

SUPPLIER SELECTION IN AN INDUSTRY OF SHORT LIFECYCLE PRODUCTS USING BAYESIAN NETWORK ANALYSIS

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ABSTRACT: This study presented an innovative Bayesian Network (BN) modelling and simulation for supplier selection problem of an actual electronic parts manufacturing firm of Pakistan. The list of qualitative and quantitative factors which affect this supplier selection decision was extracted from a variety of studies in literature. The problem was modelled and solved in respective BN software platform using the standard recommended procedure. Results showed that “Quality” and “Costs” were the most crucial factors for the Short Life Cycle (SLP) products industry under investigation. The supplier alternative which was strong in these factors, had emerged as the most suitable option. The results were found to be beneficial for other SLP industries of Pakistan too.

Keywords: Bayesian Network Modelling, Supplier Selection, Electronic Industry, Quality and Costs.

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INTRODUCTION

The ultimate success of an industry of short lifecycle products (SLP's) is contingent to the optimization of raw material supply (Talluri and Narasimhan, 2003). Raw material and component costs account for approximately seventy percent of the original cost of a product (Ghodsypour and O'Brien, 1998). Researchers claim that about fifty percent of the quality defects in produced parts are because of the defective materials delivered by suppliers (Talluri and Narasimhan, 2003). Decision of selecting the appropriate raw materials and components is, therefore, very crucial for top management of industries (Stevenson and Hojati, 2007). In this rapidly changing technology era, the short lifecycle products (SLP's) are increasing day by day thus requiring quicker and dynamic responses from the suppliers (Aytac and Wu., 2013). Since there are many parameters which influence supplier selection decision, the problem comes under the domain of multi-criteria decision making (MCDM).

The factors affecting selection decision can be qualitative, quantitative, or combination of both. A number of MCDM supplier selection methods are available including cluster analysis (Luitzenet *et al.*, 2001), reasoning systems based on cases (Choy *et al.*, 2003), statistical models (Luitzen *et al.*, 2001) and other decision support systems. Bayesian networks (BNs) is one of the approaches found in MCDM which has the ability to tackle the uncertainties (Wathayu, 2009). BN has been used in image processing, system reliability analysis, medicine, decision making and other similar research areas (Iqbal *et al.*, 2015). BN model is difficult to build

and complexity of model is directly proportional to number of inputs.

Contrary to industries dealing with longer product lifecycles, the SLP based industries need a more dynamic and detailed evaluation of criteria and supplier alternatives. It is because of the reason that SLPs survive in market for a shorter period thus requiring quick and in-depth analysis of the changing environments. Normally, there is a large number of criteria and alternatives which increases the inputs of BN conditional probability tables (CPT's). This is, probably, one of the reasons why researchers have only rarely applied BN's in supplier selection problems of SLP industries.

In the present study, BN modeling and simulation of a real world supplier selection problem in electronic industry of Pakistan was evaluated using actual data and expert opinions. The basic aim of deploying BN techniques is to identify potential supplier with maximum prospective to consistently meet organization's requirements.

MATERIALS AND METHODS

Construction of Bayesian Network Model: Bayesian Network (BN) models were constituted and their concerned framework was developed with respect to the software platform. A three step process for Bayesian Network modeling as described by Wathayu and Peng (2004) was developed. Bayesian network (BN) was built with network structure (A_N) and network parameters (P_N) i.e. $BN = f(A_N, P_N)$.

The network structure $A_N = (N, E)$ was a qualitative descriptor having acyclic structure, and was composed of node variable set ($N = N_1, N_2 \dots N_n$) and

directed edges set $E = (N_i N_j | N_i, N_j \in N)$. Node variables were used to represent the factors affecting the decisions in the network. The reliance between variables was expressed by directed edges. Each node was assigned a series of 'states', which represented the range of conditions that the node potentially occupied under different conditions. The range of discrete state was described by series of separate states; whereas, the continuous states expressed in the form of Normal (Gaussian) distribution function. The directed edges represented causal relationships between nodes. The direction of directed edge initiated from cause and ends at effect. When two nodes were linked together, the destination node was termed as 'child'; whereas, the node from which the link originated was called as the 'parent'. When a node had no links, the user was expected to define the state of the node. The parentless variables used were: (a) a possible action, (b) a scenario that might arise, or (c) an observed (known) condition (Bromley *et al.*, 2004).

