Using Bayesian Belief Networks for Modeling of Communication Service Provider Businesses

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Abstract

This paper analyses the usage of Bayesian Belief Networks (BBNs) for Communication Service Provider (CSP) business modeling and simulation. Large and complex BBNs have been created to describe the causal relationships in CSP business domains. As a part of the study, a novel method to collect knowledge from a large number of independent experts living in different countries has been introduced. A BBN from each expert result was created (referred to here as a sub-BBN). Business model ontology was utilized to combine sub-BBNs together into a comprehensive model. The resulting BBN represents typical business circumstances in the European telecommunications domain. The experts participating in the study represented expertise in different business related categories such as technology, processes, customer experience, regulation, organization and products. Experts were asked to list causality triplets for business categories including causal connection strengths, in order to assess the belief part as well. The triplets were manually converted to a graphical causal map and conditional probability tables constructed. The benefit of the method is the capability to introduce rapidly a high number of variables and causal relationships. A challenge is that experts use different terms with the same underlying meaning.

1. INTRODUCTION

The Communication Service Provider (CSP) business is facing major restructuring due to several disruptive factors. These include new business players like Google and Facebook, technologies like the Internet, cloud computing and smart-phones, as well as a growing number and size of applications. It is clear that the CSP value chain structure has to be re-evaluated. To respond to these changes and customer requirements, and to adapt successfully to new business challenges, CSP top management needs reliable methods to model and to analyze the essential factors driving the change, and to understand the impact of these factors on their current and future business. In addition, trusted and unified information is needed for strategy planning processes and day-to-day management. Today the strategic decisions are often made by a small group and they are based on insufficient knowledge due to lack of data or expert knowledge and under time constraints.

Bayesian Belief Networks (BBNs), also called belief networks, Bayes Nets and causal probabilistic networks are increasingly popular methods for modeling uncertain and complex domains (Uusitalo, 2007). In this paper we examine how the BBN methodology can be utilized to help CSP management in their day-to-day work, strategy planning and to better control the business.

A BBN is a probabilistic model which represents a set of random variables and their conditional dependencies via a directed acyclic graph. Two basic approaches are used to construct Bayes networks: data-based and knowledge-based approaches. Data-based methods use conditional independence semantics of Bayes networks to infer models from data whereas the knowledge-based approach utilizes causal knowledge from domain experts to construct BBNs. The benefits of BBNs in data analysis are, according to Nadkarni, 2004; Uusitalo, 2007; Jensen, 2001; Lee, 2009:

1) Possibility to combine prior knowledge and data,
2) Managing situations where some data is missing,

3) Modeling of causal relationships,
4) Structural learning possibilities,
5) Support for different kind of analyses, such as making inferences about probabilities of different causes given the consequences and
6) Fast response to queries from the model.

Known challenges in BBNs are

1) Difficulty to obtain prior knowledge in a form that can be converted into probability distributions. However, for example a weighted sum algorithm utilizing compatible parent configurations has been developed to ease the calculation of conditional probability tables in complex environments (Das 2004).
2) Handling of continuous variables only in a limited manner (Uusitalo 2007) and
3) Lack of support of feedback loops due to acyclic nature of a BBN. Feedback loops are useful when analyzing phenomena like new disruptive CSP technologies as a function of time (Casey et al. 2010).

According to our knowledge, BBNs have in the past not been used to model the CSP industry in a large scale. The utilization of causality itself is wide spread in business management due to widely used performance measuring and management tools such as the Balanced Scorecard (BSC) and Tableau de Board. 66% of enterprises used BSC in 2007 (Rigby, 2007). Both the BSC and the Tableau de Board rely on causal assumptions (Kasperskaya, 2006). Causal mapping tools like fishbone diagrams, cause-and effect diagrams, impact wheels, issue trees, strategy maps, and risk-assessment mapping are tools to help managers to understand and improve complex systems in the areas of quality, strategy, and information systems. (Scavarda et al., 2006). The causalities in the performance measuring and strategy creation have been normally deduced by using human interaction techniques such as brainstorming or interviews. These methods rely on person-to-person or group interaction in eliciting the knowledge and are fraught with biases associated with inter-person dynamics. Methods to elicit a non-biased knowledge in large scale have been developed (Nadkarni et al., 2004; Scavarda et al., 2006). Scavarda introduces a formal Collective Causal Mapping Methodology (CCMM), which collects information asynchronously from an expert group which is dispersed and diverse. Person-to-person interaction possibility is eliminated and a large amount of experts can be utilized in a controlled way. Nadkarni introduced a procedure for constructing BBNs from domain knowledge experts, where through four steps of a text analysis process the first round interview results can be converted into causal relationships. Once the causal map is available, the states of the variables can be defined and validated with experts through subsequent interviews and finally the probability assessment done either manually or by using noisy-OR method or weighted sum algorithm utilizing compatible parent configurations (DAS, 2004) to reduce the number of probability assessments.

