A Bayesian Network based on MCDM Framework for Reverse Logistics

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Abstract—Under the pressure from global competition, Companies are looking to reduce costs and business Process, and to increase their capacity for rapid development of new services and products. In order to ensure this, firms over the last decade focused increasingly on the integration of reverse logistics (RL) activities. The RL is considered as complex and dynamic network that involves many stakeholders including: suppliers, manufacturer, warehouse, retails and customers. This complexity is inherent in such process due to lack of perfect knowledge or conflicting data. Our research work emphasizes on decision making that is quite difficult process leading to the analysis of several variables or criteria which are characterized by uncertainty.

In this paper we propose a decision framework based on Bayesian network (BN) and influence diagram (ID) inspired by multi-criteria decision making (MCDM) design, in order to structure and manage the decision making process with explicit modeling of uncertain interactions among the reverse logistics stages.

Keywords—Reverse Logistics, Decision making, MCDM, Bayesian Network, Influence Diagram.

I. Introduction

RECENTLY due to driving factors such as environmental legislation and social requirements, and economic incentives, product recovery has received increasing attention. Reverse logistics is practiced in many industries including those producing: medical devices, commercial carpet, Computers, automobile and chemicals. Consequently, more and more firms have integrated the reverse logistics activities into their processes [1].

The Reverse logistical activities include return, remanufacture, disassemble and dispose of products consist of planning, implementing and controlling the efficient cost effective flow of raw material, in process inventory, finished goods and related information from the point of consumption to the point of origin with the primary purpose of recapturing value, or proper disposal [2]. Thus the associated decisions may drive a large extent of development in the process of manufacturing and remanufacturing, forward and backward material flows and related operational functions [3].

As the Reverse logistics is increasingly uncertain network, the process of decision-making becomes more complicated. This complexity arises from the fact that a decision maker does not dispose about information which quantitatively or qualitative is appropriate to describe, prescribe or predict, deterministically and numerically the decision-making criteria.

According to [4] the companies need to decide how to collect recoverable products from their former users, where to inspect collected products in order to separate recoverable resources from worthless scrap, where to reprocess collected products to render them remarketable, and how to distribute recovered products to future customers.

In fact, making these decisions requires an intelligent modeling methodology to capture and support the uncertainty in reverse logistics process. Therefore the aim of this work is to propose a particular structure of Bayesian network to enhance decision-making process under uncertainty. It will help producers in each stage of reverse logistics including: Collection, Sort/ Testing, and Re-Processing to select appropriate object among a large set of alternatives. The proposed model is illustrated with an industrial case of study of medical device remanufacturing.

The presentation of our work on developing a Bayesian network based on Analytical hierarchy process (AHP) design as MCDM methodology is organized as follow. Section II outlines the background of MCDM and Bayesian network/influence diagram. The decision making in reverse logistics is stated in section III. We present the probabilistic reasoning Approach in Section IV. Finally, Conclusion and further research are discussed in section V.

II. Background

A. Multi-criteria Decision Making (MCDM)

The Multi Criteria decision- Making (MCDM) involves “making preference decision (such as evaluation, prioritization, selection, and so on) over the available alternatives that are characterized by multiple, usually conflicting criteria” [5]. Basically, a MCDM problem is defined into hierarchy composed of four elements: Goal, the objectives, the criteria and the alternatives. These elements

