INTEGRATION OF BAYESIAN NETWORKS WITH DEMATEL FOR CAUSAL RISK ANALYSIS: A SUPPLIER SELECTION CASE STUDY IN AUTOMOTIVE INDUSTRY

SEBEPSEL RİSK ANALİZİ İÇİN BÜTÜNLEŞİK BAYES AĞLARI VE DEMATEL YÖNTEMİ: OTOMOTİV ENDÜSTRİSİNDE TEDARİKÇİ SEÇİMİ VAKA ÇALIŞMASI

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Öğrencinin Adı Soyadı

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This thesis is dedicated to
my dear cousin Aylin who recently passed away.

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RUKİYE KAYA

ABSTRACT

INTEGRATION OF BAYESIAN NETWORKS WITH DEMATEL FOR CAUSAL RISK ANALYSIS: A SUPPLIER SELECTION CASE STUDY IN AUTOMOTIVE INDUSTRY

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Bayesian Networks (BNs) are effective tools in analysis of causal relations in uncertain environments. BNs can make probabilistic calculations when a part of their variables are unknown. They can be constructed based on expert knowledge. However, there is not a widely accepted method for building BNs from expert knowledge. A common way of building BNs from expert knowledge is asking experts directions of arcs between nodes. However, this approach is not systematic as experts can be subject to errors and biases about existence and directions of causal relations. This approach is also difficult to apply especially when there are multiple experts with conflicting opinions. This thesis proposes a method to build BN models based on multiple experts' opinion by using the Decision Making Trial and Evaluation Laboratory (DEMATEL) approach. DEMATEL is a Multi Criteria Decision Making (MCDM) Method to determine cause-effect relationships between multiple criteria. In our method, the causal structure of BN is determined by asking experts pairwise direct influence values of criteria on each other via DEMATEL survey. Then, our method systematically revises the structure based on DEMATEL results and expert opinion. After construction of the BN structure, the BN is parameterized by using ranked nodes. DEMATEL survey is also used to determine the parameters of ranked nodes. Sensitivity analysis of parameters is conducted to measure the robustness of the model. And sensitivity analysis of evidence is conducted to evaluate the consistency of the model by comparing its results with the total relation matrix of DEMATEL. DEMATEL alone is not able to make probabilistic calculations to handle uncertainty.

When DEMATEL and BN are integrated with our method, DEMATEL provides the causal structure of BN and then BN makes it possible to analyse risk and uncertainty based on the causal relationship between the decision criteria. They complement each other and integration of them provides a practical decision support tool.

We applied our proposed method to a supplier selection case study in a large automotive manufacturer in Turkey. Our proposed method is suitable for the supplier selection problem as it has multiple interrelated decision criteria and uncertainty. In addition to these, buyers usually do not have perfect information regarding their suppliers, and the BN model developed by our approach is also able to deal with that. In the case study, the cause-effect relations between supplier selection criteria were determined by DEMATEL survey and the risks related with the criteria among their interactions were analyzed by BN according to knowledge of 14 experts from the automotive manufacturer. Experts can use the model to estimate the values of supplier selection criteria and analyse decision scenarios. The proposed approach presents a novel way of building BN model from the expert knowledge by using DEMATEL surveys and ranked nodes. Another contribution of the thesis is to provide a practical decision support tool for supplier selection decision analysis in automotive industry.

Key words: Bayesian Networks, DEMATEL, Multi Criteria Decision Making, Supplier Selection, Ranked Nodes

ÖZET

SEBEPSEL RİSK ANALİZİ İÇİN BÜTÜNLEŞİK BAYES AĞLARI VE DEMATEL YÖNTEMİ: OTOMOTİV ENDÜSTRİSİNDE TEDARİKÇİ SEÇİMİ VAKA ÇALIŞMASI

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Bayes ağları, belirsizlik içeren sebep-sonuç ilişkilerinin analizinde etkili araçlardır. Bayes ağları olasılıksal grafiksel ağlardır. Risk ve belirsizlik içeren karar analizlerinde olasılıksal hesaplamalar ile avantaj sağlamaktadır. Grafiksel yapısı sayesinde sebep-sonuç ilişkileri düğümler ve bağlantı okları ile gösterilmektedir. Bayes ağları, kısıtlı bilgi ile olasılıksal hesaplamalar yaparak, bilinmeyen değişkenleri, bilinen değişkenler ve değişkenler arası ilişkilere bağlı olarak tahmin edebilmektedir. Bayes ağları, uzman bilgisine dayalı olarak kurulabilmektedir. Fakat Bayes ağlarının sebepsel grafik yapılarının kurulumu için geçerli bir yöntem bulunmamaktadır. Uzmanlara değişkenler arasındaki ilişkilerin yönü sorulmakta ve alınan cevaplar doğrultusunda sebep-sonuç ilişkisi ağları oluşturulmaktadır. Bu yöntemle, birden fazla uzman görüşü alındığında, farklı görüşler arasından uygun yönün seçimi sistematiksiz bir şekilde yapılmaktadır. Bu yöntem hatalara ve yanlılığa sebep olabilmektedir. Bu tezde, Bayes ağlarının sebep-sonuç grafiksel yapısının uzman bilgisine dayalı olarak kurulmasına yönelik DEMATEL (Decision Making Trial and Evaluation Laboratory) metodu kullanımı önerilmiştir. DEMATEL ankete dayalı bir çok kriterli karar verme yöntemidir. Kriterler arasındaki sebep-sonuç ilişkisini ve kriterlerin ağ içerisindeki etki derecesini belirlemek için kullanılır. DEMATEL yönteminin direk ve toplam ilişki matrisi olmak üzere iki önemli matrisi vardır. Direk ilişki matrisi, kriterlerin birbirleri üzerindeki direk etki değerlerinden oluşmaktadır. Toplam ilişki matrisi ise kriterler arasındaki direk ve dolaylı olmak üzere toplam etki değerlerine ilişkin değerlerden oluşmaktadır.

Bu tezde önerilen yönteme göre, DEMATEL anketi yardımıyla uzmanlara kriterler arasındaki direk ilişkilerin etki dereceleri sorularak direk ilişki matrisi oluşturulmaktadır. DEMATEL yönteminden elde edilen direk ilişki matrisine dayalı olarak Bayes ağlarının sebep-sonuç ilişkisi yapısı belirlenmektedir. Böylece birden çok uzman görüşü sistematik bir şekilde alınarak Bayes ağı oluşturulabilmektedir. Ayrıca uzmanlar sadece ilişkilerin yönünü değil gücünü de sayısal ölçekte belirleyebilmektedir. DEMATEL'in direk ilişki matrisine dayalı olarak belirlenen sebep-sonuç grafik yapısı içerisindeki döngüler, Bayes ağları yapısıyla uyumlu hale getirmek için elenmektedir. Uzman görüşü yardımıyla gerekli görülen yapısal değişiklikler sistematik şekilde yapılabilmektedir. Elde edilen Bayes ağının parametreleri ranked nodes yöntemi aracılığıyla belirlenmektedir. Ranked nodes yöntemi, Bayes ağları içerisindeki büyük şartlı olasılık tablo değerlerini belirlemek yerine, sadece ata düğümlerin ağırlıklarını ve alt düğümlerin varyans değerlerini belirleyerek modeli çalıştırabilmektedir. Bu tezde, önerilen yönteme göre, ranked nodes parametreleri DEMATEL anket sonuçlarından elde edilmektedir. DEMATEL yönteminin toplam ilişki matrisi sonuçları ile kurulan Bayes Modeli üzerinde yapılan kanıt duyarlılık analizi sonuçları karşılaştırılarak modelin geçerliliği test edilebilmektedir. Ayrıca parametre duyarlılık analizi yardımıyla modelin gürbüzlüğü test edilmektedir. Önerilen yöntem, Türkiye'de büyük bir otomotiv üreticisi firmanın tedarikçi seçim karar analizinde kullanılarak test edilmiştir. Tedarikçi seçimi konusunda yapılan geçmiş çalışmalar ve firma içerisindeki uzman bilgisi yardımıyla tedarikçi seçimine ilişkin kriterler belirlenmiş. DEMATEL anketi yardımıyla, firma içerisindeki 14 uzmana, tedarikçi seçim kriterlerinin birbirleri üzerindeki etki dereceleri sorularak, direk ve toplam ilişki matrisleri hesaplanmıştır. Direk ilişki matris sonuçlarına göre, Bayes ağı modeli yapısı belirlendikten sonra, matris değerlerinden modelin parametreleri ranked nodes yöntemine göre belirlenmiştir. Parametre duyarlılık analizi ile modelin gürbüzlüğü test edilmiştir. Kanıt duyarlılık analizi sonuçlarının DEMATEL toplam ilişki matrisi ile karşılaştırılarak modelin geçerliliği kontrol edilmiştir. Ürün kalitesi, sevkiyat performansı gibi doğrudan gözlemlenmesi mümkün olmayan kriterlere, dolaylı olarak tahminini kolaylaştıracak indikatörler eklenmiştir. Bu indikatörler yardımıyla, uzman bilgisi modele aktarılmış ve bilinmeyen kriterler tahmin edilerek çeşitli senaryo analizleri yapılmıştır. Böylece uzmanlar, kısıtlı bilgileri ile kriterlerin tahmin değerlerini analiz ederek tedarikçilerini değerlendirebilmektedir. Otomotiv üreticisi firma ürünlerinin bileşenlerinden biri için bir tedarikçi aramaktadır. Bunun için daha önce çalışmış olduğu ve hiç çalışmadığı iki tedarikçi, önerilen yöntem yardımıyla değerlendirilmiştir.

DEMATEL yöntemi tek başına karar verme aracı olarak kullanılamayıp, belirsizlik içeren karar analizlerinde yetersiz kalmaktadır. Bayes ağları belirsizlik içeren karar analizlerinde etkin bir araç olarak DEMATEL yöntemini tamamlayıcı bir araç olarak önerilmektedir. DEMATEL yöntemi sayesinde, Bayes ağlarının sebepsel yapısı sistematik bir şekilde kurulabilmektedir. Böylelikle bütünleşik Bayes ağları ve DEMATEL metodu, sebepsel risk analizleri için etkin bir yöntem olarak önerilmektedir. Bu tez aynı zamanda otomotiv endüstrisinde tedarikçi seçim karar analizi için kullanışlı bir karar destek modeli sunmaktadır.

Anahtar Kelimeler: Bayes Ağları, DEMATEL, Çok Kriterli Karar Verme, Tedarikçi Seçimi, Ranked Nodes.

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SYMBOLS AND ABBREVIATIONS

Abbreviations

BN	Bayesian Network
DEMATEL	Decision Making Trial and Evaluation Laboratory
MCDM	Multi Criteria Decision Making
AHP	Analytic Hierarchy Process
ANP	Analytic Network Process
DEA	Data Envelopment Analysis
TCO	Total Cost of Ownership
TOPSIS	Technique for Order of Preference by Similarity to Ideal Solution
ELECTRE	Elimination and Choice Expressing the Reality
MP	Mathematical Programming
AI	Artificial Intelligence
NPT	Node Probability Table
WMEAN	Weighted Mean
WMAX	Weighted Maximum
WMIN	Weighted Minimum
PLS	Partial Least Squares
FMEA	Failure Mode Effect Analysis
FTA	Fault Tree Analysis

1. INTRODUCTION

Bayesian networks (BNs) are powerful tools for providing risk analysis and decision support under uncertainty due to their probabilistic nature. A BN is a probabilistic graphical model that is composed of a graphical structure and a set of parameters [1]. The graphical structure of a BN contains nodes representing variables and directed arcs representing causal relations between these variables. Each variable has parameters that are stored in a Node Probability Table (NPT). These parameters define the conditional probability distribution of a variable with its direct causes. As a result, a BN can be used for making probabilistic calculations for its variables. Unlike many other statistical tools, BNs use both causal relations and independencies encoded in its structure, and the probability distributions in its NPTs to make calculations. And analysis of cause-effect relations is considered to be useful in decision analysis [2].