Network parameter (P_N) on the other hand, represented the probabilities between variables. It was reflected in conditional probability table (CPT) and was expressed through the following relation, $P_N = P_N(N_i | N_1, N_2, \dots, N_{i-1})$, $N_i \in N$.

The strength of a link between two nodes was expressed as a 'probabilistic dependency', which was quantified by a conditional probability table (CPT). Each node within a network contained associated CPT. In this case, the selected state depended on the nature of the node and was based on existing evidence of the state of the variable. Setting the states in this way was described as entering 'evidence'. Entering evidence in a node resulted in a chain reaction of impacts on all variables linked to it. When a network was run with a new set of starting conditions the probability distributions reflecting the state of each linked variable was changed. The data was obtained from three different sources including (i) direct measurements, (ii) output from models, and (iii) expert opinion. The complete Bayesian Network (BN) model was represented by $B_N = (A, P_N) = (N, E, P_N)$. If there was 'n' number of nodes set, the cumulative probability was obtained through $P_N(N) = P_N(N_1, N_2, \dots, N_n) = \prod_{i=1}^n P_N(N_i | N_{pi})$ relation (Zhang and Guo, 2006).

Framework of Bayesian Network Model: The Bayesian network of present study included different nodes constituted in the respective software (Netica®).

Expert Opinion Nodes: Expert opinion nodes were the starting nodes in the network. These were input nodes which took data from experts. The nodes were 'n' in number corresponding to 'n' number of expert opinions. Main criteria were defined in the form of states which were basically factors identified through literature review and recommendations by experts. The experts assigned

importance weights by evaluating these states from zero to hundred percent.

While working in the mentioned BN software, data was entered through bars available against each state. States of each node were connected as per relationships. For instance if state '1' was assigned hundred percent weight, other nine states would have got zero. On the other hand, if nine states were assigned ten percent weight each, then remaining tenth states had got a weightage of ten percent by default. Since expert opinion nodes were input nodes, there was no need to enter CPT (Conditional probability table) values. CPT values of nodes without parents (input nodes) were randomly assigned by software.

Resultant Node: Resultant node was the mid position node. It got input from expert opinion nodes and passed output to decision node. It had same states like expert opinion node. Its states represented the average resultant of data from expert opinion nodes. It provided the relative importance of one state over the other. CPT values were computed to provide the probability of resultant node being in a particular state based on the states of its parents (expert opinion nodes). For example, if experts from one to 'n', selected state '1' with highest probable value then state '1' of resultant node had got highest probability and vice versa. Bars against each state represented the probable resultant value of each state.

Characteristics of Alternative Nodes: The alternatives to be compared were defined in nodes. Characteristics of alternative nodes were similar to expert opinion nodes with same states. The weights of factor states were defined on the basis of alternative performance. Bars available against each state were used to enter data for specific state. Each state contained values from 0% to 100%. Since these were also input nodes, there was no need to compute CPT values. These nodes existed at the same level as that of the expert opinion node.

Decision Node: Decision node was the closing node of the network. It was the output node which was situated between resultant node and characteristics of alternative nodes. The decision node gave us an output based on resultant node inputs and characteristics of alternative nodes. Its state represented the alternatives. It provided the relative evaluation of one alternative over the other. The alternative with the highest score was selected as the best option. CPT was evaluated to provide probabilities for decision. For example, if resultant node had assigned the highest probable value to state one, the alternative with highest state one value would have got highest probability for selection. The bars against each state represented the probable value for selection. The state with highest probable value was selected as best option (Fig. 1).

RESULTS AND DISCUSSIONS

The BN models proposed in previous sections were solved by taking the real world data of an actual electronic parts manufacturing firm in Pakistan. The main objectives of the implementation of current BN models were to evaluate the suppliers and prioritize the factors affecting selection decision. The experts from the procurement department of the selected electronic industry provided necessary information about three shortlisted suppliers for a specific purchase order of LM324 (general purpose transistors). The main and sub criteria were determined through detailed literature review followed by the recommendations of concerned experts.