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can be presented in a matrix format. Let $A = \{a_1,\ldots,a_m\}$ be a set of decision alternatives and $C = \{c_1,\ldots,c_n\}$ a set of criteria according to which desirability of an action is judged. A decision matrix D is a $m \times n$ matrix, in which element d_{ij} indicates the performance of alternative a_i, evaluated against the decision criterion c_j. It is often assumed that the decision maker has determined the weights of relative importance of the decision criteria, $W = \{w_1,\ldots,w_n\}$ [6]. The total score for each alternative is obtained by the following formula:

$$S_i = \sum_j w_j d_{ij}$$

When the overall scores are calculated for all the alternatives, the one with the highest score (utility node) is chosen. The multi criteria decision making includes such well known techniques as linear programming (only relevant when the criteria all have equal weighting and can be measured on a ratio scale) and other more recent techniques which help us to solve problems in more general cases when we do not have such ideal circumstances [7]. For example, among the well known MCDM Method we have the Analytical Hierarchy Process (AHP) proposed by [8] reflects the natural behavior of human thinking. This technique examines the complex problems based on their interaction effects, in other words the AHP model provides a way to detect interactions between various high-level decision factors, some of which are not easily quantifiable. The details of AHP procedure are described in [9]-[10].

However The MCDM has limitations that we must take account of by using Bayesian belief network in a complementary way. Specifically, the vast body of MCDA techniques makes three critical assumptions:

- That the relevant criteria are well defined (and hence for a given action a it is obvious how you can compute $f(a)$ for a given criteria f.
- That the relevant criteria are certain (and hence for a given action a and criteria g the value $g(a)$ is deterministic rather than stochastic).
- That the relevant criteria are independent of each other.

The Bayesian network and influence diagram provide a theoretically well-founded and operational basis for modeling MCDM and problem-solving.

B. Bayesian Network

Bayesian networks (BN), are widely used for knowledge representation and reasoning under uncertainty in intelligent system [11]-[12]. In general it's a graph with a probability for representing random variable and their dependencies. The uncertainty of the interdependence of the variables is represented locally by the conditional probability table (CPT) $\Pr(x_i / \Pi_i)$ associated with each node x_i, where Π_i is the parent set of x_i. An independence assumption is also made with BN that x_i given its parent Π_i is independent of any other variables except its descendents. The direct acyclic graph of BN comes up with unambiguous representation of interdependency between variables. The joint probability distribution of random variables $X = \{x_i,\ldots,x_n\}$ in a Bayesian network is calculated by the multiplication of the local conditional probabilities of all the nodes is given by:

$$\Pr(X = x) = \prod_{i=1}^{n} \Pr(x_i / \Pi_i)$$

According to [13] the inference in Bayesian network with General DAG structure is NP-hard. Inference is the task of computing the probability of each value of a node in a BN when other variables' values are known. While there are different algorithms for doing inference in a Bayesian network, the most important among them are algorithms for computing posterior probabilities $\Pr(x_i / e)$ where e denotes evidence (or observed values for some variables). These class of algorithms encompass belief propagation [11], and junction tree [14]-[15]-[16]-[17] and for exact solutions, and various statistical sampling techniques (Markov Chain Monte Carlo sampling) for approximate solutions with extremely large BN, a detailed explanation of the most common algorithms can be found in [18].

C. Influence Diagram

Influence diagrams are a conceptual modeling tool that graphically represents the causal relationships between decisions, external factors, uncertainties and outcomes. Influence diagram extend BN with two additional types of nodes: decision nodes and utility nodes. Nodes for the random variables in the BN are called chance nodes. The parents of random variables and values are the conditioning variables for their distributions, while the parents of decisions represent those variables which will be observed before the decision must be made. Shaded random variable nodes, called evidence nodes, represent variables whose values have already been observed [19].

In an ID, let $A = \{a_1, a_2 \ldots, a_n\}$ be a set of mutually actions, and H be the set of determining variables. A utility table $U(A,H)$ is need to yield the utility for each configuration of action and determining variable in order to decide between the actions in A. the problem is solved by calculating the action that maximizes the expected utility:

$$EU(a) = \prod_H U(a,H) P(H / a),$$

Where $U(a,H)$ are the entries of the utility table in the value node U. The conditional probability $P(H/a)$ is can be computed from CPT of the variable $h_i \in H$, given the action a is fired.