A BN can be built based on expert knowledge or data. This is also beneficial for risk analysis problems because expert knowledge is available but data is limited or not available in many risk analysis problems. However, building BNs from expert knowledge is a difficult task especially when there are multiple experts. There is still not a generally accepted method to build BN structure with experts. There are several previous studies for building causal graphs for BNs or for other models. Nadkarni and Shenoy [3] proposed a causal mapping approach for building BNs. Their approach transforms expert knowledge to causal map and causal map to a BN. There are some differences between the structures of causal maps and BNs. Causal maps are composed of causal concepts, causal connections and causal values. Causal connection has “+” or “-” signs based on the increasing or decreasing effects of causal concepts. Causal maps also differ from BNs in terms of conditional independence conditions. In causal maps, absence of an arc between variables does not necessarily mean that they are independent. However, in BNs, absence of arc means that there is conditional independence between variables. Moreover, the arcs in causal maps can represent indirect relations and contain cycles. However, BNs are directed acyclic models. Nadkarni and Shenoy’s approach considers these differences and transforms a causal map to a BN. Wu [4] proposed integration of Partial Least Squares(PLS) and BN for causality analysis. Their method uses a BN as a basis for a PLS model. Tan and Platts [5] discussed the strengths and weaknesses of different causal mapping techniques. According to Tan and Platts, a Fishbone diagram is a causal diagram that is inadequate for representing complex causal relations as it focuses only on main effect. Influence diagrams are suitable for quantitative relations which have increasing or decreasing effect on each other. Mindmapping is suitable for educational activities, and cognitive mapping tend produce complex and unstructured networks.

Decision Making Trial and Evaluation Laboratory (DEMATEL) is a Multi Criteria Decision Making (MCDM) method to determine causal relations between multiple criteria. It presents cause-effect relationships between variables as directed graphs. It is a survey based method composed of series of matrix calculations. Firstly, direct causal relations between variables are asked to multiple experts by using surveys. Then, by other matrix calculations, total relation matrix that shows direct and indirect relation values of criteria is calculated. According to the total relation matrix, causal graph is constructed and the influence strength of criteria on the other criteria are determined. Criteria that have high influence on other variables and that are highly influenced by other vairables are divided into two groups called the cause and effect group. Decision makers put emphasize on the cause group during decision making. DEMATEL's integration with fuzzy logic is common for DEMATEL to deal with uncertainty. For example, experts may have difficulty to submit their opinions precisely. Fuzzy logic supports DEMATEL in vagueness of the expert knowledge. Lin and Wu [2] proposed fuzzy DEMATEL method as a causal analytical method for group decision making in R&D project selection. Dalalah et al. [6] integrated fuzz logic, DEMATEL and TOPSIS for supplier selection. DEMATEL is useful for understanding direct and indirect causal relations in a problem. However, unlike BNs, DEMATEL cannot be used for making probabilistic calculations for different events and scenarios, and this limits their use as a decision support tool.

In this thesis, we propose a method that integrates DEMATEL and BNs to build decision support models based on expert knowledge. DEMATEL cannot be used as a decision support tool for uncertainty alone. Although BNs have powerful properties for making probabilistic calculations with causal relations, it is still difficult to build BNs from expert knowledge. However, DEMATEL uses the expert opinion of multiple experts. Therefore, these two methods complement deficiencies of each other. We use surveys and results of the DEMATEL to build a BN based on expert knowledge. Although both BN and DEMATEL works with causal graphs, the properties of their causal graphs are different. DEMATEL causal graphs may have cycles and its arcs represent the sum of direct and indirect causal relations between variables. However, BN arcs represent only direct relations, and its causal graphs are acyclic. Our method has a series of steps to transform

DEMATEL results to BN causal graphs. Moreover, we also evaluate the BN produced by our method by comparing the total relation matrix of DEMATEL with the sensitivity analysis results of BNs. The total relation matrix is composed of total direct and indirect influence values of criteria on each other. Sensitivity analysis in BNs also shows the total direct and indirect impact of criteria on each other. Since our method make revisions on the initial results of DEMATEL, we do not expect 100% consistency in this evaluation. The aim of the evaluation is to provide the experts opportunity to review the model systematically. The experts can evaluate whether the inconsistencies present due to the structural differences between BNs and DEMATEL, or due to errors.

In our proposed approach, ranked nodes are used to parameterize the BN model with less parameter instead of eliciting probability values for large NPTs. DEMATEL survey results are used for the determination of parameters.

We applied our proposed method to a case study of supplier selection in a large automotive manufacturer in Turkey. Due to the uncertain nature of supplier selection criteria and complexity of interactions between them, supplier selection is a challenging multi-criteria decision making problem that involves uncertainty [7]. Uncertainty could be due to the uncertainty of selection criteria as cost and delivery performance, or due to limited information or lack of past experience. BNs can handle such uncertainties, and our proposed method can build a BN model for this problem by determining and quantifying causal relationships between decision criteria via DEMATEL. The model developed by the proposed approach analyses the cause-effect relationship between supplier selection criteria in a probabilistic manner by considering uncertainty of the criteria. Analyses can be conducted even if there is incomplete information about some of the criteria.

The main contribution of this thesis is a novel and systematic method to build and evaluate BN decision support based on expert knowledge and DEMATEL approach. The secondary contribution of this thesis is a novel application of this method to provide decision support for supplier selection in a large automotive manufacturer in Turkey.

The remainder of this thesis is organized as follows: Chapter 2 and Chapter 3 presents BNs and DEMATEL respectively. Chapter 4 reviews the previous modelling studies in supplier selection. Chapter 5 presents the proposed method and illustrates it with the automotive case study. Chapter 6 discusses the results of the case study, and Chapter 7 presents our conclusions.

2. BAYESIAN NETWORKS

Bayesian Networks are powerful tools for risk assessment problems. BNs are graphical probabilistic models based on Bayes' theorem [1]. Bayes' theorem provides a mathematical correction way to revise our beliefs or prior probabilities about events based on new information or evidence. It can make inferences with even partial evidence (i.e. when only a subset of the variables is known) [7]. For example, when we have a prior belief (prior probability) about an event and observe some evidence about this event, we can revise our belief by using Bayes's theorem.

BNs enable us to apply and compute Bayes' theorem for a large number interrelated variables. When an evidence is entered to a BN variables or a group of variables, the probabilities of the rest of the variables can be updated by using a BN solving algorithm. These algorithms are readily implemented in software such as Genie and AgenaRisk.

A BN is composed of a graphical structure and a set of parameters. The graphical structure of a BN is composed of nodes and arcs. Nodes represent variables and arcs represent direct causal relation between events. The structure of a BN is a directed acyclic graph. Therefore, cycles are not allowed between the nodes. If there is an arc from event A to B, it means event A is parent of event B, and event B is child of event A. The parameters of a BN are encoded in node probability tables (NPT). Each node has an associated NPT that defines the conditional probability distribution of that node conditioned on its parents.

The main benefits of BNs compared to other probabilistic modelling tools can be summarized as follows:

1) They offer a clear and compact representation of joint probability distributions and causal relations,
2) They offer a powerful way of making probabilistic inferences such as backward (diagnostic) and intercausal inference,
3) They are suitable for using expert knowledge in probabilistic risk analysis.

The graphical structure of a BN encodes independence assumptions on its variables. Due to these independence assumptions, BNs can represent and calculate a joint probability distribution in a compact way. Suppose that we have events A, B, C and D. By chain rule, the joint probability of these variables are computed as follows:

$$P(A,B,C,D)=P(A|B,C,D)P(B|C,D)P(C|D)P(D)$$

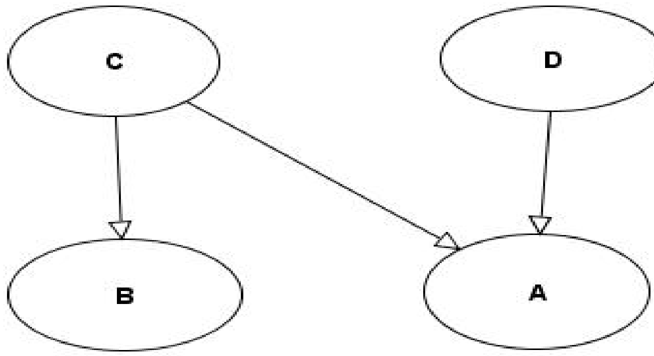

Figure 1. Example Bayesian Network

Suppose we know that A is caused by C and D, and B is caused by C. We can build the BN shown in Figure 1 to represent these causal relations. In this BN, every variable is conditioned on its parents (direct causes) so the joint probability distribution of these nodes can be calculated in a much more compact way as shown below:

$$P(A,B,C,D)= P(A|C,D)P(B|C)P(C)P(D)$$

A BN makes these causal relations and independence assumptions clear and it can use them for probability calculations. If we modelled the joint probability distribution without any independence assumptions or causal relations in a BN, it would look like Figure 2 where all the variables are connected.

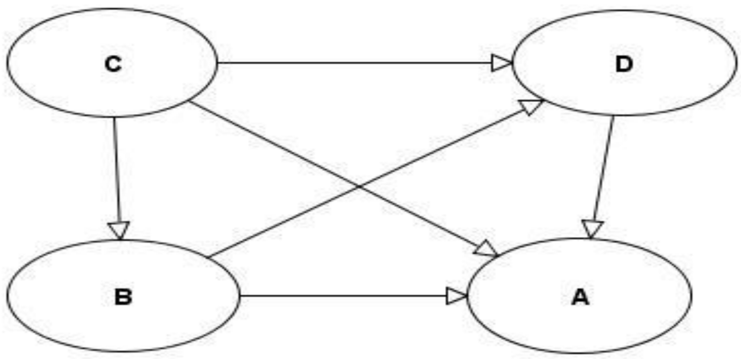

Figure 2. Causal Network without Indpenedence Assumptions

Any BN can be divided into three kinds of structures as serial, diverging and converging. All independence assumptions that can be encoded in a BN can be explained in these three kinds of strucutres. A serial connection is as in Figure 3. Evidence can flow from Y to Z through X. But any evidence to X interrupts this flow. So we say, Y and Z are conditionally independent, or d-separated, given X.

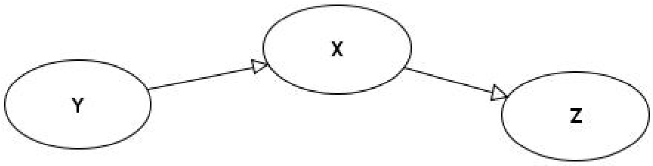

Figure 3. Serial Connection

A diverging connection is shown in Figure 4. X is common cause of Y and Z. Evidence from X is transferred to Y and Z. Evidence from Y to Z and Z to Y are transferred if any evidence is not entered to X but the flow of information is blocked if evidence is entered to X. So Y and Z are conditionally independent, or d-separated, given X.

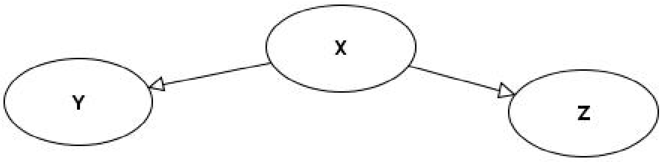

Figure 4. Diverging Conection

A converging connection is shown in Figure 5. X is common effect of Y and Z. Evidence from Y and Z are transferred to X. Evidence from Y is not transferred to Z, if there is no evidence on X. However, if an evidence is entered to X and to Y, the evidence from Y is transferred and updates the probability of Z. So Y and Z are conditionally dependent, or d-connected, given X.

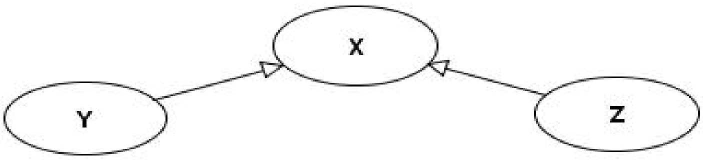

Figure 5. Converging Connection

If variable Y is conditionally independent of Z given X, we say Y and Z are d-separated given X. In serial and diverging connections, Y and Z are d-separated in case of X is observed. And in converging connections, Y and Z are d-separated unless X or descendants of it are observed. If variables are not d-separated, they are called d-connected.