The expert opinion was collected through oral interviews as well as using standard BN questionnaires. Since very rare studies on supplier selection had previously been performed in Pakistan, the experts agreed that all of these main and sub-criteria, initially explored from the respective literature, should be taken into account due to their vital impact on production decisions. However, once BN analysis was complete, a few factors were eliminated and others got higher priorities due to particular socio-economic and cultural conditions in Pakistan.

After identification of the supplier alternatives and screening of the affecting factors, the next step was construction and evaluation of the Bayesian Network which included: (i) construction of nodes, (ii) development of links between these nodes, and (iii) construction of conditional probability tables (CPTs) behind each node to calculate the states.

As per requirements of our case study, eight nodes were constructed. Three experts from the mentioned electronic industry were selected to assign weights to criteria and sub-criteria. Input nodes represented the experts whereas their 'states' represented the criteria. Since there were ten main criteria for supplier selection, the number of states was also ten. The nodes were named as "Expert_1", "Expert_2" and "Expert_3". Three nodes along with ten states were observed (Fig. 2). Once the experts' response in form of questionnaire and interview was fed into the input nodes, the resultant node was computed. An instance of the CPT for resultant node is shown (Fig. 3). CPT of resultant node was evaluated by probabilities based on Bayesian theorem.

If all the three experts gave hundred percent probability to 'Delivery' then its probability of being the most preferable factor became hundred percent. Similarly if two experts assigned hundred percent probability to 'Delivery' and third expert to 'Quality', then 'Delivery' had seventy percent chances of getting the most preferable factor and "Quality" has thirty percent.

Final probabilities of criteria calculated by BN model is presented (Fig 2). Results showed that there was

13.9% probability that 'quality' was the most preferable factor. Cost had second highest preference as it had second highest probability. Therefore, 'quality' was emerged as the highest priority factor followed by 'costs' and 'services'. The factors like 'packaging ability' and 'reputation' (impression) seemed to be least important factors for specified product. As far as the comparison of these findings with other Pakistani specific studies was concerned, it was proved that "Quality" remained the most important factor in all cases. For instance, it was on top of the list in the studies on automotive industry by Abbasi *et al.* (2015) and on the telecom industry by Rashid (2014). However, other criteria rankings were not similar to other studies due to nature of electronic industry problem and the stochastic approach of BN analysis.

Three supplier nodes were constructed and named as "Characteristics_of_Supplier1", "Characteristics_of_Supplier2" and "Characteristics_of_Supplier3". The weights to suppliers were assigned based on collected data. The nodes were linked as per standard format (Fig 2). Conditional probabilities as recommended by the experts based on their previous experiences were entered in node CPT's. The decision node selected best possible alternative. The CPT for decision node is shown (Fig. 4). The probabilities of the suppliers were assigned with respect to each factor.

As far as the rankings of alternatives were concerned, supplier-3 was computed to be the best option based on cumulative rating, due to its excellent weights for factors like 'costs', 'quality' and 'packaging ability'. Supplier-2 was strong in 'quality, cost and delivery'. Though Supplier-3 had got the least overall rating, it was not far behind its competitors.

One of the problems with most of the previous studies on supplier selection like data envelopment analysis (Luitzen *et al.*, 2001 and Zhu, 2004), total cost of ownership models (Degraeve *et al.*, 2000 and Luitzen *et al.*, 2001) and artificial intelligence (Choy *et al.*, 2003 and Luitzen *et al.*, 2001) etc. was that they could not take into account the real world uncertainties. These methods were successfully applicable for supplier selection problems and often failed to cope with associated uncertainty particularly for SLP's. Socio-economic conditions which were highly volatile in Pakistan thus requiring those MCDM techniques which could handle the vagueness and uncertainty in data pools and collected information. One way of coping with these uncertainties could be using such methodology which was reinforced by authentic probability theories. Other methods applied so far in supplier selection problems were mostly unable to do that. Present implemented BN analysis was, therefore, an innovative approach in Pakistani electronic manufacturing firms which had the ability to tackle that

uncertainty as has been recommended by Watthayu (2009).

