DECISION SUPPORT SYSTEM FOR COST-BENEFIT ANALYSIS IN SERVICE PROVISION

Emadoddin Livani[1], Elham Paikari[1] and Günther Ruhe[1, 2]
[1] *Department of Electrical and Computer Engineering, The University of Calgary, Alberta, Canada*
[2] *Department of Computer Science, The University of Calgary, 2500 University Dr. NW Calgary, AB, Canada*

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Abstract: Cost-benefit analysis is an approach to relate effort and cost of an activity to the resulting benefit. In this paper a novel decision support system for cost-benefit analysis in the context of service provision is proposed. Four decision support scenarios are investigated: (i) analyzing the impact of the services on cost and benefit, (ii) sensitivity analysis for the system variables, (iii) goal-seek analysis, and (iv) analyzing the impact of the services on operational resources. The key engine of the analysis approach is a Bayesian Belief Network (BBN). The BBN incorporates the key incoming, control and outgoing service parameters as well as their probabilistic relationships. In the sense of a hierarchical system, the variation of some of the parameters is guided by the results of optimizing operational resources being some of the BBN parameters. We've evaluated the framework in a case study with the City of Calgary's Waste and Recycling Services. The results showed that using such a DSS facilitates the decision making process and improves the overall cost-benefit ratio.

1 INTRODUCTION

Service Engineering (SE) is a technical discipline concerned with the systematic development and design of services using suitable models, methods and tools. A service can be any kind of material, energy, and information. Many studies have investigated on SE, e.g. (Bullinger, 2003), (Sakao, 2007), (Kapitsaki, 2009), (Sundin, 2010).

Providing services needs resources, like time, human, and budget. In the other hand, each service has unique value for the service consumer, hence for the service provider. As the resources are always limited, selection of services is needed to increase the value (benefit) of them. If we aggregate all the resources as cost and present the value of them as benefit, then the problem would be cost-benefit trade-off analysis. This analysis needs to be performed before an appropriate decision can be made or a proper action can be taken (Liu, 2003).

There is no deterministic relationship between a question and an answer in decision-making, as the process normally involves a great deal of personal experience and sophisticated reasoning. So, it's difficult to be modeled mathematically (Liu, 1999) (Liu & Alderson, 1999). Probabilistic techniques like Bayesian belief network (BBN) can be utilized for this purpose. BBN has been used in the literature as a decision making (and often decision support) tool for representing and reasoning with uncertain knowledge (Fenton, 2001) (Fenton, 1999) (Shirazi, 2009) (Heckerman, 1997) (Ibrahim, 2009) (Fineman, 2009).

Decisions are normally formulated by managers as three levels: strategic, tactical, and operational. The decision support systems in the literature usually focus only on one type of decision and do not consider the link between them (Liu, 2003) (Zoric, 2011) (Nanazawa, 2009). So, there isn't any sophisticated decision support system for cost-benefit analysis that evaluates both strategic and tactical level decisions in one coherent solution.

In this paper a novel decision support system for cost-benefit analysis of the services is proposed. It addresses the above gap, by answering the following questions:

- What's the impact of a certain service on cost and benefit?
- Which services dominate the others in terms of cost and benefit?

  Which system variables have the highest

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impact on cost and benefit?
- What's the impact of a certain service on tactical level variables?

In the next section, the architecture of the proposed decision support system will be explained. Then, the results of a case study evaluation of the framework will be analyzed in Section 3. Finally, Section 4 concludes the paper.

2 ARCHITECTURE OF THE DECISION SUPPORT SYSTEM

The decision support system proposed in this paper, as shown in Figure 1, consists of three layers: user, strategic, and tactical. These layers will be discussed in depth in the following subsections.

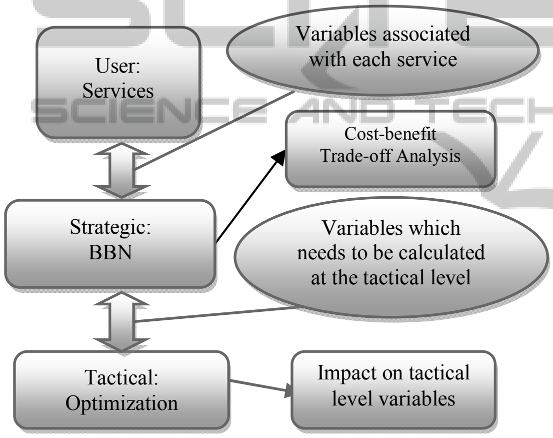

Figure 1: Architecture of the DSS.

2.1 User Layer: Services and their Mapping to the System Variables

Services are realized by unique combination of the system variables and are associated with their own cost and benefit. This layer, basically, maintains the definitions of the services, system variables, and the mapping between them. Mapping of a service to the variables means determining the variables which are affected by implementing it. This effect is measured by changing in probability distributions of the input variables in the BBN model (see the next subsection).