This study focuses on BBNs as a methodology for modeling and analysis of CSP business. As part of the study, both multiple sub-BBNs (one per expert) and a comprehensive CSP BBN combining sub-BBNs have been created. The experts were asked to list and categorize the variables they considered to have an effect on CSP business and also how strong this effect would be. The used seven categories are the same as in typical Balanced Scorecards and business models (Kasperskaya, 2006; Osterwalder, 2002 and 2005; Faber, 2003) namely financial variables, customer-related variables, product and service innovations, staff and internal processes, technology and architecture, strategy and competition, local and global economy and legislation.

The following types of information can be derived from the comprehensive model and sub models:

- Financial variables: Effect of variables like customer experience on revenue, OPEX (operating expense) and CAPEX (capital expenditure).
- Customers: The causes and consequences related to customer satisfaction.
- R&D organization: How do organization agility, managerial structures, salary and incentives affect on efficiency, productivity, OPEX and customer experience.
- Technologies: How do new technologies like rapid growth of smart-phones affect on CAPEX, revenue and data traffic.

BBNs that include all the seven categories are very complex. The number of variables and arcs, and especially the size of conditional probability tables play great effect on the practical usability of the BBN for CSB business analysis purposes. Optimization between practical usability and model granularity and accuracy is examined through creating the comprehensive BBN from sub-BBNs.

The remainder of this article is structured as follows:

Chapter 2 introduces a novel method for the collection of the expert knowledge, and describes how the expert knowledge is converted into BBNs.

Chapter 3 describes the constructed sub-BBNs and comprehensive BBN and elaborates on key variables and their analysis states. Also some result examples are given.

Chapter 4 discusses challenges in eliciting and conversion of prior knowledge into BBN and how well these models truly represent different aspects of CSP businesses. Also future research topics for this line of study are identified.

2. METHODS

2.1 THE KNOWLEDGE COLLECTION METHOD

Five targets were set for the developed method: 1) to combine different expert knowledge from various business categories with the help of a broad expert team and 2) give the experts freedom to focus on those causalities they feel, by their expertise, to be important in order to make sure that new innovative cause-consequence –relationships would arise, 3) to discover as much as possible variable candidates from CSP business domains, 4) to ensure that the experts acted as individuals and no group –thinking possibility existed and 5) to facilitate also disruptive proposals. Thus a pre-defined variable list was not introduced but instead experts had freedom to also name the variables. The financial category was seen more a deterministic than a probabilistic cause- consequences structure and thus it was decided that only a few experts need to be dedicated to financial topics.

An email was sent to 100 expert candidates working in 12, mostly European countries, for CSPs, universities, CSP infrastructure vendors and software and consulting companies which offer services to CSPs. The email included extensive background information about the study targets, introductions of BBN and causality, example variables and an excel template based on the seven CSP business categories. With the help of the template, experts were asked to list variables they considered to have effect on CSP businesses and to categorize the variables to the correct category. Basically experts were asked to list causality triplets of “variable X has some cause on variable Y, which has some effect on variable Z”, see *table 1*. It was supposed, that with this method, an expert can easily just start to write the triplets without need to first have a big picture in mind. In addition, experts were asked to estimate the strength of effect by using numbers:

Strong effect=3,
Moderate effect = 2,
Weak effect = 1

These values were used for measuring the expert’s degree-of-belief value for causal connections. The plan was to use a simplistic method, where both weight and belief parts originate from this strength of effect.

Triplets are in fact mini causal maps (see *Figure 1*) and constructing of one full BBN required combining these triplets together. This was done with a BBN tool called BayesiaLab (www.bayesia.com) by hand. The plan was to review the achieved model with each expert.

Table 1: Part of given example triplets.

Causing - variable(s)	List of variables	Effected variable(s)
Number of staff 2	Marketing effort	2 Market share, 1 aver. service usage, 2 OPEX
Network equip. need 1, current network equipment capability 1	Number of staff	3 OPEX, 2 marketing effort

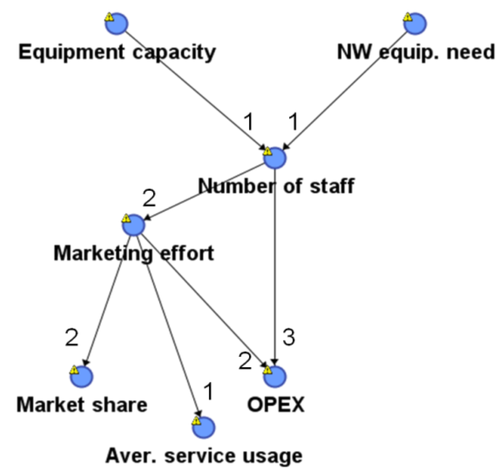

Figure 1: A causal map of two triplets from Table 1 including strengths.