Sensitivity analysis was performed to observe the effect of changing inputs on the final decision. The model was used to analyze different situations by changing the experts' preferences. These hypothetical scenarios are provided (Fig. 5). By considering all these extreme options, the associated risks where was the main focus of research by Garvey *et al.* (2015) were considered. In scenario 1, the preference of 'delivery' was raised to maximum i.e. 100% and all other factors were kept at minimum i.e. 0%. Supplier-1 was the best

option for decision makers under these circumstances. Same procedure was applied to analyze the sensitivity of each factor.

Supplier-1 became the best option if the factors like flexibility, service, impression, packaging ability and reciprocal arrangement were considered as the most important factors one by one. Supplier-3 secured the top position for imaginary scenarios when quality, cost, financials and flexibility were given the maximum weights. On contrary, Supplier-2 was not a suitable supplier for any supposed scenario (Fig. 5).

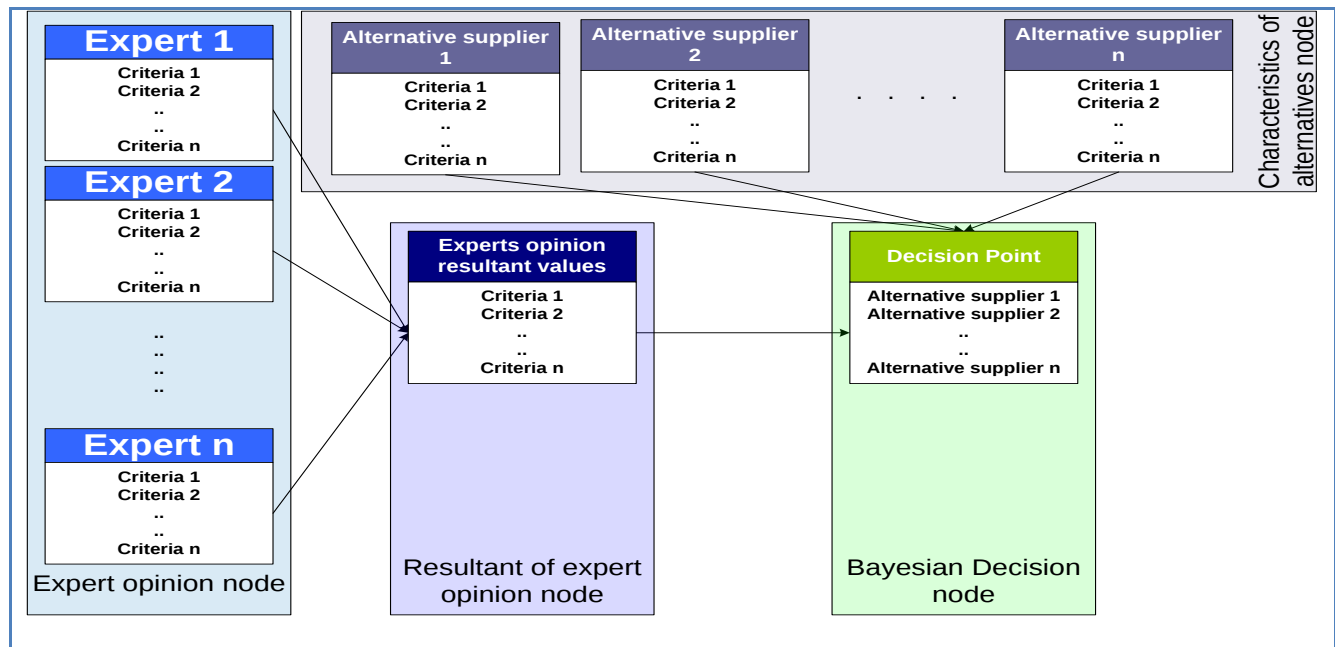


Figure 1: Bayesian Network Framework

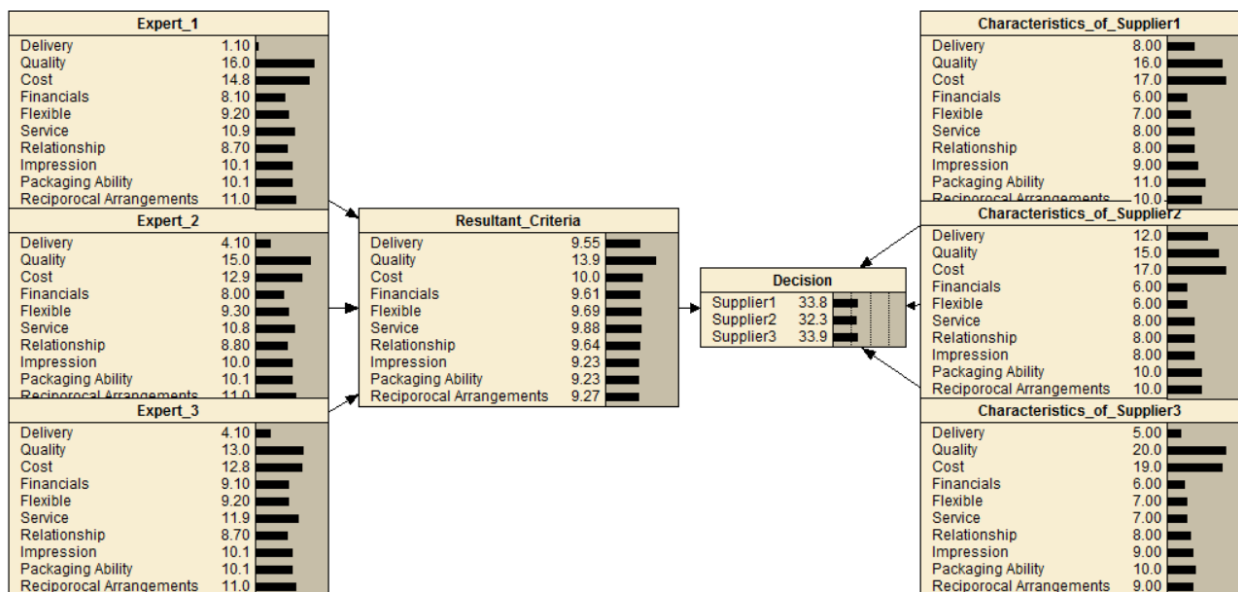


Figure 2: BN Structure

Person_1	Person_2	Person_3	Delivery	Quality	Cost	Financials	Flexible	Service	Relations...	Impression	Packagin...	Reciporo...
Delivery	Delivery	Delivery	100	0	0	0	0	0	0	0	0	0
Delivery	Delivery	Quality	70	30	0	0	0	0	0	0	0	0
Delivery	Delivery	Cost	70	0	30	0	0	0	0	0	0	0