When an evidence is entered to a BN, information can flow both from causes to effects (as forward inference), from effects to causes (as backward evidence) and between the causes (as intercausal inference).

Backward and inter-causal inference is another important advantage of BNs compared to other statistical methods. Evidence propagation depends on the structure in BNs.

Below, we explained evidence propagation in serial, diverging and converging structures based on burglar alarm example in Figure 6. In this example a house alarm sounds and it can be due to burglar or an earthquake. If there is an earthquake, we will probably hear a radio report about it as well.

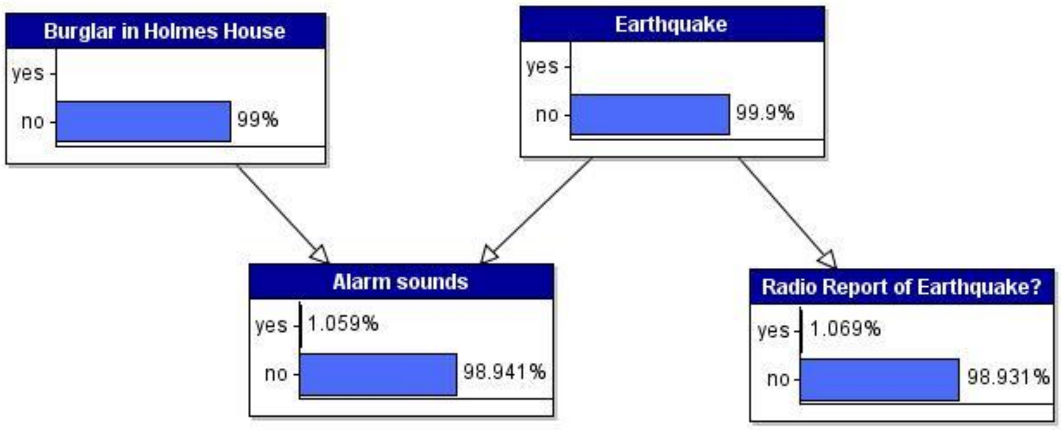

Figure 6. Burglar Alarm Example

In scenario 1, we entered hard evidence to alarm sounds, and posterior probabilities of earthquake, burglar in Holmes house and radio report changed as shown in Figure 7. Alarm sounds is a common effect of burglar in Holmes house and earthquake. The evidence on alarm sounds updates the probabilities of burglar in Holmes house and Earthquake. Earthquake is a common cause of alarm sounds and radio report of earthquake. Since there is a diverging connection between alarm sounds and radio report, the evidence also updates the radio report of earthquake, if we don't enter any evidence to earthquake.

Prior probabilities of burglar alarm BN is shown in Figure 6. Scenario with evidence to alarm sounds is transferred to radio report of earthquake as in Figure 7.

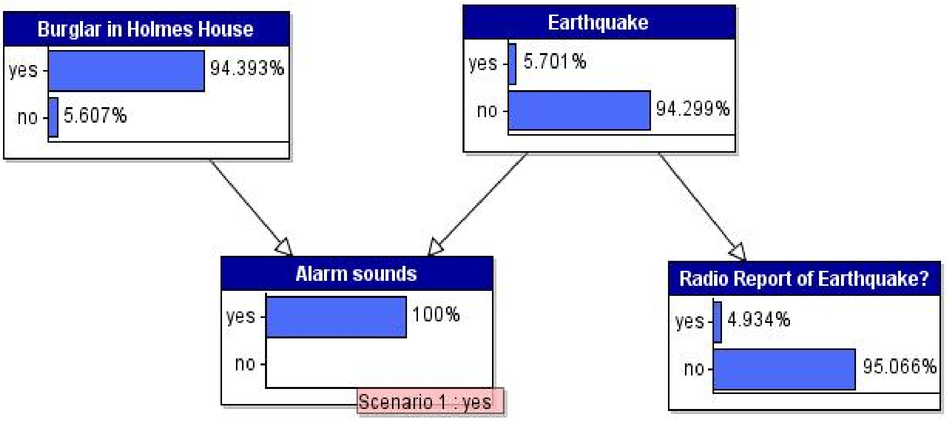

Figure 7. Scenario 1 Burglar Alarm Example

In the second scenario, we entered evidence to earthquake and obtained posterior probalities as shown in Figure 8. The alarm sounds and radio report variables are updated as they are directly connected to the earthquake variable. However, the "Burglar in Holmes House" variable is not updated by the evidence from earthquake because there is converging connection between these variables and there is no evidence on "alarm sounds".

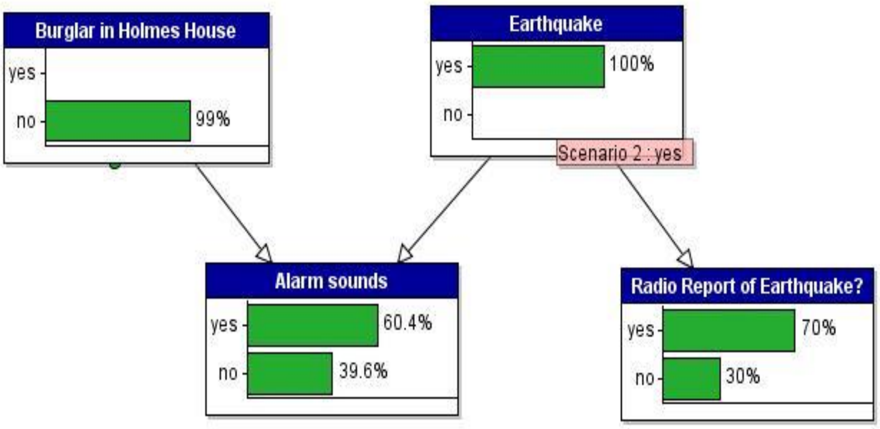

Figure 8. Scenario 2 for Burglar Alarm Example

In the third scenario, we entered evidence to "alarm sounds" after "earthquake" and we saw that evidence of alarm sounds is not transferred to radio report of earthquake as shown in Figure 9. Posterior probability of radio report of earthquake is not affected from the evidence of alarm sounds, as earthquake blocks the diverging relation between these variables.

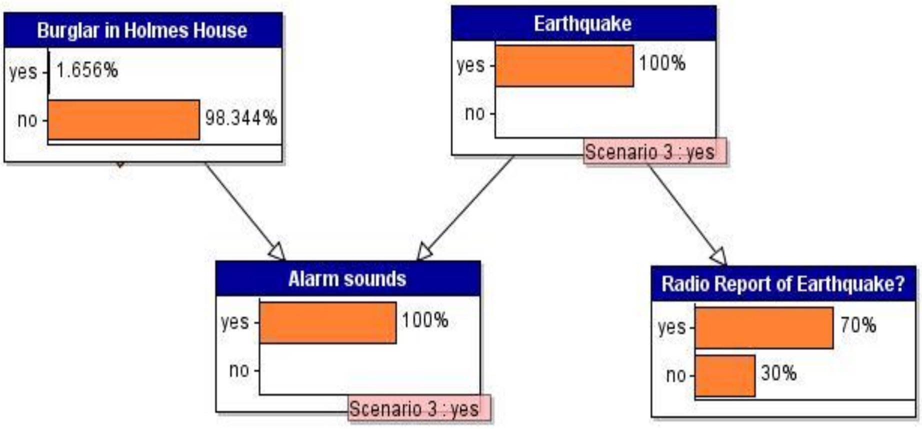

Figure 9. Scenario 3 for Burglar Alarm Example

Alarm sounds is common cause of burglar in Holmes house and earthquake. There is a converging connection. When entered evidence to burglar in Holmes house in Scenario 4 as shown in Figure 10, the evidence updates alarm sounds but not earthquake due to the converging connection.

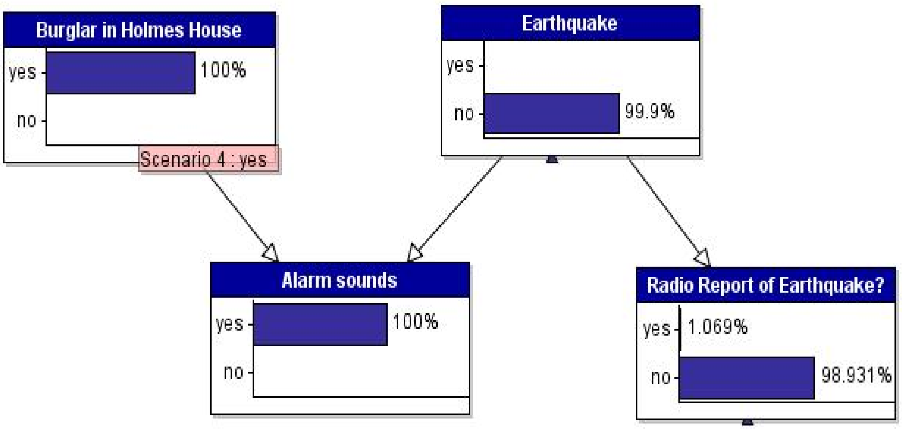

Figure 10. Scenario 4 for Burglar Alarm Example

In Scenario 5, we entered evidence to only alarm sounds and obtained the posterior probabilities of burglar in Holmes house and earthquake as shown in Figure 11.

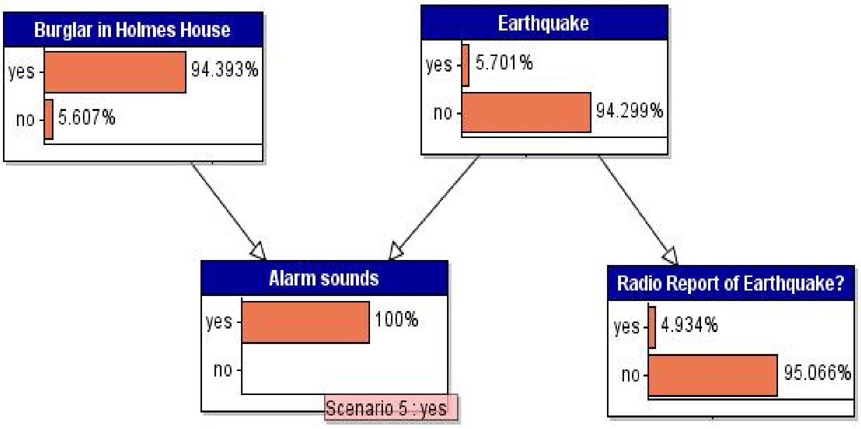

Figure 11. Scenario 5 for Burglar Alarm Example

Then, we entered evidence both to burglar in Holmes house and to alarm sounds in Scenario 6 and we saw that evidence from burglar in Holmes house updates the probability of earthquake as there is a converging connection and there is evidence on alarm sounds as shown in Figure 12. Burglar in Holmes house and earthquake conditionally dependent given evidence to alarm sounds. This is type of reasoning is called inter-causal inference and it is useful to make root-cause analysis in uncertain domains such as supply chain risk management [8]. It enables to solve problems under uncertainty by finding root-cause of it systematically.

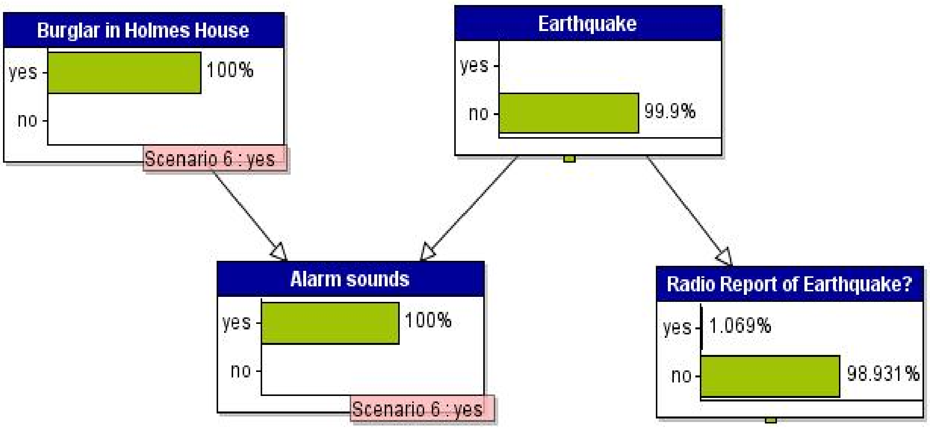

Figure 12. Scenario 6 for Burglar Alarm Example

Another advantage of BNs is that they offer a convenient way to use expert knowledge when there isn't enough data. This is especially beneficial in problems, such as supplier selection, where data is limited. BN arcs represent causal relations and experts express their knowledge in causal relations. Therefore, even if we have limited data about a problem, we can construct the causal structure of a BN based on expert knowledge.