The algorithm for evaluating an ID According to [12] described as follows: (1) set the evidence variables for the current state, (2) for each possible value of the decision node, set the decision node to that value; (3) calculate the posterior probabilities for the parent nodes of the utility node using a standard probabilistic inference algorithm, and (4) calculate the resulting utility function for the action and return the action with the highest utility.

III. Decision Making In reverse logistics

Since most of reverse logistics activities are triggered by customer, and are hard to predict return, making decisions requires an intelligent modeling methodology to capture and support the reverse logistics tasks. Consequently, many researchers showed a deep interest into uncertainty problem in RL process. Some of these studies use of conventional analytic and multi criteria approaches, deterministic, stochastic modeling and artificial intelligence technique to support decision making.

In 2008 [20] developed a framework for RL decision-making with three main stages of flow: Collection, Sorting and Processing, each of these three stages in the framework has two options and there are eight possible alternatives (as is shown in Table I). The decision options for each stage are listed as follows:

Collection: proprietary (P) collection, in which the producer collects their own products, or industry-wide collection, in which multiple producers' products are in a single return stream (I).*Sort-test*: Centralized sort-test sites, which products are taken to a centralized location for sorting and testing (C), or distributed sort-test sites, in which products are sorted and tester or near to collection site (D). *Processing*: In this stage producer has two options: Original facility processing, which products are processed at the producer's own facility (O), or secondary facility processing, which products are processed at a Secondary facility (S).

TABLE I
Eight Network Configuration

Notation	Collection	Sort-test	Processing
(P,C,O)	Proprietary	Centralized	Original facility
(P,C,S)	Proprietary	Centralized	Secondary facility
(P,D,O)	Proprietary	Distributed	Original facility
(P,D,S)	Proprietary	Distributed	Secondary facility
(I,C,O)	Industry-wide	Centralized	Original facility
(I,C,S)	Industry-wide	Centralized	Secondary facility
(I,D,O)	Industry-wide	Distributed	Original facility
(I,D,S)	Industry-wide	Distributed	Secondary facility

In this context, and bearing in mind the importance of efficiently decide the fate of the return, we have proposed in [21] a conceptual design for reverse logistics based on multi-agent system (MAS). It consists of four layers which are: *Database layer*: Many information systems exist in this layer, for example we found respectively for reverse logistics Processes and Product data PDM and PLM systems, ERP, Step standardization, and among others. These systems are mainly used for query, maintenance, and communication; they can effectively utilized by the different actors (human /software agent) through the ontology layer. *Ontology (semantic web) layer*: It uses semantics-web technology to improve the flexibility of access in different terms; different system may have their own terms, this layer used to resolve the semantic conflicts arising from the cooperation between different and heterogeneous systems used in reverse logistics network [22]. *Coordinating system layer:* it's composed of 5 agents who act respectively during the 5 steps of reverse process: Gate keeping Agent, Collection Agent, Sorting Agent, Processing Agent and Disposal Agent, each agent has its own knowledge base that contains knowledge about the system environment. *Decision-making layer:* decision making is quite difficult process in reverse logistics leading to the analysis of several variables which are characterized by uncertainty, for this reason, the brain of agent is composed of a Bayesian network (BN). This option allows the agent to make a probabilistic inference for taking best decision about return, estimating benefits in cost and time. The relations among the four layers are shown in Fig. 1. Hence to construct this Bayesian network we were based on the multi criteria decision making design for RL network using AHP described above.