Delivery	Delivery	Financials	70	0	0	30	0	0	0	0	0	0
Delivery	Delivery	Flexible	70	0	0	0	30	0	0	0	0	0
Delivery	Delivery	Service	70	0	0	0	0	30	0	0	0	0
Delivery	Delivery	Relationship	70	0	0	0	0	0	30	0	0	0
Delivery	Delivery	Impression	70	0	0	0	0	0	0	30	0	0
Delivery	Delivery	Packaging...	70	0	0	0	0	0	0	0	30	0
Delivery	Delivery	Reciporoc...	70	0	0	0	0	0	0	0	0	30
Delivery	Quality	Delivery	70	30	0	0	0	0	0	0	0	0
Delivery	Quality	Quality	30	70	0	0	0	0	0	0	0	0
Delivery	Quality	Cost	33.33	33.33	33.33	1.43e-3	1.43e-3	1.43e-3	1.43e-3	1.43e-3	1.43e-3	1.43e-3
Delivery	Quality	Financials	33.33	33.33	1.43e-3	33.33	1.43e-3	1.43e-3	1.43e-3	1.43e-3	1.43e-3	1.43e-3
Delivery	Quality	Flexible	33.33	33.33	1.43e-3	1.43e-3	33.33	1.43e-3	1.43e-3	1.43e-3	1.43e-3	1.43e-3
Delivery	Quality	Service	33.33	4.167	4.167	4.167	4.167	33.33	4.167	4.167	4.167	4.167
Delivery	Quality	Relationship	33.33	4.167	4.167	4.167	4.167	4.167	33.33	4.167	4.167	4.167
Delivery	Quality	Impression	33.33	4.167	4.167	4.167	4.167	4.167	4.167	33.33	4.167	4.167
Delivery	Quality	Packaging...	33.33	4.167	4.167	4.167	4.167	4.167	4.167	4.167	33.33	4.167
Delivery	Quality	Reciporoc...	33.33	4.167	4.167	4.167	4.167	4.167	4.167	4.167	4.167	33.33
Delivery	Cost	Delivery	70	0	30	0	0	0	0	0	0	0
Delivery	Cost	Quality	33.33	33.33	33.33	1.43e-3	1.43e-3	1.43e-3	1.43e-3	1.43e-3	1.43e-3	1.43e-3
Delivery	Cost	Cost	30	0	70	0	0	0	0	0	0	0
Delivery	Cost	Financials	33.33	1.43e-3	33.33	33.33	1.43e-3	1.43e-3	1.43e-3	1.43e-3	1.43e-3	1.43e-3