In BNs, sensitivity analyses can be conducted to see how variables are affected from change of other variables. There are two type of sensitivity analyses: parameter sensitivity analysis and evidence sensitivity analysis. Sensitivity analysis of evidence is conducted to see how evidence on other variables changes the posterior probability of a target variable. It also ranks the strengths of effects of variables. The sensitivity analysis of parameters is conducted to see robustness of the model. It shows how changing each parameter affects the results of the model.

The parameters of BNs can also be defined from expert knowledge by using ranked nodes or similar techniques. The ranked nodes technique is described in the following section.

2.1. Ranked Nodes

The conditional probability distributions of BNs are generally defined in NPTs. An NPT has probability values of a node for each state combination of its parents. Therefore, the number of parameters in an NPT is the cartesian product of the number of its parents' states and its states.

Figure 13 shows the NPT of "Alarm Sounds" from the Burglar Alarm example. In this NPT, there are 8 parameters as this node has 2 states and 2 parents each with 2 states.

Burglar in Holmes House	yes		no	
Earthquake	yes	no	yes	no
yes	1.0	1.0	0.6	0.0
no	0.0	0.0	0.4	1.0

Figure 13. NPT of Alarm Sounds

However, it is difficult to elicit probabilities from experts for NPTs in larger models. For example, the BN model in Figure 14 have three variables A, B, C and A is dependent on B and C, and each node has 5 states. Without using ranked nodes, 125 probability values must be elicited from experts for the NPT of A, and this is a considerably difficult task. A part of the NPT of A is shown in Figure 15.

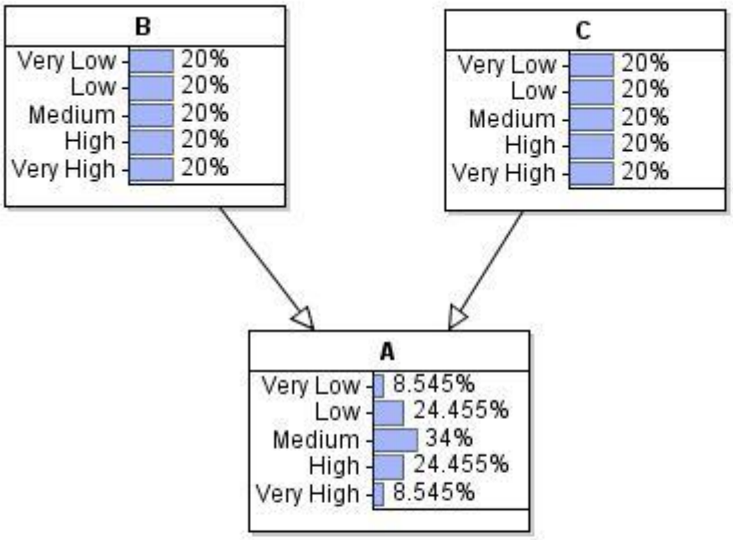

Figure 14. Example network

B	Very Low					Low							
C	Very Low	Low	Medium	High	Very High	Very Low	Low	Medium	High	Very High	Very Low	Low	M
Very Low	0.9535406	0.4101524	0.0120168	1.3051401	8.881784E-	0.5898474	0.046459	6.5284116	9.858781E	0.0	0.1223205	1.5595605E	5
Low	0.0464593	0.5896916	0.8656626	0.2463031	0.00186440	0.410146	0.907081	0.4101459	0.0120168	1.3051401E	0.8656626	0.5896916	
Medium	5.139835E-	1.5595605	0.1223205	0.7518322	0.7518322	6.528411	0.046459	0.5896916	0.865662	0.2463031	0.0120168	0.4101459	
High	0.0	0.0	1.2117948	0.0018644	0.24630319	0.0	5.139835E	1.5595605	0.122320	0.7518322	9.858781E	6.5284116E	
Very High	0.0	0.0	0.0	8.881784E	1.3051401E	0.0	0.0	0.0	1.2117948	0.00186440	0.0	0.0	5

Figure 15. A part of NPT of A

Ranked nodes work based on Truncated Normal (TNormal) distribution with central tendency to probability of parent nodes due to weighted function [9]. Ranked nodes approximate BN nodes with ordinal states with a doubly truncated TNormal distribution with scaled states [0-1].

A ranked node has an underlying TNormal distribution, and it approximates this distribution to a discrete BN node with intervals that have equal widths [10]. Figure 16 shows a TNormal distribution with mean 0.7 and variance 0.1. Figure 17 shows a ranked node approximation of this distribution. This ranked node has 5 states, so it approximated the probability density under 5 equally width intervals in the TNormal distribution (i.e. [0,0.2), [0.2,0.4), [0.4,0.6), [0.6,0.8) and [0.8,1]) for each state in the corresponding ranked node.

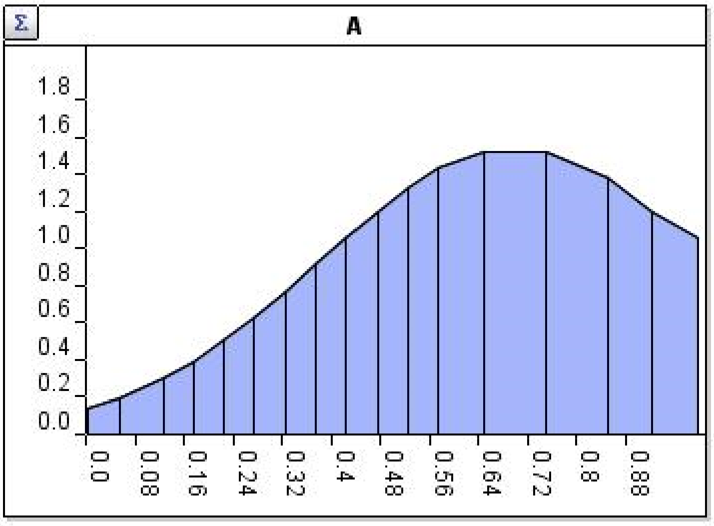

Figure 16. Graph of node with Tnormal Distribution

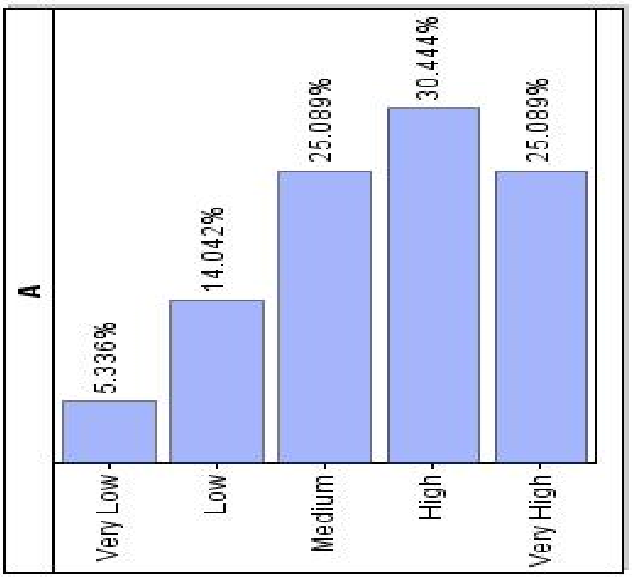

Figure 17. Graph of node with ranked nodes

The main advantage of ranked nodes is that they require fewer number of parameters than usual NPTs and they can define a wide variety of shapes.

Moreover, ranked nodes work with weighted functions of parents such as weighted mean(WMEAN), weighted minimum(WMIN), weighted maximum(WMAX), mixture of minimum and maximum(MIXMINMAX) [10]. Weight expressions are used to determine central tendency of child node depending on parent nodes on truncated normal scale [0-1].

WMEAN calculates means of child nodes by multiplying means of parents' probabilities with weights of them.

If weighted function is chosen as WMIN, the value of child node tends to be closer to the parent node with the lowest value. Similarly, in WMAX, the value of child node tends be close to the parent with the highest value.

Construction of NPTs by ranked nodes consists of five steps. Firstly, the states of a ranked node are determined and type of weighted function is selected. Then the weights and variances of its parents are determined. In the last step, NPTs are automatically calculated based on TNormal approximation by AgenaRisk. If we use ranked nodes for our example model in Figure 14, we need to define only 3 parameters; weights of B and C and variance of A to define NPT of A as shown in Figure 18.

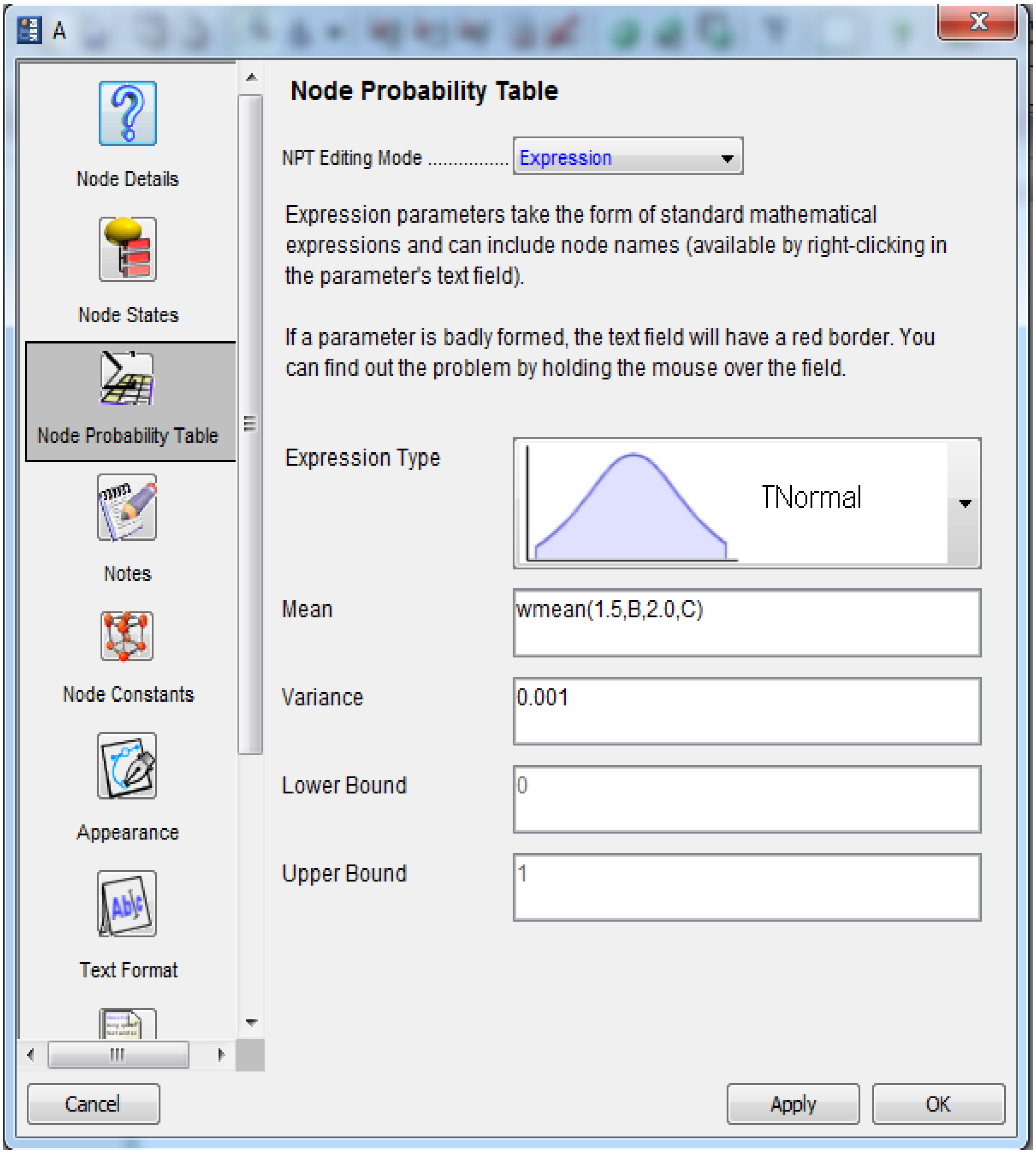

Figure 18. Parameters for NPT of A with ranked nodes

3. DECISION MAKING TRIAL AND EVALUATION LABORATORY (DEMATEL)

Decision Making Trial and Evaluation Laboratory (DEMATEL) is a Multicriteria Decision Making (MCDM) Method to determine causal relations between multiple decision criteria. DEMATEL analyzes interdependencies between criteria [11]. It determines causal relationships and strength of the criteria among the others. DEMATEL has two important matrices as average matrix and total relation matrix. Average relation matrix shows direct influences of criteria on each other. Total relation matrix shows direct and indirect influences of criteria on each other. After calculation of total relation matrix, a threshold value is determined and the influences with greater value than the threshold are accepted as valid directions and smaller ones are neglected. Based on these directions causal network for the multi criteria problem is obtained. It divides criteria into cause and effect groups [12]. It is a survey based method. Steps of DEMATEL are as follows:

1. A direct relation matrix is constructed by asking influence of decision criteria on each other on a 0 to 3 scale (0=no influence, 1=low influence, 2=medium influence, 3=high influence). Surveys conducted with multiple experts to collect this information, and the average of their response for each influence is recorded in the direct relation matrix.
2. A normalized direct relation matrix is obtained by dividing values of direct relation matrix with the maximum of sum of rows and columns. We denote the direct relation matrix with A and the normalized direct relation matrix with M, rows with index i and columns with index j and average matrix values with a_{ij}, calculation formula of M as in the following formula:

$$M = A * \min\left(\frac{1}{max \sum_{i=1}^{n} a_{ij}}, \frac{1}{max \sum_{j=1}^{n} a_{ij}}\right)$$

3. A total relation matrix is calculated. The total relation matrix represents the sum of direct and indirect influences between criteria. If we denote normalized matrix by M, total relation matrix T represents

$$T = M + M^2 + M^3 + M^4 + \dots$$

It is calculated by the following equation:

$$T = M(I - M)^{-1}$$

4. Sum of rows and columns of total relation matrix are calculated. Then, for each row and column, their sums and differences are calculated. The sum of a row represents

the total effect of that criteria on other criterion, and the sum of a column represents the total effect of other criteria on that criterion. We denote the sum of rows by R and the sum of columns by C, we calculate R-C and R+C values in this step. If R-C value is positive, that criterion is accepted as a cause or sender criterion as it has a higher effect on other nodes than the combined effect of other nodes on itself. Whereas, if R-C value is negative, that criterion is considered as receiver criterion. And criteria whose R-C value is positive are considered as essential criteria. And R+C values of criteria show the total inward and outward relation strength of criteria with other criteria.

5. Cause and effect diagram is constructed by setting a threshold value for the total relation matrix values. A threshold value is determined by the help of experts and the influence values greater than threshold value are accepted as valid influences and are indicated by arcs between related criteria.

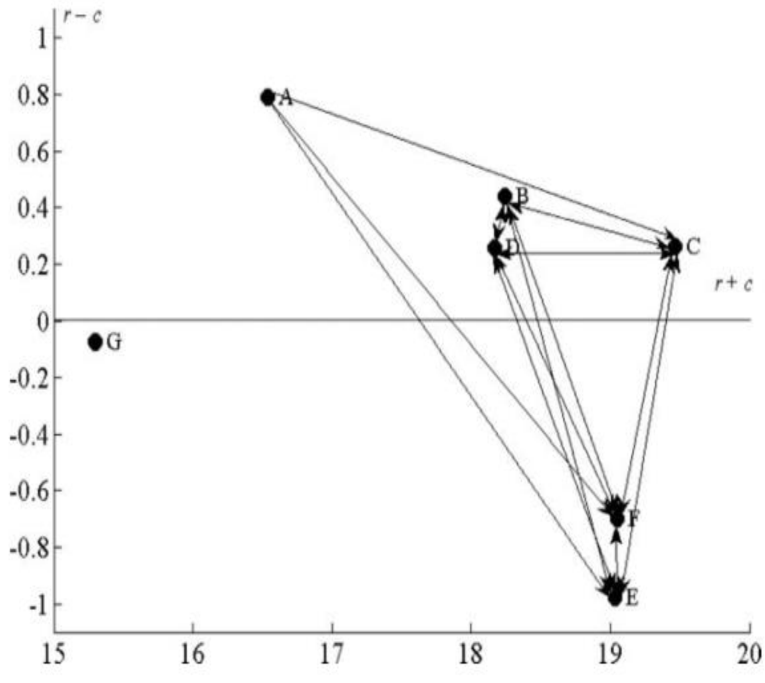

Figure 19. A DEMATEL causal graph built by Shieh et al. [21]

A causal graph built by DEMATEL is shown in Figure 19. This graph is built by Shieh et al. [13] to determine importance of criteria and causal relations between them for the hospital service quality. Note that the variables are placed according to their R-C and R+C values in the graph.

In our proposed approach, DEMATEL is used to construct BN causal structure. Other causal structure methods are also reviewed. Nadkarnia and Shenoy [3] used causal mapping approach to construct BN. Their approach transforms expert knowledge to causal map and causal map to a BN. Causal maps composed of nodes, directionless causal connections that indicates positive or negative and causal value shows the power of the connection. BNs are directed graphs.

Causal maps also differ from BNs in terms of conditional independence conditions. In causal maps, absence of an arc between variables does not necessarily mean that they are independent. However, in BNs, absence of arc means that there is conditional independence between variables. Causal maps include indirect relations and contain cycles. However, BNs are directed acyclic models. Nadkarni and Shenoy transform a causal map to a BN by considering these differences. On the other hand, Wu[4] proposed integration of Partial Least Squares(PLS) and BN for causality analysis in decision making since PLS is ineffective in absence of knowledge. They used BN as a basis for PLS model. Tan and Platts [5] compared causal mapping techniques and analysed their strengths and weaknesses. According to Tan and Platts, Fishbone is inadequate complex causal relations. Why/Why? causes ever-lengthening network. Influence diagrams are suitable for quantitative relations causing decrease or increase on each other. Mindmapping is only usage of educational activities. Cognitive mapping tends to complex and unstructured networks. Lin and Wu [12] proposed fuzzy DEMATEL method as a causal analytical method for group decision making in R&D project selection.

We propose to use DEMATEL to construct causal structure of BN models. DEMATEL constructs causal graphs according to total relation matrice of it. The arcs in this graph represent a completely different thing than BN arcs. While BN arcs represent direct causal relations, DEMATEL's arcs represent the sum of direct and indirect effects betwen variables. For example, the arc between A and C shows that the sum of direct and indirect effect from A to C was considered to be significant. As a result, it is currently not possible to transform DEMATEL's causal graphs into BN models and systematic approaches are required. In Chapter 5, we present a novel approach to build and evaluate BNs based on DEMATEL surveys.

4. SUPPLIER SELECTION PROBLEM

Supply Chain Management has significant importance to provide competitive advantage to companies. Suppliers constitute essential components of a supply chain, and supplier selection is a key decision in supply chain management. A global, fast changing and competitive environment makes selection of suppliers even more important. Suppliers have to work in coordination with the customers as meeting requirements of them. Insufficient analysis of supplier selection risks can lead to severe consequences as disruptions in the suppliers can affect the whole supply chain [7].

This section reviews the relevant studies about modelling methods that have been used for supplier selection. An overview of MCDM techniques in supplier selection is discussed in Section 4.1. BNs in supplier selection is presented in section 4.2.

4.1. MCDM techniques in Supplier Selection

Many different methods including MCDM Techniques, Mathematical Programming (MP) and Artificial Intelligence (AI) have been used for supplier selection [14]. In this section, we focus on MCDM techniques in supplier selection as our proposed method is based on an MCDM technique. The most commonly used MCDM techniques are Analytic Hierarchy Process (AHP), Analytic Network Process (ANP), Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE), Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) and DEMATEL [14].

AHP is based on a pairwise comparison matrix which is constructed according to relative preferences of decision makers. AHP is beneficial method for supplier evaluation as it considers both quantitative and qualitative criteria. AHP provides opportunity to use subjective judgment of multiple decision makers [15]. Another important benefit of AHP is measurement of consistency of the judgments of decision makers by eigen values. But high consistency ratios can be difficult to obtain.

By using AHP, decision makers evaluate all criteria from the main objective through the sub-criteria in a hierarchical structure [16]. But when a new criterion is added, all comparisons must be conducted over again. As a result, AHP is not considered to be appropriate for problems with dynamic nature. Moreover, AHP is not suitable for representing causal relations between factors. Akman and Alkan [17] used fuzzy AHP method to measure supplier performance. Due to fuzzy nature of the pairwise comparison process, decision makers prefered to assign a range or linguistic value to their preferences.

TOPSIS is also an MCDM technique that is commonly used for the supplier selection problem. TOPSIS's working principle is based on the similarity to an ideal solution. The best decision alternative should have the longest distance from the negative ideal solution and the shortest distance to the positive ideal solution [18]. Wanga et al. [19] used fuzzy hierarchical TOPSIS for the supplier selection problem. Samvedi et al. [20] integrated fuzzy AHP and fuzzy TOPSIS to analyse supplier selection risks. However, the integrated approach is also inadequate in analysing relationships between the risk events.

Another widely used MCDM technique for supplier selection is DEMATEL. DEMATEL aims to determine the causal relations between decision criteria [21][22]. Chang and Chang [12] used fuzzy DEMATEL method to determine the most important supplier selection criteria for evaluation of supplier performance and stable delivery of goods is determined as most effective and connected criteria with the other criteria. The main advantage of DEMATEL compared to other methods is its ability to identify causal relations between the criteria and the strength of these relations. Chang and Chang [12] visualized causal relationship of the matrices with arrows and also strength of the criteria with thickness of the circled nodes based on the total relation matrix. Büyüközkan and Çifci [21] integrate fuzzy DEMATEL, fuzzy ANP and fuzzy TOPSIS methods to evaluate green suppliers for an automotive manufacturer in Turkey. They visualize the causal relations using DEMATEL, conduct pairwise comparisons by ANP, and lastly calculate distance to the ideal solution by using TOPSIS. They use fuzzy logic to elicit human judgement in all three approaches.

MCDM techniques have disadvantages when dealing with problems in uncertain and dynamic nature. In such problems, MCDM techniques are often combined with MP and AI techniques as hybrid approaches [23] [6] [19] [7]. MP techniques are useful for dynamic supplier selection problems where uncertainty is relatively low and data is available [24][25]. AI techniques such as BNs are useful for problems with high uncertainty. Hybrid approaches complement inadequancies of MCDM, MP and AI techniques. Ramanathan [23] integrated Data Enveleopment Analysis (DEA), Total Cost of Ownership (TCO) and AHP methods to analyse supplier selection problem. By TCO, the problem is analysed in cost perspective by objective data, AHP enables using subjective judgement and DEA measures relative performance of suppliers. Considering the nature of the supplier selection problem, dependence between supplier selection criteria, uncertainty and dynamic environment of the problem are most significant points that must be taken into account. In previous studies, deterministic approaches to the problem, stationary assumptions did not take the uncertain nature of the problem into account. And most of the previous studies focus on cost minimization or profit maximization while the selection of suppliers. Supplier selection criteria other than cost or profit must be evaluated with dependence between them. BN meet all these requirements. It is able to analyse causal relations in probabilistically considering uncertain and dynamic nature of the problem. Using BNs in supplier selection will be discussed in section 4.2.