2.2 Strategic Layer: Cost-benefit Trade-off Analysis with BBN

At the strategic layer, Bayesian belief network (BBN) is used to analyze the effect of the input variables on the outputs of the model. A BBN is a directed acyclic graph consisting of nodes and arcs with a conditional probability distribution associated with each node (Heckerman, 1997) (Fenton, 1999). Nodes represent domain variables, and arcs represent probabilistic dependencies between them.

Basically, in a BBN model there are three types of variables: root, internal, and leaf. Root variables are the inputs to the model so they don't have any incoming link from the other variables, as opposed to the leaves which are output of the model and only accept incoming links. Internal variables lie in the middle connecting the former two types to each other.

The BBN model in this research is used for three well-known analysis types: user scenario, sensitivity, and backward (goal-seek). A scenario can be created by changing the probabilities of the input variables or considering them as evidence i.e. setting them to one of their possible values (by 100%). Each scenario leads to different probabilities for the leaf variables. The comparison of the scenarios means comparison of the probabilities of the leaf variables. We assume that in the BBN model there are two output variables, one for cost and one for the benefit. But the model is extensible to more outputs.

We define an abstract function F to map each scenario (S) to a point in a 2-dimensional Cartesian space. For each dimension, one for cost and one for benefit, the function F is represented by Formulas 1 and 2. In Formula 1, c is the size of the states for the 'Cost'. $V_{Cost}(k)$ is the probability of the 'Cost' being state k. Similarly, in Formula 2, b is the size of the states for the 'Benefit' and $V_{Benefit}(k)$ is the probability of 'Benefit' being k.

$$F(S, Cost): \{V_{Cost}(k) | \, k = 1 \dots c\} \rightarrow \mathbb{R} \quad (1)$$

$$F(S, Benefit): \{V_{Benefit}(k) | \, k = 1 \dots b\} \rightarrow \mathbb{R} \quad (2)$$

This mapping function, which is abstract, plays an important role in the scenario analysis. A simple concrete form of it could be the difference of the probabilities compared to the baseline situation (baseline is the initial model without any evidences). See Formulas 3 and 4 as examples. The goal is to minimize the F(., Cost) and maximize the F(., Benefit).

The sensitivity analysis is pretty similar to the scenario analysis, except the fact that the scenarios are created, not by prior knowledge instead, by setting each root variable (or internal) to its states one by one and keeping other variables unchanged. As a result, $\sum_{k=1}^{r} P(R_k)$ scenarios will be created for root variables, where r is the size of the root variables and $P(R_k)$ is the size of the states for variable R_k. Similarly, for the internal variables $\sum_{k=1}^{i} P(I_k)$ scenarios are created, where i is the size of the internal variables and $P(I_k)$ is the size of the states for variable I_k.

In any of the above analyses, user scenario and sensitivity, the probability of the leaf variables (cost and benefit) will be calculated for each scenario. Using Formulas 1 and 2, the trade-off graph will be created for all the scenarios. Figures 2 and 3 are example results (they will be discussed in Section 3). We used Pareto optimal solution (POS) to analyze the trade-off graph.

Definition 1. Assume we have set P of points, each point representing a scenario's impact on Cost and Benefit, measured by Formulas 1 and 2. Set $P^* \subseteq P$ is called Pareto set if no point in P* is dominated by a point in P (Nanazawa, 2009). We say point A dominates B if it has lower cost but higher benefit. For example, in Figure 2 the circled points are Pareto points.

In the backward analysis, evidence is set for a leaf variable instead of a root or internal one. The model will then suggest new probability distributions for the root and internal variables. This analysis specifies the requirements of the model in order to create the desired outputs. However, the suggested probabilities for the root variables might not always be feasible. So, an interaction with the expert (user of the BBN model) is usually needed to come up with an acceptable scenario.

2.3 Tactical Layer: Optimizing Operational Resources

Although analyzing the services at the strategic layer gives an insight on their cost and benefit, it can be further supported by measuring their resource consumption in the tactical layer. In this paper, the resources are the vehicles; so the problem will then be the vehicle routing (VR) optimization. However, our approach is a bit different from the traditional VR problem as we consider the intersections of the roads as the nodes of the graph and the roads between them as the edges. This will reduce the size of the problem dramatically.

We introduced a customized solution to this problem (named DCPP) by combining Chinese Postman Problem (CPP) (Edmonds, 1973) and Dijkstra shortest path algorithm (Cormen, 2009). H. Thimbleby (Thimbleby, 2003) proposed a heuristics for CPP in a connected directed graph. We extended it in order to make it work in disconnected graphs as well. Table 1 shows the pseudo code of DCPP algorithm.