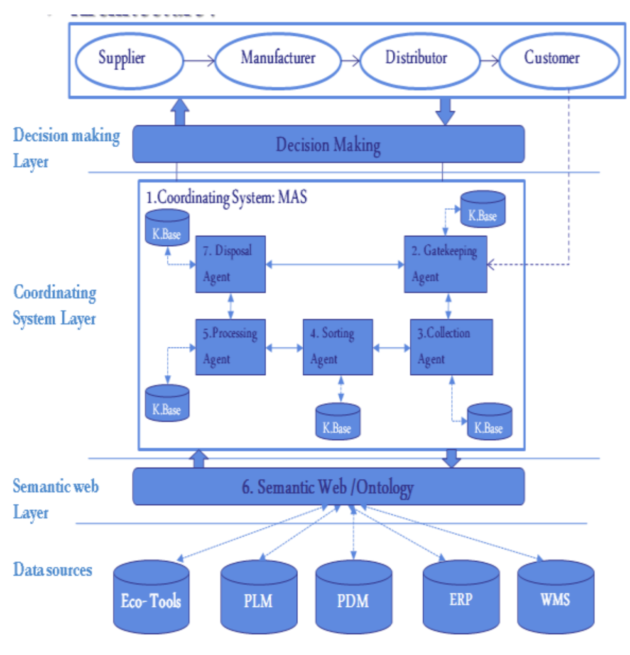


Fig.1 MAS Design for Reverse Logistics Management.

IV. Proposed Approach

The multi criteria decision making design proposed in [23] is composed of an overall goal, two principle criteria, six sub criteria, and eight alternatives. Therefore, our framework will be composed of three types of nodes: the three decision nodes, it represents the set of alternatives listed in Table I $A = \{a_1, ..., a_8\}$, the utility node represents set of objectives (overall goal) to be optimized, and the chance nodes include the set of criteria and sub-criteria:

$$C = \{C_1, C_2, C_{11}, C_{12}, C_{13}, C_{14}, C_2, C_{21}, and C_{22} \}.$$

The criteria and their sub criteria used in the system are listed As follows:

1) The cost savings criterion indicates the potential for cost savings and its relative importance as compared to business relations. This criterion has four main sub criteria: *Recycled Product Sub criterion*: is the return product going to be recycled, carpet or end of life consumer electronics? This sub criterion will have a high chance if there's a high potential for cost Savings for recycling the product, while if the product won't be recycled but instead will be reused or remanufacturing then there is a low chance for cost savings due to recycling. *Testing Cost Sub criterion*: how will the quality and the condition of the return product be determined? Does it require high cost equipment, specialized labor or materials? Or is the quality decision based on low cost procedures…. This sub criterion will be assigned a high ranking if the product involves high testing costs with potential to reduce those costs and it will have low chance if there's a little or no opportunity to save cost. *Scrap Shipped:* is there a high proportion of scrap in the return product stream? Does it need to be sent directly to a disposal location? If there is a high potential for costs for scrap in return product return stream. Then transportation costs for scrap will be high, and that allows a high chance for cost savings. In contrast, if there's a little scrap, then this sub criterion will have a low chance for cost savings. *Original Facility Sub criteria:* does the producer have the capacity in its original plant to reprocess return product? Is it willing to dedicate specialized labor or machines to the reprocessing system? This sub criterion will have a high chance for cost savings when the original facility have the capacity of reprocessing, and low chance for cost saving where a secondary facility would need to be obtained.

2) Business relations criterion consists of whether strong customer relationships exist and whether proprietary knowledge needs to be protected. There is an implicit balance between cost savings and business relation. Two sub criteria are grouped under the business relations criterion: *Proprietary knowledge*: Does the companies want to keep a return product out of the competitor's hands? If it's important that the producer control the return product process this sub criterion will have a high ranking. And if there's a little proprietary knowledge or no desire to control the return process, then it will be given a low chance. The second sub criterion is *Customer Relationships*: if the producer has a high degree of customer interactions and good customer relationships this sub criterion will have strong chance. If there are no direct relations, it will have a weak chance.