2.2 SUCCESS OF KNOWLEDGE COLLECTION

Out of 100 expert candidates, 48 answered with survey results. The resulting causal models were reviewed with 60% of these 48 experts. The distribution of expertise was:

- Product and service innovations 21%
- Technology and architecture 20%
- Staff and internal processes 20%
- Strategy and competition 19%
- Customers-related 11%
- Local & global economy and legislation 5%
- Financial 4%

Experts used between 1 and 5 hours for the survey, with the average being 2,5 hours. More than 2200 variables and 3400 arcs and 40 sub- BBNs were created from the survey results. Text analysis (www.textanalyser.net) was used in order to understand word frequencies used in variable names. Out from about 5000 used words, 40% were unique. The top 12 used words for variable names were “product and service” 80 times, “customers” 60 times, “costs” 56 times, “market” 50 times, “product” 36 times, “brand 28” times, “new” 22 times, “revenue” 20 times, “price”, “marketing”, “personnel”, “network” 16 times.

From the text analysis it was clear that:

- The process to create a comprehensive BBN is challenging because of the high number of different variable names that have closely the same meaning. The plan was to give full freedom to experts in order to make sure that there were innovative approaches, but this study demonstrated clearly the need of business dictionary if Bayes Belief Networks are to be widely used in CSP business modeling and simulation.
- The competition for customers and tight cost control in European CSP markets might explain the top 12 used words, as the majority of experts were from European countries.

2.3 CONSTRUCTION OF A SUB-BBN

It was quickly concluded that the creation of a comprehensive CSP business model directly from triplets was a too complicated task. It was decided that individual BBNs, called sub-BBNs would be first created. One sub-BNN was created per expert and then the comprehensive BBN was merged from these sub-BBNs. This approach has two benefits: 1) it filters out excess of variables with the same meaning in the sub-BBN review –process with the expert and 2) innovative sub-BBNs will be documented individually.

The creation of a sub-BBN is straightforward: Variables and their causal connection were created manually from triplets by using BayesiaLab-tool (www.bayesia.com). A model review was organized whenever possible with the expert including the states. Each variable has typically only two states which describe best the variable in question like true/false, big/small, high/low, positive/negative, fast/slow.

2.4 PROBABILITY CALCULATIONS FOR A SUB-BBN

The conditional probability tables were calculated with weighted sum –algorithm utilizing compatible parent configurations defined by Das (Das, 2004). This algorithm allows for simplification of the calculation through the utilization of compatible parent configurations for the evaluations performed by the expert, limiting the need of individual probability state combinations needed to be evaluated.

For this study a simplistic method was used in calculation: The weights 3, 2, 1, -1, -2, -3 were used as relative weights and the same weight as probability after

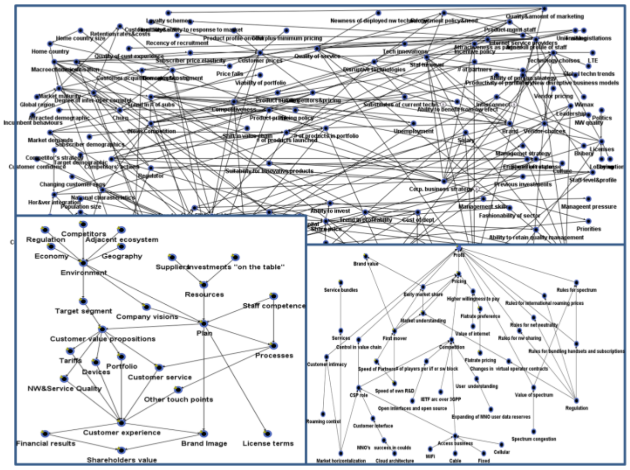

Figure 2: Sub-BBNs derived from expert surveys covered in 70% of cases all seven categories of CSP businesses but granularity varied greatly depending on expert.

converted them in the following way: 3=> 90%, 2=> 75%, 1=> 60%, -3=>10%, -2=>25% and 1=>40%.

In further studies, when the model(s) will be tested in CSP environment, the dual review method with experts will be used, namely first a causal model review with states alone, and after it second review with weights and confidence values.