4.2. Bayesian Networks in Supplier Selection

Recently, the use of BNs has been increasing in many domains [26] [27] [28] including supply chain management and supplier selection. Dogan and Aydin [7] used integrated BN and Total Cost of Ownership method for supplier selection analysis. Supplier selection criteria have causal relationships in an uncertain environment. The integrated approach provides probabilistic environment to deal with uncertainty and evaluates suppliers based on many qualitative and quantitative criteria and their causal relations between cost items. And when buyer has no past data or inadequate data about the supplier only has a belief about the supplier, this approach via BN allows using expert knowledge. Its causal and graphical structure provide convenience to experts and researchers when determining criteria, factors, cost items, states and cause-effect relations of them. With these abilities the approach has a distinction on the many other methods enhanced for the supplier selection problem. They constructed a BN that includes supplier selection criteria and factors related to criteria and lastly cost items connected with factors to analyse the supplier performance. And TCO provides assesment of the supplier selection performance in terms of the total cost and also the other costs arising from the supplier capability. By means of this integrated approach on the contrary of traditional supplier selection decision based on only unit price, other important cost types and factors related with them were also assesed as a whole manner. Financial data and domain knowledge were used. The integrated approach was designed for tier-1 supplier automotive sector. Criteria, state of the criteria, factors, cost items and relations between them were determined by the experts. Unknown was also one of the states of the criteria. Criteria were defined as discrete variables and also cost items were defined as continuous variables in the model. After propogation of the model, suppliers were compared based on factor distributions and also based on the effects of the factors on each cost item.

Output graphs give opportunity to assess supplier performance in every operation field and based on the total cost to buyer and also supplier for self-assesment.

Dogan and Aydin [7] selected the best supplier by considering both mean and variances of total cost. Sensitivity analyses were also conducted in the study. One of the sensitivity anlayses were made to analyse the value of information for selection factors. Results of this sensitivity analysis showed the upper and lower bound of total cost, which is respectively the worst case and the best case. Difference between the best case and worst case reveals the improvement space for the supplier. Another sensitivity analysis was conducted by full factorial experiment for the different information levels of the selection criteria. In this sensitivity analysis unknown state is also assessed as a state for the factors. Total cost mean and variances were calculated for each state and total cost improvements were examined between factor levels. And it was seen that especially improvement in flexibility, delivery performance and price will provide important improvement in cost. If supplier improve itself, its rank in the alternatives will get higher.

Ferreira and Borenstein [28] combined fuzzy logic and influence diagrams (ID) for supplier selection decision. IDs are BNs extended with decision and utility nodes. Combined approach provides dynamic environment for the supplier-buyer relationship. Buyer has opportunity to track the supplier performance in many aspects such as quality or on-time delivery. Fuzzy enables linguistic variables for assessment and weighting of the criteria. Firstly, supplier selection criteria were determined by the decision-makers and influence diagram constructed due to relationship between the criteria. Then state of the criteria were determined as linguistic variables (extremely low (EL), very low (VL), low (L), average (A), high (H), very high (VH) and extremely high (EH).) For priorisation, criteria were weighted (extremely important (EI), very important (VI), important (I), moderately important (MI) and unimportant (U)). Marginal probabilities of the barren nodes were calculated and conditional probabilities of the intermediate nodes were caculated. Lastly, preferability of the value node was calculated. This integrated approach is modeled by the Java language in a modular structure. Model consists of Purchasing Strategy Module, Decision Network Module, Database Module, Enterprise Database, Fuzzy Module and Supply Chain Simulator. Determination of criteria and states and construction of BN are performed in Purchasing Strategy Module. Determination of the importance weight of criteria, and computation of the aggregated fuzzy importance of each criterian by the experts are conducted in Decision Network Module.

Database Module supplies data propogation of ID. Enterprise Database Module provides historical data to Fuzzy Module. Fuzzy Module collects historical data from Enterprise Database Module, simulation output data from Supply Chain Simulator and membership functions and linguistic terms from the Purchasing Strategy Module. Supply Chain Simulator provides data learning of the parameters dynamically. Decision Network Module provides initial values using historical data for prior probabilities. And after each simulation run, new data is obtained and used for the posterior probability calculation. A case study in biodiesel plant was carried out. An influence diagram was constructed for the supplier selection of oil used for the biodiesel production. Supplier performance was considered as a final node. Economic, social and technological factors were considered as main criteria which affect supplier performance. Main criteria were also divided into multiple sub-criteria. Then decision-makers evaluated importance weights of each criterion. Prior probabilities were assigned for each oil type. Ratings of criteria were determined based on historical data and expert knowledge. After processing data, oil alternatives are assessed and most appropriate oil supply was chosen as soybean oil. They set initial probabilities to zero and entered new evidences to show learning ability and dynamic structure of the approach. With this test, the posterior probabilities were revised and the oil supplier preferences were changed. By the Bayesian approach, the modular decision model updated results dynamically due to changes and evidences.

Lockamy and McCormack [29] analysed supply chain risks by using BNs. In the study, risk profiles for the casting suppliers of a US automotive company were constructed. By BNs, supplier's external, operational, network risk probabilities and the potential revenue impact on the buyer with value-at-risk(VAR) were examined. The approach gives also opportunity to see which risk events are the most effective on revenue and have a high occurence probability. The proposed model analyses supplier risks due to disruption throughout the whole supply chain. According to the model, risk factors include relationship factors, supplier past performance, human resources(HR) factors, history of supply chain disruptions, environmental factors, disaster history and financial factors. The risk profile score shows the disruption chance. Risk factors were classified into operational, network and external risks and risk profiles were calculated according to this classification. A case study was conducted for casting supplier of an automotive company in the United States. The data were collected from the supplier's representatives, account representatives, key personnel in the supply chain departments and off-site research.

Risk index was calculated by five-point Likert scale. Network, operational, external risks and suppliers’ reveneu impact on the company were calculated based on prior probabilities.

BN was constructed as a final node is Supplier Revenue Impact and its parents are Network Risks, Operational Risks and External Risks. Network risks are dependent on the misalignment of interest, supplier financial stress, supplier leadership change, tier 2 stoppage, supplier network misalignment. Operational risks are dependent on quality problems, delivery problems, service problems and supplier HR problems. And lastly parents of the external risks are supplier locked, merger/divestiture and disaster. VAR value is calculated by multiplying revenue impact with its probability. For each supplier it was calculated monthly. In the case study supplier risk profiles and reveneu impact of them were calculated for 15 suppliers and suppliers have highest and lowest reveneu impact on the company were determined. Risk profiles for suppliers were calculated as in the following: Firstly, the probability of network, operational and external risks were calculated by multiplying total probability of related risk events with probability of corresponding event occurence and dividing by total probability of event occurence. Then probability of reveneu impact was calculated via dividing sum of probability of each risk category product probability of occurence by total probability of risk occurence. VAR was calculated for each supplier by multiplying probability of revenue impact with supplier’s monthly reveneu impact. To see which risk category improvement has highest risk reduction effect on the company, all risk improvement combinations were set to zero and evaluated results of reveneu impact on the company for each supplier. According to base supplier risk profiles and corresponding best risk reduction combination of network, operational and external risks with VAR results for each supplier, the highest reduction in VAR between base and best risk reduction combination was in supplier 5. When examining all suppliers, while most effective risk reduction combination was operational and external risk reduction combination, most ineffective risk reduction combination was network and operational risk reduction combination. And according to analysis results, supplier has worst effect on the company reveneu is supplier 6. Supplier 6 has to focus on its best risk reduction combination and highest probability of occurence risk events in these categories. Major company can end working with supplier 6 or collaborate them to overcome these risks. This approach lead companies choosing supplier and also helping suppliers in enhancing risk profiles.

BN provide to see updated supplier profile continuously. Companies have opportunity to track suppliers' improvements and take decision about continuity of relationship. The company may decide to end up relationship with a supplier if the risk profile is getting worse. And also if the company decides to work with a new supplier, they can evaluate supplier candidate by creating risk profile via this network.

This was a successful study for risk classification and analysis, but the authors did not provide a method to build such models for similar problems.

Badurdeen et al. [8] analysed and modeled supply chain risks quantitatively with BNs. Risk events have effects on each other. In this study supply chain risk taxonomy was used to analyse risks and their relationships. The approach was applied a case study in aerospace industry to show its practicality, and sensitivity analyses were conducted. In their study risks were classified into three main categories as organizational, industry and external by the SC risk taxonomy. Organizational risk consists of operating uncertainty, credit uncertainty, liability uncertainty and agency uncertainty. Industry risk consist of input market uncertainity, product market uncertainity and competitive uncertainity. Environment risks included political, policy, macroeconomic, social and natural uncertainities. These sub categories were also divided into risk-dimensions. Authors used Delphi method to elicit expert knowledge. By risk taxonomy, risks were described and risk network map constructed to analyse interdependencies between the risks. And last step of the study was modelling. Authors analysed some modeling techniques that are used for SC risk management. They believe that BN, (Fault Tree Analysis) FTA and (Failure Mode Effect Analysis) FMEA are suitable methods for supply chain risk management. But they think that FTA is mostly suitable for the system risk events cause a final issue. But supply risk events have effect on many parts of the chain. So FTA is inadequate from this point of view. And FMEA requires past data. However, BN is effective tool in modelling complicated cause-effect relationships and making root-cause analysis even if there is no data but it has also limitations as computational diffuculty when the network is getting larger. They implemented their approach in a software. The proposed approach was evaluated in two ways. One of them was conducted at Boeing Company. Supply chain map for the company was 11 suppliers including OEM, US Airforce, US Navy and 19 inernational customers. After the supply chain map, risk network matrix that shows the relationships between the risk factors was constructed. Prior conditional distributions were gathered from the experts and posterior conditional probabilities were calculated based on the Bayesian approach. Secondly sensitivity analysis was conducted to analyze how nodes affect each other.

The studies above used BNs for the analysis of supplier selection decisions. However, there is still tendency to focus on cost/revenue perspective in a traditional way [7] [29]. Nezir and Doğan [7] determined final node as a total cost and, Archie and Lockamy [29] evaluated effect of all criteria on revenue impact of the company.

In all these studies, expert knowledge was used when there was lack of data and experts provided the probabilities of the risk events in these models. For example, Ferreira [28] used fuzzy sets to incorparate expert knowledge. Moreover, these studies presented BN models that have been developed for specific supplier selection problems. They did not present a methodology to modify these models or to develop a new model for a supplier selection problem with different properties. In this study, rather than presenting an individual model, we propose a methodology for developing a causal BN model for practically any supplier selection or decision making problem where data is limited and expert knowledge is available. Our methodology uses the DEMATEL approach to build a causal structure from expert surveys and then transforms it into a computable BN model. In traditional way of constructing causal graph of BN, directions of arcs between criteria are asked to experts. If there are multiple experts, they can submit different opinions. And there isn't systematic way of choosing right direction between the answers in this way. It can cause errors and biasness. By DEMATEL survey, direct influences of criteria on each other are asked to experts. And they submit their opinion into quantitative scale. And direct relation matrice of DEMATEL is calculated. In our proposed method, causal graph of BN is constructed based on the direct relation matrix. So view of multiple experts can be considered systematically by our proposed method. Our method uses ranked nodes to determine the parameters of the model from experts. Ranked nodes provide a convenient approach to transform the qualitative expressions of experts into quantitative probability distributions. We illustrate the use of our proposed method by using a supplier selection case-study. Our method could also be used for different supplier selection problems or even in other domains as long as domain knowledge and experts are available.

5. THE PROPOSED METHOD

In this chapter, we proposed a novel method to build causal BNs based on DEMATEL surveys from multiple experts. We applied our proposed approach to build a decision support model for supplier selection for a large automotive manufacturer in Turkey. The remainder of this chapter is organized as follows: Section 5.1 presents the case study of supplier selection problem in a large automotive manufacturer. Section 5.2 describes our method and illustrates it by applying it to the case study.

5.1. Case Study: Supplier Selection in a Large Automotive Manufacturer

Automotive sector is an extremely competitive sector, and supply chain performance is a crucial factor to gain competitive advantage. Supplier selection decision is an essential element of the whole supply chain performance. Automotive manufacturers have numerous suppliers since their products are highly complex and require many different components. Consequently, automotive manufacturers may have limited information about some of their suppliers, so they need to make risk analysis for selecting such suppliers. Insufficient analysis of supplier selection risks can lead to severe consequences such as disruptions, and it can affect the whole supply chain [7]. In summary, decision makers in automotive manufacturers need to evaluate potential suppliers based on limited information.