First (steps 1-2), the graph G´ is created by removing the edges with weight 0 (no service point on them) from G. Then (steps 3-5) the closest sub-graph in G´ to the starting node is found. The closest sub-graph is defined as the one which has a node that is closest to the start node, based on Dijkstra shortest path algorithm. In step 6 the CPP problem is solved for this sub-graph. Then the next closest sub-graph to the last visited node of the previous sub-graph is found, again using Dijkstra. This process is repeated until all the sub-graphs are visited. At the end, the shortest path is taken to the starting node to complete the circuit.

The optimized values will then be used for two purposes:

1. As an additional support for selecting the decision alternatives (services) by presenting the actual effect on resource consumption;

Table 1: Pseudo code of the DCPP algorithm.

0	Algorithm DCPP (G: input graph, S: start node);
1	G´ ← Remove edges with weight 0 from G;
2	SG´ ← Set of sub-graphs in G´;
3	V ← S;
4	Route ← {};
5	SG ← Find the closest sub-graph in SG´ to node V based on Dijkstra shortest path algorithm;
6	Route ← Solve the standard CPP problem for SG and append to previous Route;
7	SG´ ← Remove SG from SG´;
8	V ← last node visited in SG;
9	Repeat steps 5-8 until SG´ goes empty
10	Find the shortest path from the last visited node to S

2. To feed back the BBN model with, potentially, the new probabilities (or even evidences) for some of the input variables. Input variables in the BBN model could be indirectly related to each other, so the optimization will suggest the optimized value for one, based on a change in the other one.

3 CASE STUDY

The City of Calgary business unit for Waste & Recycling Services (WRS) manages residential waste and recycling collection for 300,000 residential homes and operates three landfills and various community recycling depots. Examples of the decisions made regularly at the WRS include:

- Strategic level decisions like the budget, type and level of the services, training of the staff, etc.; and
- Tactical (or operational) level decisions like the number of humans and vehicles, routing of the vehicles, etc.

In the following subsections, the results of the case study evaluation for each component of the decision support system, presented in Section 0, will be discussed.

3.1 User Layer

Examples of the services at WRS are: collection of the residential waste and recycling, commercial waste and recycling, and Christmas tree collection. These services are unique as they need their own planning, budget, resources, and income. The cost of the services is measured by the actual resource consumption, which are mainly the human/vehicle used. The income (benefit) is a bit different though. For the commercial collection, the benefit is simply the charge, but for the residential units it's measured as the quality of the services (QoS). The WRS runs a survey each year to measure the customer satisfaction and interprets it as the QoS. So, if WRS increases the collection days per week for the residential waste, the QoS will increase but at the same time the cost will increase too. Therefore, the trade-off between cost and QoS is always pursued.

3.2 Strategic Layer

In this experiment we focused on the residential waste collection. To elicit the system variables, we used a tool named Very Best Choice *Light* ™ (VBC) (Ruhe, 2010). VBC is a collaborative DSS for eliciting and ranking system variables, requirements, or features. Stakeholders are defined in VBC to rank the variables. Consulting with the WRS experts, 20 stakeholders (from WRS and some external ones) and 20 initial variables were defined and devised as 5 groups: human, vehicle, routing, quality of service, and logistics. The stakeholders were asked to:

- Revise the variables, introduce new ones, or remove existing ones
- Rank the variables based on their impact on the cost

We selected the top 15 variables and built the BBN model using knowledge of the domain experts at WRS. The model and its variables are accessible on (Livani, 2011). SamIam (SamIam, 2011) was used to analyze the BBN model.

The objective function of Formulas 1 and 2 has been instantiated as Formulas 3 and 4, for Cost and QoS respectively.

$$F(S_i, Cost, S_0) = \left(Cost_i^H - Cost_0^H\right) + \left(Cost_0^L - Cost_i^L\right) \quad (3)$$

$$F(S_i, QoS, S_0) = \left(QoS_i^H - QoS_0^H\right) + \left(QoS_0^L - QoS_i^L\right) \quad (4)$$

In Formula 3, $Cost_i^H$ is the probability of Cost being 'High' for scenario S_i and $Cost_0^H$ for the baseline scenario (S_0). $Cost_i^L$ is the probability of Cost being 'Low' for scenario S_i and $Cost_0^L$ for the baseline. The objective function is defined similarly for QoS as Formula 4. So if the probability of being 'High' is increasing by a change in the inputs, it means the Cost (or QoS) is increasing in that scenario. But if the probability of being 'Low' is increasing, it means the Cost (or QoS) is decreasing. We've ignored the 'Medium' category for now because increasing (or decreasing) of it doesn't affect the Cost or QoS directly.

The baseline scenario resulted in probabilities for Cost and QoS respectively being as (46%, 49%, 5%) and (67%, 18%, 15%) for (High, Medium, Low) categories.