2.5 CONSTRUCTING OF COMPREHENSIVE BBN

The 40 sub-BBNs varied in granularity and coverage (*Figure 2*) because experts were not asked to focus solely on their own expertise topic. Merging the sub-BBNs to a comprehensive BBN became challenging without a standard “kernel”. The Osterwalder business model ontology (Osterwalder, 2002) is used as a standardized causal kernel (*Figure 3*) to which sub-BBNs was merged.

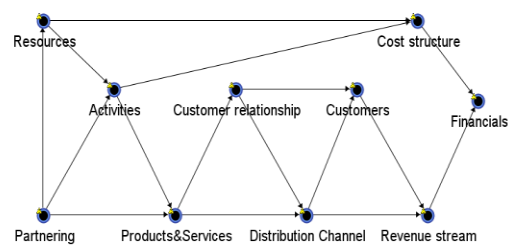

Figure 3: Osterwalder business model blocks, which are used as “a kernel” for comprehensive BBN.

The comprehensive BBN can be seen as an onion-like structure, where the kernel is from the business model ontology and surrounding layers represent experts’ sub-BBNs (*Figure 4*).

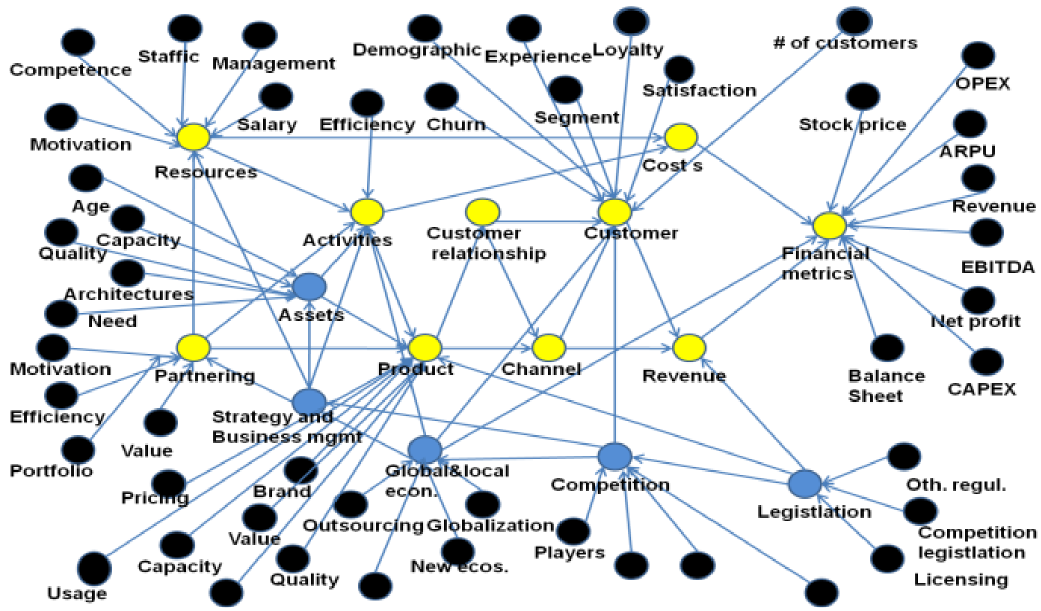

Figure 4: The comprehensive BBN constructs onion type of layers (black and blue circles) around the kernel model (yellow circles)

Comprehensive BBN with different granularities (number of variables and arcs) were created to test the tool and computer environment constraints. When the number of variables exceeds 100, and at the same time the relationship between number of arcs divided by number of variables is on the average greater than three and if a few of variables have five to ten common effects, the practical utilization of the comprehensive BBN for different kind analysis decreases due to slowness of the PC-environment. The objective of this study is not to focus on the tool usability nor model complexity topics but to discover a Bayes Belief Network which can be utilized in practice, contains all the seven business categories and which reflects the expert's common view about CSP variables effecting on business.

The merge process was performed manually, with variables and arcs being combined from each sub-BBN to the comprehensive network around it's kernel. If certain variable and causal connection existed in many sub-BBNs, the weights (used in sub-BBNs) were summed together. Thus, if 10 sub-BBNs have a variable "customer satisfaction" affecting with weight 3 "customer loyalty", then the combined weight is 30. The conditional probability tables have been calculated with the same method as described in sub-BBN-case. However, a dual review method is planned to be used when the model will be tested in real life.

3. RESULTS

This chapter presents both sub-BBNs, created based on individual expert's survey and the comprehensive BBN, merged from individual BBNs. Chapter 3.1 gives three examples of innovative sub-BBNs, which can be used, not only as an input to the comprehensive BBN but also independently. Chapter 3.2 presents results on the comprehensive BBN.