In many supplier selection studies, the supplier selection decision was made based on only a few criteria about suppliers' performance. Particularly, there is a tendency to select suppliers based on cost or revenue impact on the buyer [7], [29]. However, for automotive manufacturers, not only cost or product quality, but also many other important criteria must be considered when selecting a supplier. For example, an automotive manufacturer may prefer a supplier who produces high quality products and is flexible to changes on its product. Flexibility can be in many aspects such as product flexibility, volume flexibility or delivery flexibility, and it can affect many other criteria as product quality and delivery performance. Cooperation is another important supplier selection criterion that is related with product quality, flexibility and delivery performance. In other words, different supplier selection criteria can have interactions between them, and these interactions need to be considered when making supplier selection decisions. Many methods used for supporting supplier selection decisions do not take such interactions into account (see section 4.1), and this may cause erroneous results. Therefore, methods that analyse both the effects of decision criteria and the interactions between them should be preferred in such problems.

BNs are suitable modelling approaches for providing decision support by taking causal and associational relations between factors into account. Moreover, in supplier selection problem, the decision makers can have limited information. For example, they can have information about some criteria, but no information about the others. BNs also offer a suitable modelling approach in this case. Decision makers can only enter evidence about the information they know, and a BN can update the probabilities of the unknown criteria based on the given evidence. Considering overall interaction between selection criteria and ability to deal with unknown information can provide useful decision support to decision makers.

Although BNs offer such advantages, it is still challenging to build BN models for supplier selection problem based on expert knowledge. The method proposed in Section 5.2 offers a systematic approach to build such models.

In this thesis, we focused on a supplier selection problem in one of the largest automotive manufacturers in Turkey. Our aim is to develop a BN decision support model for this company by using the novel method that is described in section 5.2. We made interviews and surveys with 14 experts for this task.

5.2. Method to Build Causal BNs from DEMATEL Questionnaires

5.2.1. Overview of Method

We propose a general method to build causal BNs based on DEMATEL surveys from multiple experts. Our method could be used in different fields but we will illustrate the use of our method with the automotive manufacturer case study. Our proposed method is composed of following steps:

1. **Determining the decision criteria:** Firstly, we need to determine important factors for the decision problem. The criteria are determined based on literature reviews and expert knowledge.
2. **Preparing DEMATEL matrix**: After determining decision criteria, a survey is conducted to ask experts about influences of different criteria on each other. According to survey results, steps of DEMATEL are executed, direct relation matrix and total relation matrix are computed.

3. **Building Initial Causal Graph**: The total relation matrix of DEMATEL represents the sum of direct and indirect relations between criteria. However, BN arcs represent only direct relations. Therefore, we use the direct relation matrix of DEMATEL to construct the causal network and the total relation matrix to evaluate the final model. We determine a threshold value for the direct relation matrix and we include the relations that are greater than the threshold value in the direct relation matrix as valid arcs in the causal network. Threshold value is determined according to expert opinion.
4. **Eliminating Cycles:** There can be cycles in the initial causal graph that is built in Step 3. However, BNs are directed acyclic graphs so we need to eliminate these cycles in order to transform this causal graph into a BN. Cycles can exist in the initial causal graph due to the following reasons:

   - In a DEMATEL survey, experts must give answers according to direct causal relations. However, experts can be confused about correlation and causality, and they may state correlations rather than causal relations in the survey.
   - There may be no apparent causation but only a correlation between two variables. This is often due to a latent variable that does not exist in the network. Without the latent variable, it is not possible to see the causation between two variables, but the addition of the latent variable makes causal relation clear. For example, there is correlation but no causation between white hair and heart disease. The causation only becomes clear when we add age in our analysis as age causes both white hair and heart disease.
   - Some cycles can not be eliminated because there is really reciprocal causality between them. These kind of cycles are due to temporal relations. For example, humidity causes rain in time t, and rain increases humidity in time $t+1$. The correct way to eliminate these cycles is to use different time frames in the BN model.

   In our method, cycles because of the first and second reasons are eliminated by expert knowledge, and cycles that are because of third reason are eliminated by dividing the causal model into different time frames.
5. **Revising Causal Graph with Experts**: After cycle eliminations, the causal graph is revised by experts to check if there are any redundant or deficient arcs.

6. **Defining the States of the BN:** A BN is constructed according to final causal graph that is obtained after revisions. Mutually exclusive and collectively exhaustive states must be determined for each node. This is done based on expert knowledge.
7. **Parameterising the Causal BN with Ranked Nodes:** The parameters of the BN must be determined to make computations with the model. We use the Ranked nodes approach to parameterize the BN.
8. **Bayesian Network Model:** After parameterising, the final BN model is ready and it can be used to make probabilistic inferences.

The steps above give an overview of our method. In the remainder of this section, steps of our proposed approach will be explained in more detail and illustrated with the supplier selection case study of an automotive manufacturer in Turkey.

5.2.1.1. Step 1: Determining Decision Criteria

The first step in our model is to determine the main variables in our BN model. We also call these variables decision criteria as they represent important factors for decision making.

In the supplier selection case study, we first reviewed the previous studies and prepared a list of potential candidates for our model. Afterwards, we made interviews with the experts from the automotive manufacturer to select the criteria. The criteria used for our model is as follows:

- **Product Quality:** Product quality criteria refers to supplier's ability of producing quality products to meet all specifications requested by customer. Product quality is an essential factor for selecting and prioritizing suppliers [7].
- **Cost:** Cost criteria includes product price and all costs related with supply process.
- **Delivery Performance:** Delivery performance is a measure of delivery of products on time with the right quantity and in expected handling conditions as packaging and transportation conditions delivery without any damage and with all necessary fulfilled documents as invoice, dispatch note and quality control report of the products. Delivery performance is considered as an important supplier selection criterion in many previous studies [7] [29] [8].

- **Quality System Certifications:** Supplier’s quality system certifications such as ISO 9001 and ISO/TS16949. Dogan and Aydin [7] also included quality system certifications as a supplier selection criterion.
- **Flexibility:** Supplier's ability to adapt to changes and needs of customers. Flexibility criteria could be examined under three categories [7] : product flexibility, volume flexibility and delivery flexibility. Product flexibility refers to the capability of adaption of change on products. Volume flexibility is managing ability to size or quantity changes asked by customer. Delivery flexibility is ability to change in lead time and requested delivery time. Ndubisi et al. [30] also emphasize the importance of flexibility in supplier selection decision.
- **Cooperation:** Cooperation criterion shows communication and collaboration willingness of suppliers in relations. Cooperation criterion is examined in previous studies with different descriptions or components such as collaboration or communication [29].
- **Reputation:** Recognition level of supplier in market based on past performance with previous customers. Reputation could be evaluated with factors such as whether the company works with comptetitors, does foreign exports and has high production volume or not. The experts from the automotive manufacturer company stated that they give priority to suppliers who have high reputation in the market during supplier evaluation process.

5.2.1.2. Step 2: Preparing DEMATEL Matrices

DEMATEL has two essential matrices; the average direct relation matrix and the total relation matrix. The average direct relation matrix shows direct relations between the criteria. And total relation matrix shows direct and indirect relations between the criteria (DEMATEL is described in detail in Chapter 3). In this step, we compute both of these matrices. In later steps, the average direct relation matrix is used for building a causal graph, and the total direct relation matrix is used for evaluating the model.

In our case study, after determining supplier selection criteria, we conducted a survey on 14 experts from our automotive manufacturer by using Google Forms. We asked the experts direct causal influences of supplier selection criteria on each other. Survey questions are shown in Appendix.

According to the survey results, the steps of DEMATEL were conducted and its matrices were calculated. The direct and total relation matrices are in Tables 1 and 2 respectively.

D	Product Quality	Cost	Delivery Performance	Quality System Certifications	Flexibility	Cooperation	Reputation
Product Quality	0,0000	3,0000	1,0000	2,2857	1,4286	1,2857	3,1429
Cost	1,7143	0,0000	1,2857	1,0714	1,9286	1,5714	2,3077
Delivery Performance	1,7143	2,0714	0,0000	1,5000	1,3571	1,4286	2,3571
Quality System Certifications	2,6429	2,1429	1,5714	0,0000	1,5000	1,3571	2,7857
Flexibility	1,8571	2,2143	2,3571	1,0000	0,0000	2,0714	1,8571
Cooperation	2,3571	1,7143	2,2857	1,2143	2,2857	0,0000	2,2143
Reputation	1,7857	2,3077	1,2143	1,2143	1,2857	1,4286	0,0000

Table 1. Average Direct Relation Matrix of DEMATEL

T	Product Quality	Cost	Delivery Performance	Quality System Certifications	Flexibility	Cooperation	Reputation
Product Quality	0,3733	0,5955	0,3646	0,4055	0,4012	0,3754	0,6311
Cost	0,4164	0,3538	0,3357	0,2949	0,3785	0,3449	0,5123
Delivery Performance	0,4310	0,4936	0,2639	0,3299	0,3585	0,3469	0,5336
Quality System Certifications	0,5262	0,5508	0,3949	0,2722	0,4030	0,3780	0,6127
Flexibility	0,4655	0,5312	0,4293	0,3220	0,2983	0,4053	0,5391
Cooperation	0,5136	0,5303	0,4421	0,3505	0,4500	0,2978	0,5841
Reputation	0,4029	0,4702	0,3153	0,2908	0,3291	0,3220	0,3566

Table 2. Total Relation Matrix of DEMATEL

According to the direct relation matrix, largest direct relation is between product quality and reputation. On the other hand, largest total relation which includes direct and indirect relations is also between product quality and reputation.

According to total relation matrix, relation values change due to addition indirect relations.

5.2.1.3. Step 3: Building Initial Causal Graph

In DEMATEL, a causal network is constructed based on the total relation matrix. The values in a total relation matrix represent the sum of all direct and indirect relations between two nodes. However, these values are not suitable for building a BN structure as BN arcs represent direct causal relations. Therefore, we used the direct relation matrix of DEMATEL to construct a causal graph basis for a BN. A threshold value was determined with experts, and direct influence values greater than the threshold value were accepted as a valid direct influence and smaller ones are neglected.

In the case study, the threshold value was determined as 1.75. This value is determined after building a causal graph with seveal different thresholds with experts. The direct influence values greater than 1.75 were determined as valid direct influence arcs in the causal network. The initial causal network built is shown in Figure 20.

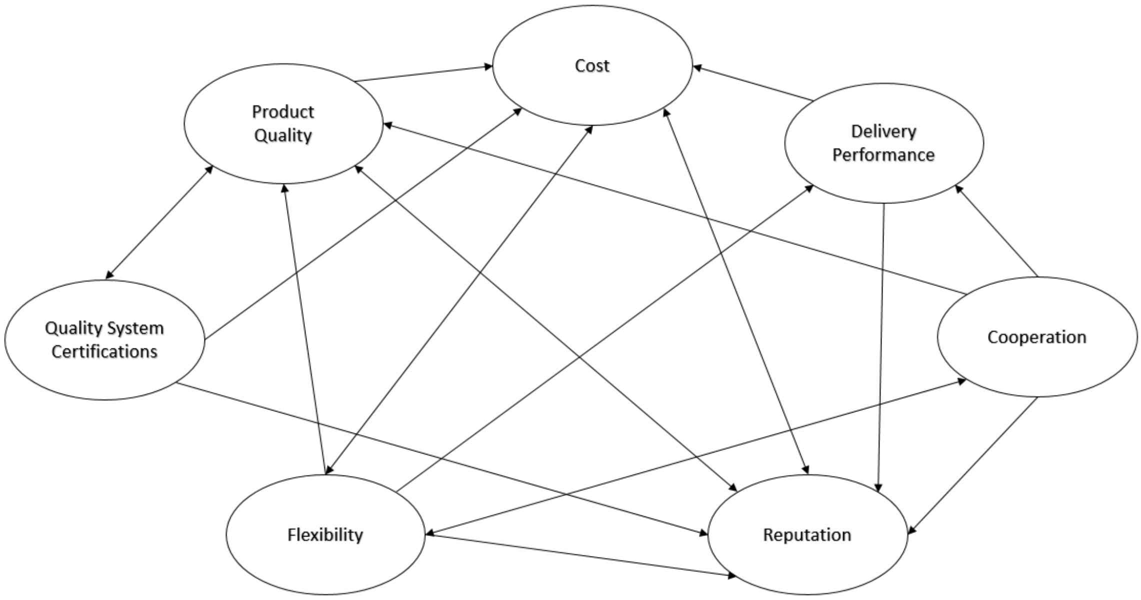

Figure 20. Initial Direct Causal Relation Network

However, the causal network in Figure 20 is still not a BN because it contains cycles whereas BNs are directed acyclic graphs. Moreover, this causal graph is dense, there are many arcs between the nodes. Some of these arcs may be unnecessary so they need to be reviewed with experts. The next step in our method is to eliminate cycles from this causal network in order to transform it to a BN.