Delivery	Cost	Flexible	33.33	4.167	4.167	4.167	33.33	4.167	4.167	4.167	4.167	4.167
Delivery	Cost	Service	33.33	4.167	4.167	4.167	4.167	33.33	4.167	4.167	4.167	4.167

Figure 3: CPT for Preference of Criteria

Preference_of_Criteria	Characteristics_of_S1	Characteristics_of_S2	Characteristics_of_S3	Supplier1	Supplier2	Supplier3
Delivery	Delivery	Delivery	Delivery	33.333	33.333	33.333
Delivery	Delivery	Delivery	Quality	50	50	0
Delivery	Delivery	Delivery	Cost	50	50	0
Delivery	Delivery	Delivery	Financials	50	50	0
Delivery	Delivery	Delivery	Flexible	50	50	0
Delivery	Delivery	Delivery	Service	50	50	0
Delivery	Delivery	Delivery	Relationship	50	50	0
Delivery	Delivery	Delivery	Impression	50	50	0
Delivery	Delivery	Delivery	Packaging Ability	50	50	0
Delivery	Delivery	Delivery	Reciprocal Arrangements	50	50	0
Delivery	Delivery	Quality	Delivery	50	0	50
Delivery	Delivery	Quality	Quality	100	0	0
Delivery	Delivery	Quality	Cost	100	0	0
Delivery	Delivery	Quality	Financials	100	0	0
Delivery	Delivery	Quality	Flexible	100	0	0
Delivery	Delivery	Quality	Service	100	0	0
Delivery	Delivery	Quality	Relationship	100	0	0
Delivery	Delivery	Quality	Impression	100	0	0
Delivery	Delivery	Quality	Packaging Ability	100	0	0
Delivery	Delivery	Quality	Reciprocal Arrangements	100	0	0
Delivery	Delivery	Cost	Delivery	50	0	50
Delivery	Delivery	Cost	Quality	100	0	0
Delivery	Delivery	Cost	Cost	100	0	0
Delivery	Delivery	Cost	Financials	100	0	0
Delivery	Delivery	Cost	Flexible	100	0	0
Delivery	Delivery	Cost	Service	100	0	0