3.1 SUB-BBN EXAMPLES

Example 1: A generic purpose financial causal map with 32 variables and their relationships (*Figure 5*). Many of the variables and causalities are more deterministic than probabilistic and values are results of mathematical equations like calculation of EBITDA (Earnings before Interest, Taxes, Depreciation and Amortization). This map can be used to analyze the effect of non financial variables analyzed in other sub-BBNs connected to a comprehensive set of financial variables in this model.

Example 2: The variable "new business opportunities" is a parent variable for many new business opportunities for CSPs in a electric-car ecosystem (*Figure 6*), The business opportunities vary from traditional bit-pipe services to content service opportunities. The model contains variables such as the effect of regulator actions, environmental circumstances, renewal energy portion, new technology, price of electricity, price of a electric car, number of electric cars and emergence of new business opportunities. The model offers ways to analyze the effect of different ecosystem variables on potential new services. The states and probabilities of key variables in the model are shown *in Figure 6*.

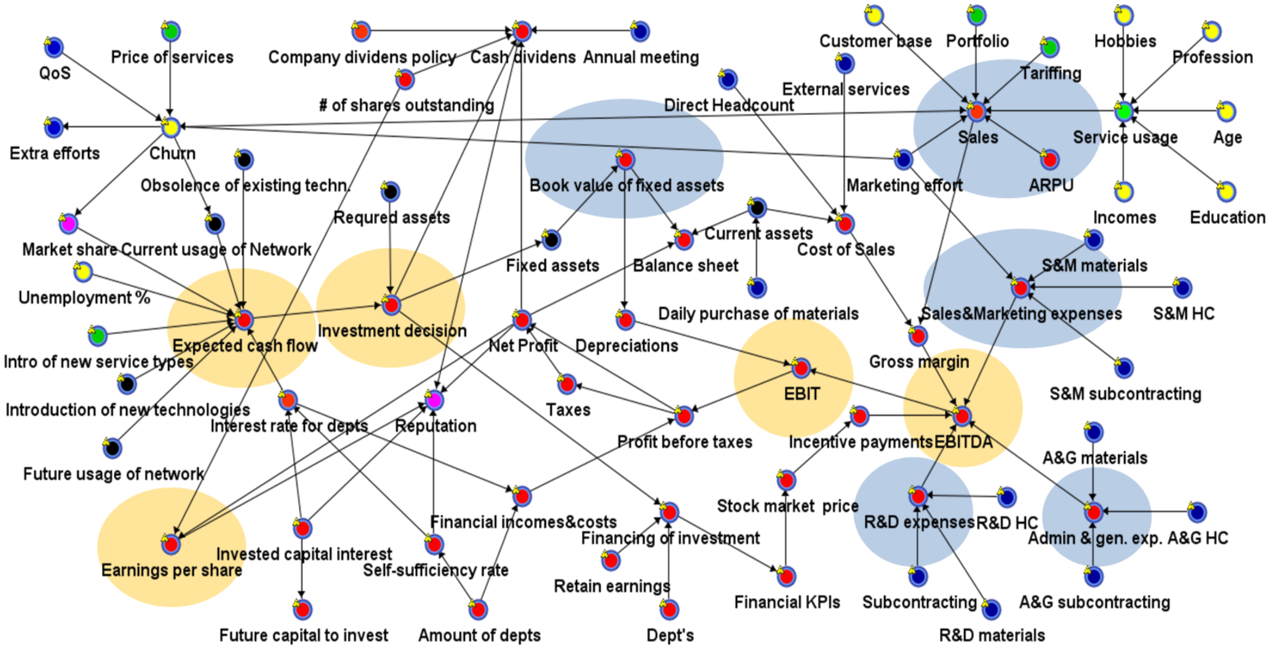

Figure 5: A generic purpose financial –related causal map. The red circles represent financial, yellow customers, blue staff and processes, greed product, black technical and pink competition-strategy –related variables. This model in its many parts is deterministic in nature and don't contain probabilities in this study. Sub-BBN's end up often to Sales, ARPU, R&D etc (blue disks) and with this map the financial analysis towards EBITDA , Earnings per share, expected cash flow and investment decisions (orange disks) can be extended.