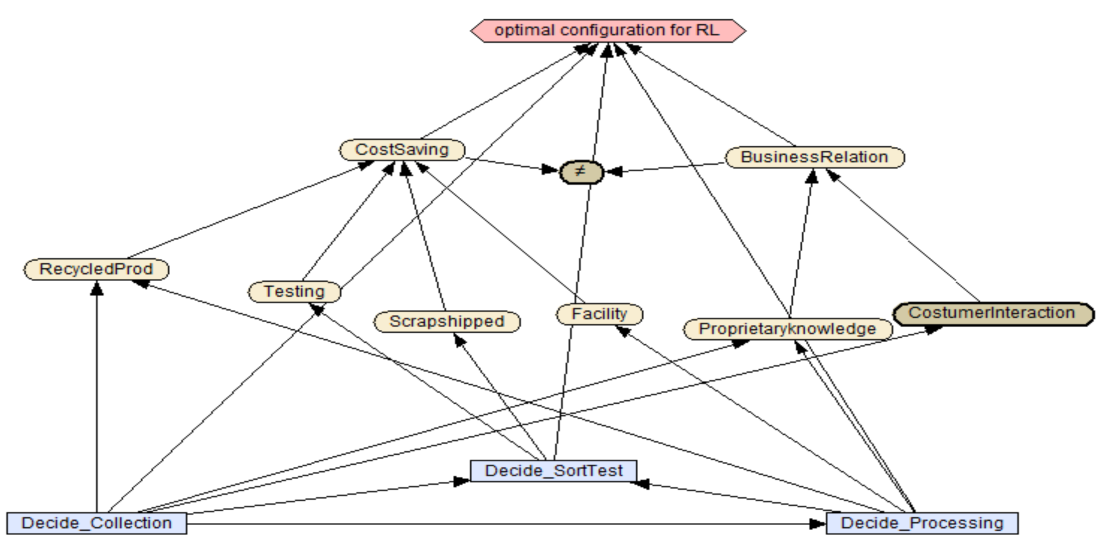
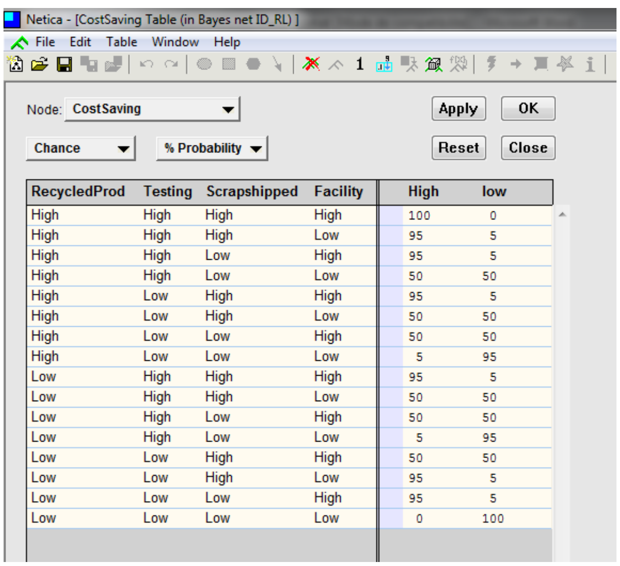


Fig. 2 Influence diagram for network design of reverse logistics.

Fig. 2 shows the influence diagram for network design for reverse logistics. The three decision nodes (Decide_Collection, Decise_SortTest, Decide_Processing) are represented by the rectangle shape. Their domains are all possible alternatives. The Cost savings and business relation are the two primary criteria. Each of these criteria has sub-criteria. Here we have four sub criteria Under the Cost saving (recycled product, Testing Costs, scrap shipped, and original facility) on the other hand, the business relation criterion has two sub criteria (proprietary knowledge and customer relations). The utility node U, represented by a diamond shape, is the utility function that measures the degree of the performance goals achieved for each decision. Once the network structure is completed, the probabilities are entered into the network in the form of CPT for each chance node. In our network, all the tables are small enough to be populated by hand, one of which (for variable "Cost Savings") is shown in Fig. 3 below:



RecycledProd	Testing	Scrapshipped	Facility	High	low
High	High	High	High	100	0
High	High	High	Low	95	5
High	High	Low	High	95	5
High	High	Low	Low	50	50
High	Low	High	High	95	5
High	Low	High	Low	50	50
High	Low	Low	High	50	50
High	Low	Low	Low	5	95
Low	High	High	High	95	5
Low	High	High	Low	50	50
Low	High	Low	High	50	50
Low	High	Low	Low	5	95
Low	Low	High	High	50	50
Low	Low	High	Low	95	5
Low	Low	Low	High	95	5
Low	Low	Low	Low	0	100

Fig. 3 The CPT for node "Cost Savings"

Since the auto-updating is turned on, Netica adds the no for-getting links from "Decide_Collection" to "Decide_SortTest" and "Decide_Processing", this indicates that "collection decision may be relevant to the other two decisions.

A. Updating Beliefs and Making Decision

Once the Bayesian network is constructed, it can be used to make various inferences about the variables in the model. The first inference we can do is to compute the prior distributions of other variables and the prior distribution of the utility, based on the priors of roots and CPT of other nodes.

Fig. 4 below shows the computation result for our network. It turns out that in the "Decide_Collection" node, Industry wide Collection system has the highest prior expected utility value (47.8333). Therefore the preferred processing option is Original facility and for the "Decide_SortTest" the distributed alternative has the highest prior expected utility value (47.8333). This result indicates that the producer should strongly consider the (I, D, O) as the best alternative.

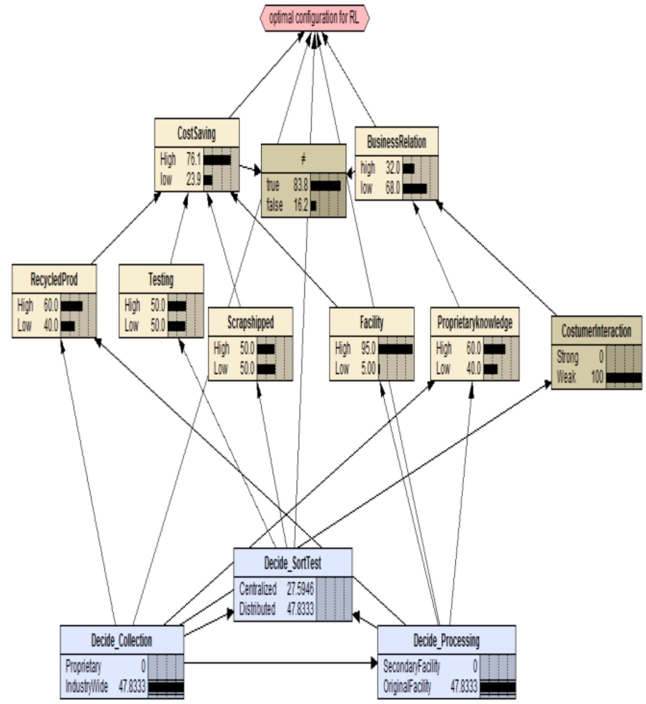


Fig.4 Prior Distributions of variables in the network.

In other hand if we observe the values of some of the observable variables (criteria and sub criteria), the corresponding variables in the network are instantiated to the observed values. The influence of these findings is propagated throughout the network to every other node, causing them to update their beliefs to become the posterior probabilities.

Fig. 5 shows the network after that evidence for medical devices remanufacturing has been entered and the probabilities updated. The details of the case of study are described as follow: *Phillips Healthcare is a major medical device manufacturer on the west coast. Its ultrasound device manufacturing division developed a remanufacturing program, which operates on a trade-in basis with customers under a service contract. The outdated product is evaluated at the customer site to be either recycled or remanufactured. Devices to be recycled are shipped directly to a national electronics recycler in Chicago, which reduces transportation costs that would be incurred if the product was shipped first to the manufacturer's warehouse on the west coast and then to the recycling facility. Device that may remanufactured are shipped back to the manufacturing plant for processing*. According to this case study the producer considers business relations to be more important than cost savings alone, because the company has invested heavily in both customer relationships through long-term customer service contracts, and proprietary product design. Therefore the business relation has high ranking.