The next step is the sensitivity analysis. We created 75 scenarios by setting each variable (root and internal variables) to one of its possible states at a time (as an evidence), while keeping the other variables unchanged. The scenarios can be found on (Livani, 2011). Two graphs have been created, one for the root (Figure 2) and one for the internal variables (Figure 3). The circled points in each graph show the Pareto points, which dominate the other points in both Cost and QoS aspects.

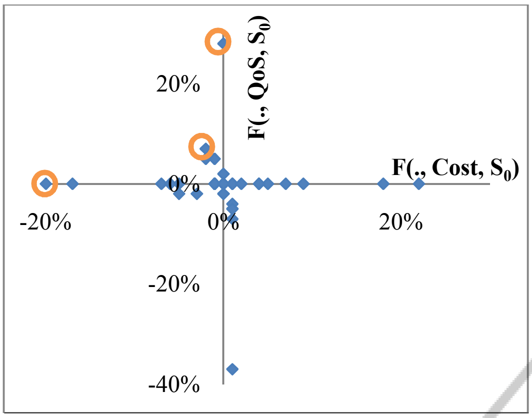

Figure 2: Cost vs. QoS trade-off for input variables.

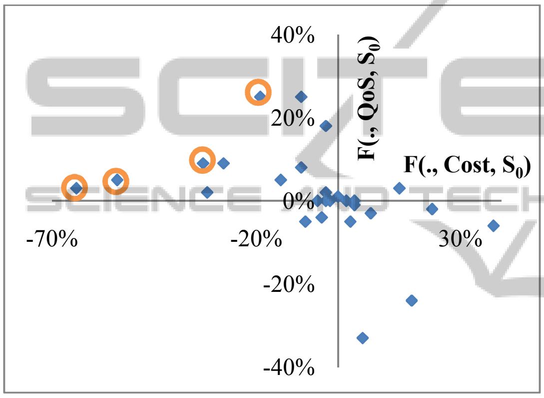

Figure 3: Cost vs. QoS trade-off for internal variables.

There is a difference between Figures 2 and 3. Pareto points in Figure 2 are related to the input variables, so they should be possible to achieve because they are the user inputs. But in Figure 3 the Pareto points are related to the internal variables which will then create new probabilities for the input variables. These new values might not be always achievable due to the restrictions in the inputs. So, the interaction with the user is needed to adjust the probabilities.

3.3 Tactical Layer

We applied the DCCP algorithm to a part of the road network of the City of Calgary. Each part is named a 'beat' and is defined as an area of the city which can be services by one vehicle in one day. The data, provided by the WRS, contained the roads and intersections between them, length and direction of the roads.
The optimized routes, created by the DCPP algorithm, showed 20% improvement in the total length of the routes taken by the trucks, compared to the actual routes taken by the city vehicles. We also integrated our results with ArcGIS (ESRI, 2011) to visualize the routes, available at (Livani, 2011).

3.4 Interaction between Strategic and Tactical Layers

The goal of the tactical layer is not just optimizing the operational resources. The results of the tactical layer are fed back to the strategic layer to re-analyze the model. One of the strategic variables in the BBN model is the 'KM Travelled per day'. This variable is directly affected by the beat design, which is usually unique for each service (waste, recycling, etc.). So, any change at the strategic layer which has an impact on the beat designs, needs to be further evaluated at the tactical layer by the optimization component. New values for this variables leads to new probabilities for the system variables. Therefore, the BBN model must be re-run. Another impact of the optimized routes will be decreasing the productivity of the collectors (human resources) every time that new routes are created. Therefore, again, the model needs to be re-run and new Pareto points will be generated.

4 CONCLUSIONS & FUTURE WORK

In this paper a novel decision support system for cost-benefit analysis in service provision has been proposed. It consists of three layers: user, strategic, and tactical. Services and their mapping to system variables are defined at the user layer. At the strategic layer, Bayesian belief network (BBN) is used to analyze the effect of the input variables on the outputs (here cost and benefit). Results are presented in the form of trade-off between cost and benefit; using Pareto optimal solution.

The strategic decisions will be evaluated further at the tactical layer through resource optimization. We evaluated our DSS in a case study with the Waste and Recycling Services (WRS) unit of the City of Calgary, Canada. Results showed that analyzing a service at the strategic level and implementing it at the tactical level is not enough. Instead, the optimization results must be analyzed to see which variables are impacted by the new values. Then the BBN must be re-run to create new Pareto points. This will lead to an iterative process for evaluating and composing the new services.

In this paper the initial (whilst recent) evaluation of an ongoing work towards creating a DSS for service engineering has been presented. Further analyses and investigations are needed to increase the accuracy and acceptance of the results. This can be done through more discussions with the domain experts and also mining the data available at the WRS. Using the Multi-Criteria Decision Analysis to further analyze and compare the Pareto points is also among our future works.

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