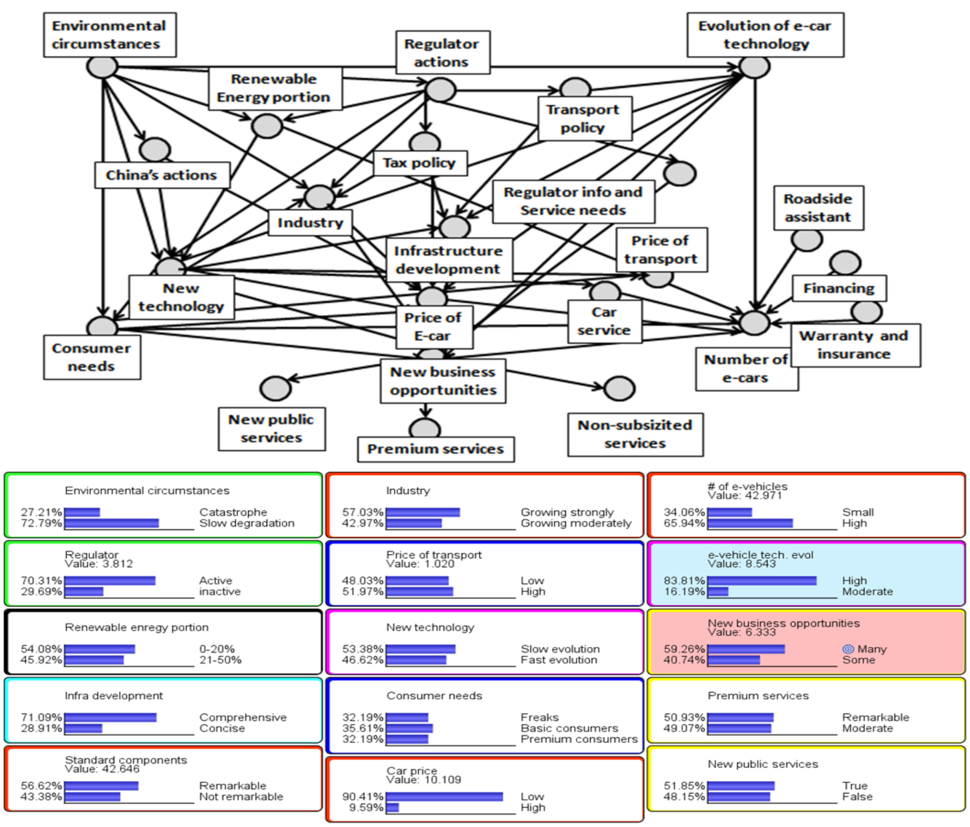

Figure 6: Key causal structure (upper part), states and conditional probabilities (lower part) of some variables in electric car ecosystem model. The variable "New business opportunities" represents potential new business for CSPs.

