoring of traffic and money transactions

	Number of calls									Net income								
	February				March				...	February				March				....
Phone number	Calls	SMS	...	USSD[1]	Calls	SMS	...	USSD		Calls	SMS	...	USSD	Calls	SMS	...	USSD	
38269xxxxxx				1									4.3					
38269xxxxxx	28	79			34	98				5.6	3.2			6.8	3.9			
38269xxxxxx					12			3									4.3	
38269xxxxxx					54	123		1						10.8	4.9		0.9	
38269xxxxxx				2									4.3					
38269xxxxxx	25	89			32	86				5	3.6			6.4	3.4			
38269xxxxxx					39	100		1						7.8	4		0.9	
38269xxxxxx	15			1	17								4.3					
.....																		

[1] *USSD represents the service for transfer of money from one account to another*

For more than 3 years, the users of Telenor company services have been able to use the service which enables the transfer of money from on prepaid account to another. In duration of the campaign for prepaid customers, related to getting the free minutes and/or SMS for each top-up, the increase in number of transactions from account to account was noticed. These transactions especially spiked in the period of launching the new plan for young people. This plan included free minutes for calls within the network for every newly activated number, and the activation cost was the same as top-up with the cheapest voucher. The fluctuation of new activations (purchases of new prepaid numbers) related to this plan was monitored for three months and the results were much better than expected. The number of new customers grew significantly, but the increase in average income, which should have followed such growth in the number of new customers, was not adequate, and that was the indicator that something is wrong.

After those three months, business analysts did the analysis of the entire traffic for customers who activated the new plan within the period of 3 months, and money transactions were also monitored. It was determined that there is a big number of new customers who, after having activated the plan, i.e. the purchase of the number, did not use the number at all, but they simply transferred the entire amount to another number. Besides that, there were also cases where the entire amount was transferred to another number, and the newly activated number was used only for calls within the network (the number had certain amount of free minutes remaining). Table 4.2 shows the report in MSTR which was created with the aim of monitoring the number of calls, SMSs and other traffic for customers who activated the new plan.On the basis of such a report, the numbers with certain traffic but no net income at all, except the revenue from USSD coming from those who had used the card exclusively for calls within the network (free of charge), are underlined, as well as the numbers with no traffic other than money transfers through USSD on the other side.

This situation was not good for healthy business and the following three reasons are given: first, after three months all newly activated numbers went to a suspended state (those which were not used, where the money was just transferred to another number) so the customers base was suddenly reduced; second, the planned incomes per customer were not achieved because of cases where new cards were used only for calls within network; third, the costs of making new cards were increased because the sellers demanded a large number of new cards, and a small number of EUR 5 vouchers, and it is understandable that for the company a new card is more expensive than a voucher.

The solution for this problem was to set up this service in such a way that the initial money on the account of the newly activated card cannot be transferred to another number, only if the number was previously topped-up with a voucher. This measure proved to be successful, after the verification of the number of transactions and their fluctuation.

In this example we saw how the problem occurred, and that the role of the business intelligence was crucial in its solving. Without DWH, there would not be a way to monitor the traffic of such a large number of new customers (around 100.000) three months retroactively, and it would be difficult to conclude to whom the money from the transactions went. Besides this, with reporting from DWH, entire series of operations of customers with their incomes and situation on the sales places were connected.

According to Stojanović (2009), in this company we emphasize that, in everyday actions, DWH, i.e. tools of business intelligence are also used when the complaints of our customers are received. Thanks to DWH, which keeps a huge number of historical data, we can react to complaints such as: a customer claims that the money disappeared from his account, that he did not set up the service which was charged to him later on, that he was activated too soon. Special departments which have the access to detailed accounts can also locate the customer (on the basis of base stations) if that is requested by the authorities. This does not provide direct profit for our company, but we maintain our rating and we acquire customers' trust.

Also, almost every year, in the summer months, when we usually organize campaigns which favor top-ups of prepaid accounts with vouchers of EUR 10, everyday monitoring of activities is done. In such conditions, direct marketing communication with customers who were previously prone to participating in prize games, significantly increases the number of EUR 10 vouchers, which increases the company's income. However, we need to emphasize that this is a company which is financially quite strong and it had no such limitations. Financial limitations are not the main reason why these systems are not used so much in our country. Case study research shows that it is possible to overcome the limitations related to time, upgrading and scalability of the system, and, the most important, inexperience and misconceptions regarding the possibilities of these systems. Case study research has shown that it is possible to implement, and also apply these systems on small markets as well and that they enable the company to achieve significant advantages in operations. The BI systems enabled this company to significantly reduce costs, and increase income and efficiency of operations.

5. CONCLUSION

In this paper we have recognized some advantages and limitations in the application of business intelligence on a small and poor market such is the one in Montenegro. Positive experience of Telenor Montenegro company shows not only the possibility for the implementation but also a large number of useful effects of these systems.

With the precise definition of business issues on which these systems are applied, as well as with good selection and training of personnel, companies can successfully implement and apply these systems in our conditions of business operations.

It is best to implement the system with the help of well known vendors, but with the participation of local personnel. The selection of local personnel needs to include people who are ready to adopt new knowledge and technologies. The personnel needs to be comprised of both IT specialists and business analysts.

Special importance should be given to the profile of business analyst, because that is the person who has to combine the knowledge from operations and complex technologies i.e. data mining methods. Success of data mining analysis frequently depends on a properly selected method. Investment in training of personnel is one of the key factors for successful implementation and positive effects of these systems.

Obsolete information systems and their data need to be purged and adjusted to the BI system. Considering poor financial conditions, complete reengineering of business processes and making a new scalable information system does not seem as the most rational solution. The experience of Telenor Montenegro company shows that the best solution is hiring technical personnel (IT specialists) who will daily take care on data quality during its loading to the data warehouse.

High price, long time of implementation and uncertainty in the success of implementation, which can be discouraging for small companies, can be overcome with the implementation of business intelligence only for some parts of a company. For example, applications can be developed only for sales and marketing and the corresponding part of data warehouse information. In this way, experiences and acquired knowledge from implementation of one segment can be used for faster and more efficient implementation in other segments.

What remains is an open issue of how to overcome the misconceptions regarding these systems, i.e. their efficiency. What is the best way to draw our companies closer to these systems and bring them to understanding of the advantages they can have from using them, and avoid companies having some unjustified expectations as if the systems are “almighty“.

Another open issue is what the empirical indicators would be of the effects of these systems with some other small markets which have a big number of BI system users. Such analysis on the market in Montenegro would be irrelevant because the number of companies using these systems is very low. Maybe the results of such analysis could be a motive for our companies to start with the implementation of the BI systems. To this effect, a further course of research could be on the subject of advantages and limitations in the implementation of the BI systems in ’small economies’.

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