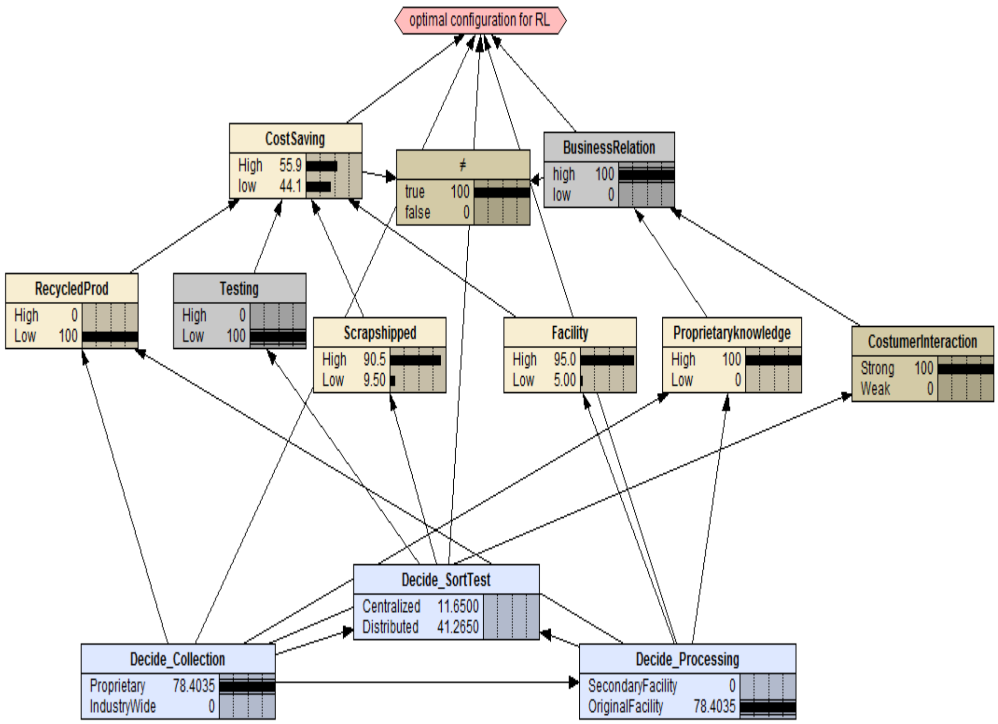


Fig. 5 Optimal Solution by entering evidence for Medical Device Remanufacturing.

The solution for the most optimal way to optimize the reverse logistic network shows that the Proprietary collection is clearly the preferred option with 78.4035, although distributed Testing site is the best option with the expected utility value of 41.2650, and for the Processing decision as is shown in the Bayesian network the Original facility is the preferred option with the excepted utility value of 78.4035. Therefore this result indicates that producer should strongly consider the (P, D, O) alternatives.

V. Conclusion

One of the major challenges for return product management is Decision-making process. This complexity is inherent in such process due to lack of perfect knowledge or conflicting information. Therefore to deal with this uncertainty we presented in this paper our ongoing work on developing Bayesian network based on multi criteria decision-making design for reverse logistics. The aim of this approach is to improve our proposed multi-agent system reasoning using probabilistic inference.

The work presented here is only the first step of our effort toward a comprehensive solution to this complex problem. Several issues need to be addressed in order to transform our architecture from conceptual one to one that is workable in real situations. First, we should incorporate the sensitivity analysis algorithms into our BN to check whether the best decision is sensitive to small changes in the assigned probabilities and utilities value.

Secondly we need to integrate the proposed Bayesian network into our proposed multi agent system design for reverse logistics.

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