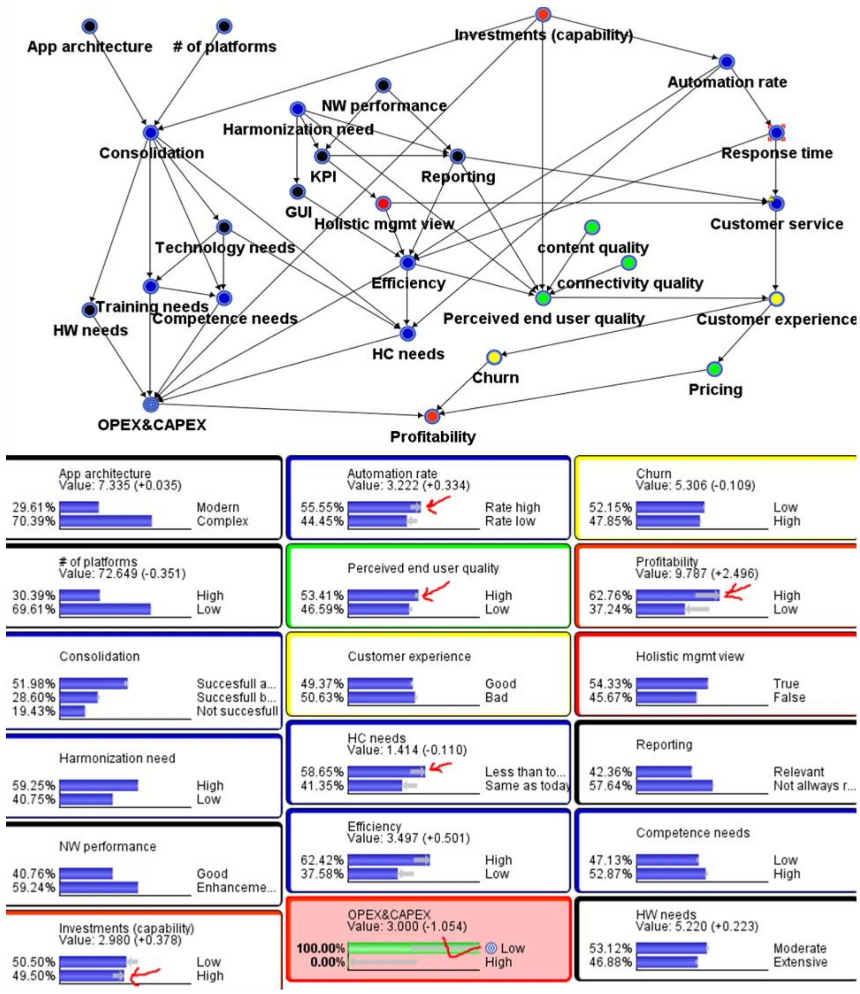

Figure 7: High level sub-BBN for typical European CSP Operations Support System (OSS) based on one expert's views. OPEX and CAPEX targets have been set to 100% in order to test the consequences: Automation rate needs to be enhanced, similarly more investment, head count reduction and activities to enhance perceived user quality are needed (red arrows).

Example 3: The task of Operations Support Systems (OSS) is to take care of day-to-day infrastructure management so that the network and related services work properly with high quality and in an optimized way.

OSS BBN parent variables are the number of today's management platforms (rather low), investment capability of the company (often restricted), current OSS architecture (often complex), network performance (often not enough) and harmonization need (typically high). The target variables in the model are OPEX and revenue/profitability. The model covers variables like training needs, technology, head count, perceived quality seen by customer, customer experience and automation need (*Figure 7*). The model, even though it is on a rather high level, demonstrates the great potential of Bayes Belief Network as a methodology for business reasoning and what-if analysis.

Also other innovative sub-BBNs were created, such as IPTV model, customer experience & satisfaction model, regulator causalities model.

3.2 THE COMPREHENSIVE BBN

The comprehensive Bayesian Belief Network was created from sub-BBNs as described in chapter 2. The BBN contains the kernel shown in *Figure 3*. The model (*Figures 8 and 9*) contains the 32 most used variables and their 93 causal connections. It is remarkable that three variables are very central in the model: 12 variables have variable called "Customer experience & satisfaction", 9

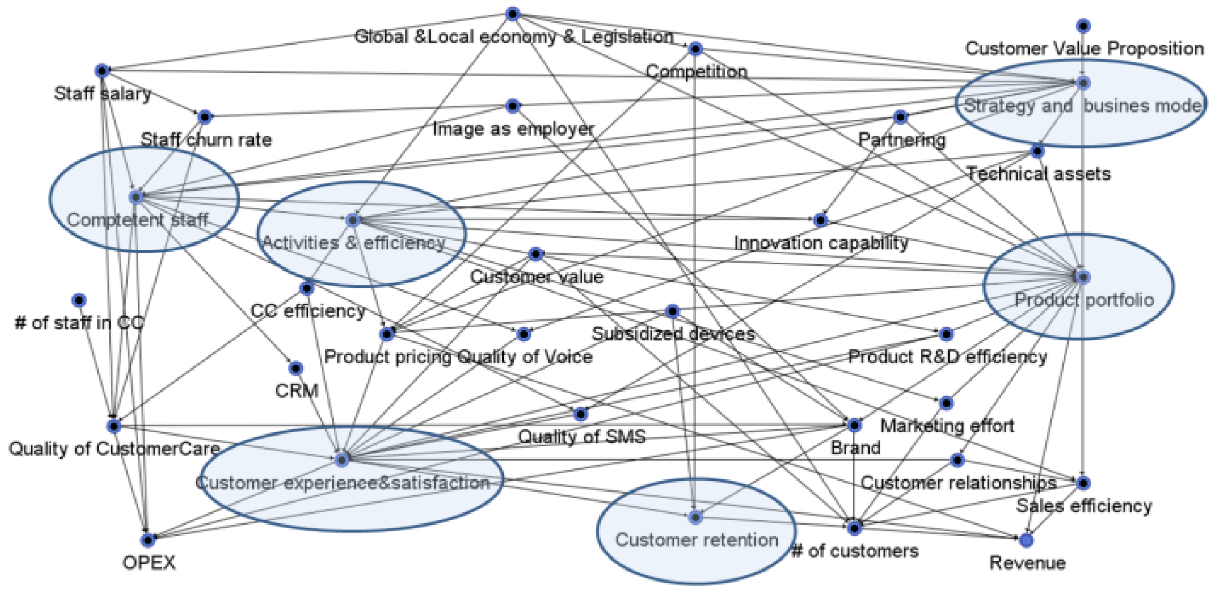

Figure 8: The comprehensive Bayesian Belief Network representing the overall feedback of the survey with granularity of 32 variables and 93 causal connections. The blue disks are the six variables, which have highest node forces as a sum of entering and outing arcs forces. Three from them, namely Customer experience & satisfaction, Product portfolio and Activity & efficiency are the central variables in the model.