Figure 4: CPT for Decision Node

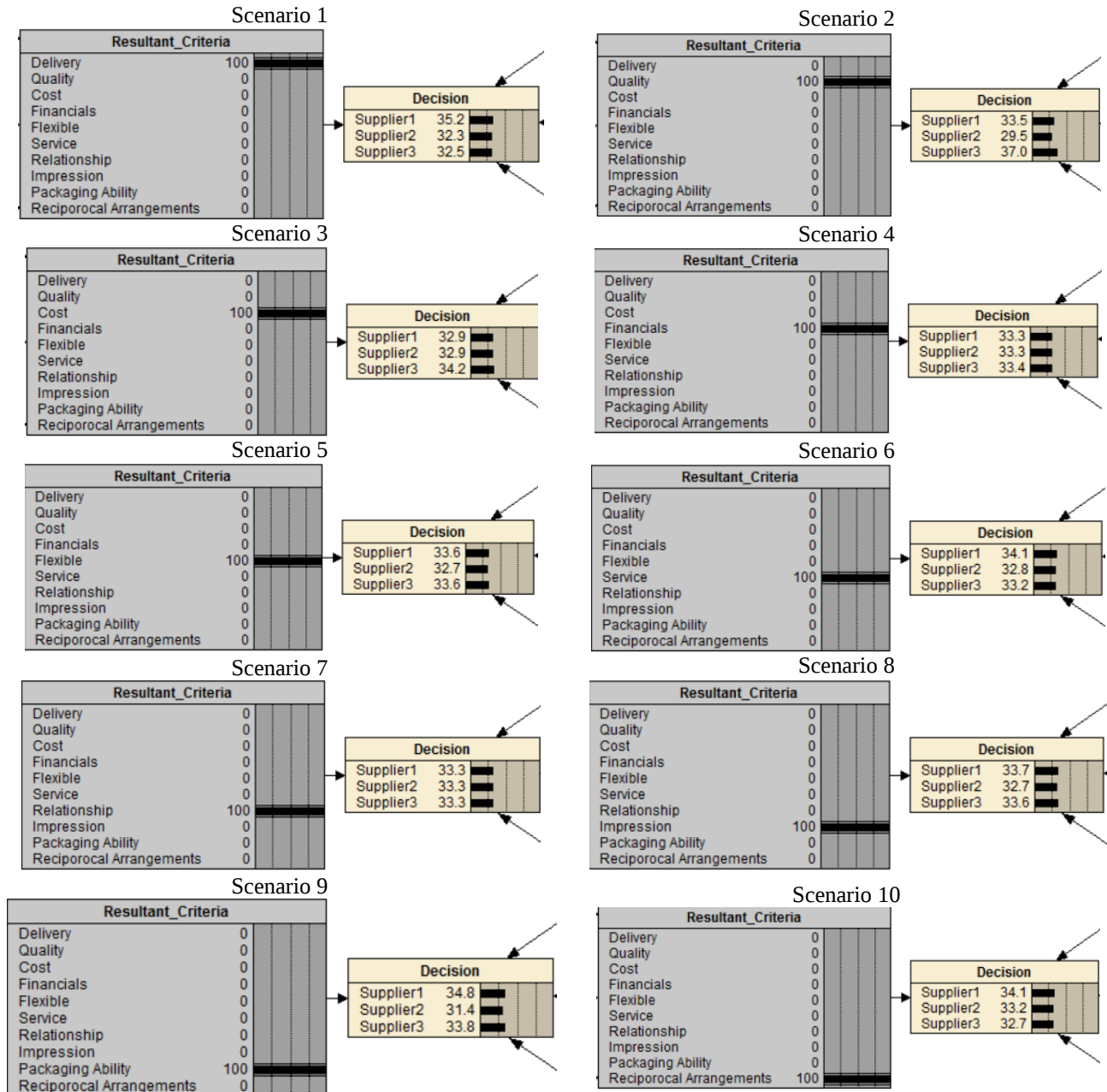


Figure 5: Sensitivity Scenarios

Conclusion: Results showed that, for this particular SLP problem, “Quality” emerged as the most crucial factor while “Costs” and “Reciprocal Arrangements” were the second and third in the ranking list. Though they were only marginally lower than others, the factors like “Packaging Ability” and “Market Impression” were at the bottom in the priority list. It was found that Supplier 3 which had strong weight for the factors like quality and costs was computed to be the best alternative among the three despite the fact that it had lower weight for ‘Delivery’ and ‘Flexibility’. Sensitivity analysis which

showed that this alternative secured its top position in most of the imaginary scenarios as well.

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