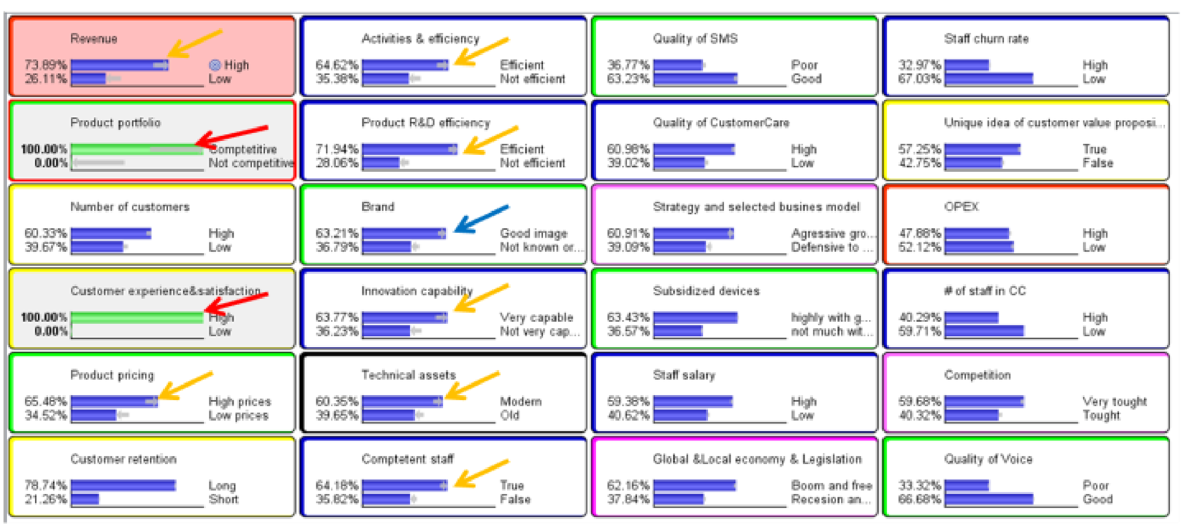

Figure 9: The states and probabilities of comprehensive BBN. The probability of the first state of variable "Product portfolio", "Customer experience and satisfaction" has been set to 100% (green bars).

variables "Product portfolio" and 5 variables "Efficiency" as a common variable. On the other hand there is only one purely technical variable even though 20% of experts had technical expertise. The reason for the lack of technical variables might be the fact that most of the experts were from Europe and the model represents thus mostly a mature European mobile and convergent operator's environment where customer experience, efficiency and portfolio play important role. The 32 variables and 93 arcs in the model were selected as a compromise between model granularity and usability and based on response times in analysis.

A light validation has been done for the model to verify whether it gives logical results especially because a simplistic conditional probability calculation method, where both weights for arcs and probabilities originate from same strength of effect value given by experts, has been used. *Figure 9* gives an example of the tests: It shows that when the probability of "Product portfolio" state "competent" is set to 100% and "Customer experience and satisfaction" state "high" is also set to 100%, the consequence will be that the revenue will increase clearly, when it is assumed that product pricing can be higher, efficiency of internal processes will be better, innovation capacity will increase, technical assets are modern and competent staff will be in place. These validations demonstrated that the model yield logical results.

4. SUMMARY AND DISCUSSIONS

An extensive study to model communication service provider businesses was performed. A novel method was used to elicit this prior information. Especially the way to create the so called causal triplets in the survey and to construct the initial BBN based on the triplets was found to be a fast, innovative and effective method that can be used to create different kind of causal maps. All together 40 Bayes Belief Networks were created, each representing an individual expert's view. These networks were then merged to one comprehensive Bayes Belief Network.

Models such as an IPTV model, OSS management model, customer experience & satisfaction model, regulator causalities model, the electric car ecosystem, financial model are examples of innovative sub-models. The biggest challenge in the knowledge collection was the excessive freedom in variable naming. Creation and usage of a dictionary would be, from work amount and quality points of view, a clear improvement for the eliciting of prior knowledge and this is highly recommended for future studies.

Calculations of conditional probability tables were based on a weighted sum algorithm utilizing compatible parent configurations for the states. The process used in this study was simplified but yielded promising results which motivate the further testing of the models in a real life environment. However, a dual review method with experts is needed in order to achieve more reliable results.

The results showed that the BBN is a potential method for what-if analysis and predictions in the strategy creation process but also in daily management and decision tasks.

Future research topics are to enhance and benchmark some of models in mobile operator environment in focused use cases as well as synthesis of expert knowledge with data in order to enhance the dynamicity of the model.

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