5.2.1.4. Step 4: Eliminating Cycles

We need to eliminate the cycles from the initial causal graph since BNs cannot have cycles. The cycles of the initial causal graph are shown in Figure 2.

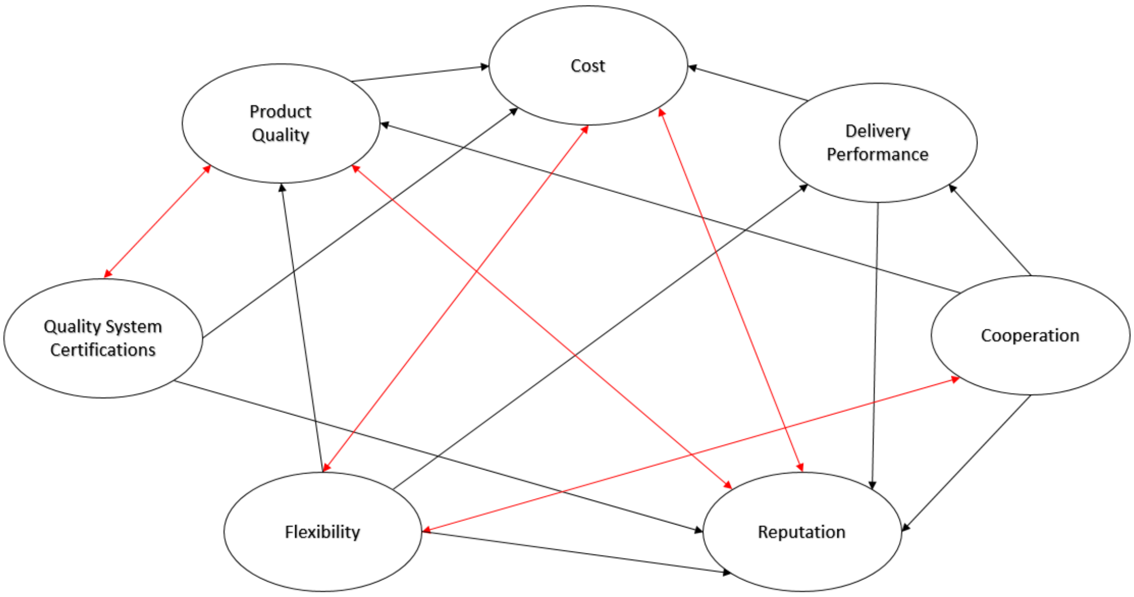

Figure 21. Cycles on Initial Causal Network

Cycles can exist in the initial causal graph due to the following reasons:

- In the DEMATEL survey, experts can be confused about correlation and causality, and they may state correlations rather than causal relations.
- There may be no apparent causation but only a correlation between two variables. This is often due to a latent variable which does not exist in the network. Without the latent variable, it is not possible to see the causation between two variables, but the addition of the latent variable makes causal relation clear.
- Some cycles may be due to the temporal relations between the variables. There may be causal relation in both directions but in different time instances.

We investigated the source of cycles in Figure 21 with domain experts for each of these reasons. We identified that cycles between product quality-reputation and cooperation-flexibility are caused by the first cycle reason.

The experts indicated that there is a clear causal relation from product quality to reputation, and from flexibility to cooperation.

DEMATEL results about the additional direction may be due to a confusion of correlation and causation from the survey respondents. Based on this information, the causal graph is modified as shown Figure 22.

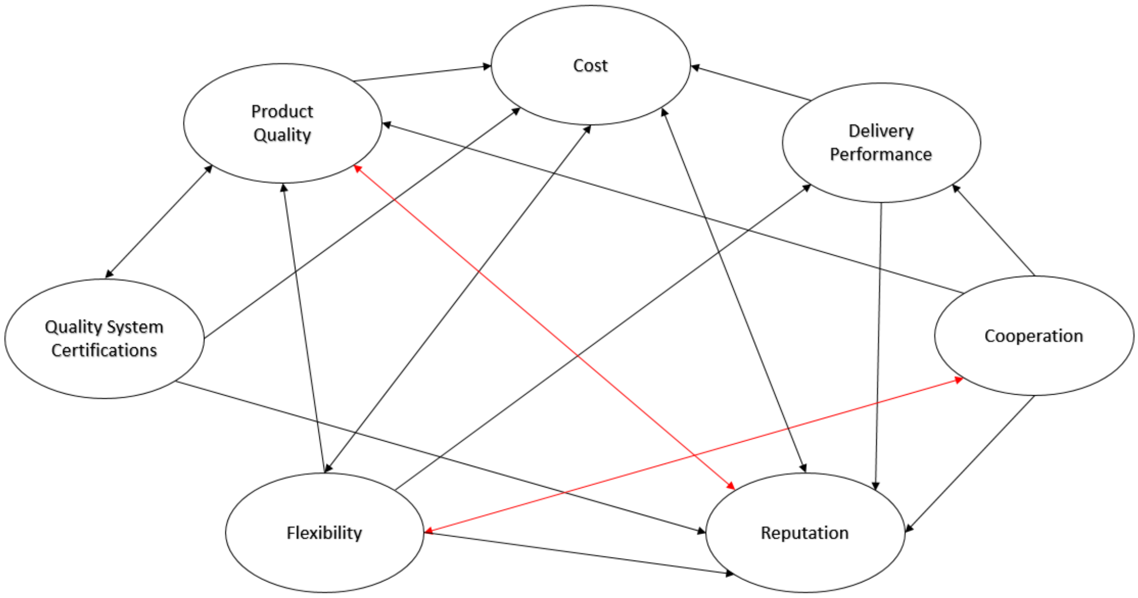

Figure 22 . Cycles because of first reason.

The cyclic arcs between cost and flexibility, and cost and reputation are considered to be due to the second reason. In other words, experts did not see a direct causal relation between these variables, but there may be a correlation due to a latent variable or other variables. For example, the relation between cost and reputation could be due to the fact that both of these factors are affected by the product quality. As a result, we removed these arcs from the causal graph as shown in Figure 23.

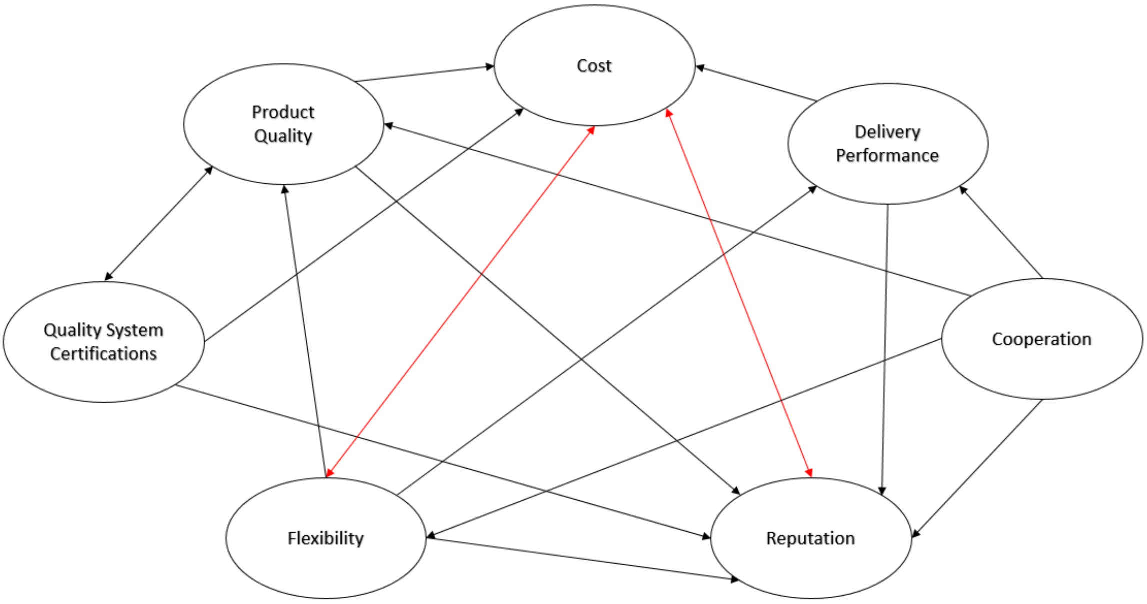

Figure 23. Cycles because of second reason

Finally, the cyclic relation between product quality and quality system certifications are considered to be caused by a temporal relation (the third cycle reason) as shown in Figure 24. In this case, increased product quality will cause the company to get quality system certifications, and the requirements to sustain these certifications will cause further improvements in product quality. This cycle can be eliminated by using different time frames.

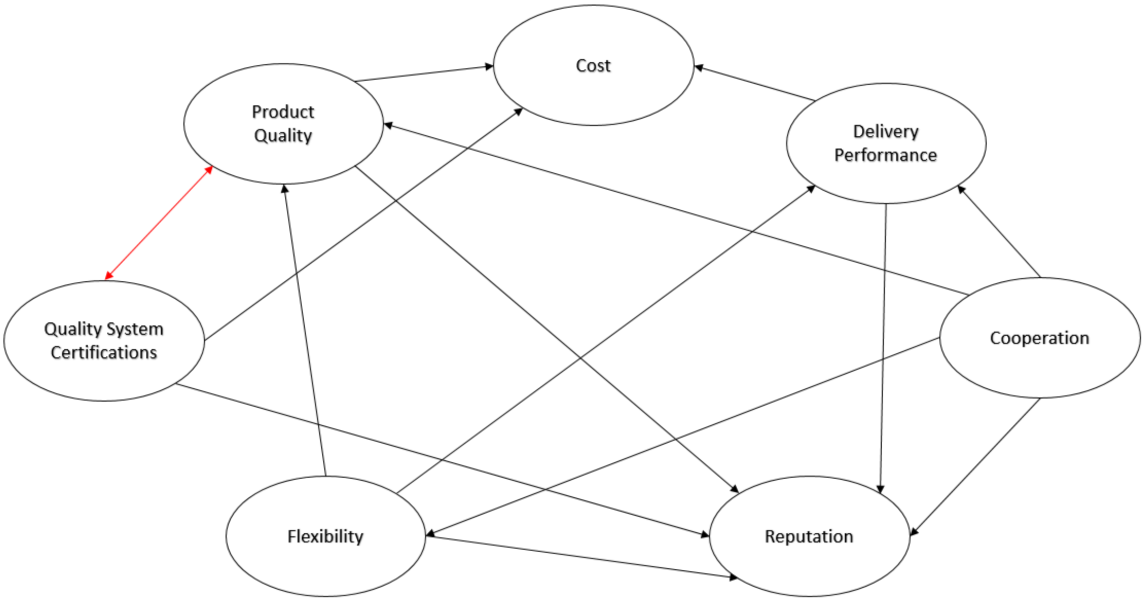

Figure 24. Cycles because of third reason

5.2.1.5. Step 5: Revising Causal Graph with Experts

After the cycle elimination step, other arc eliminations or additions may be required by domain experts. Some arcs can be redundant, or their direction can be wrong due to the reasons discussed above or other reasons. Domain experts may also want to add new arcs that are not identified in the DEMATEL surveys. Therefore, the causal graph is checked one more time with experts in our method.

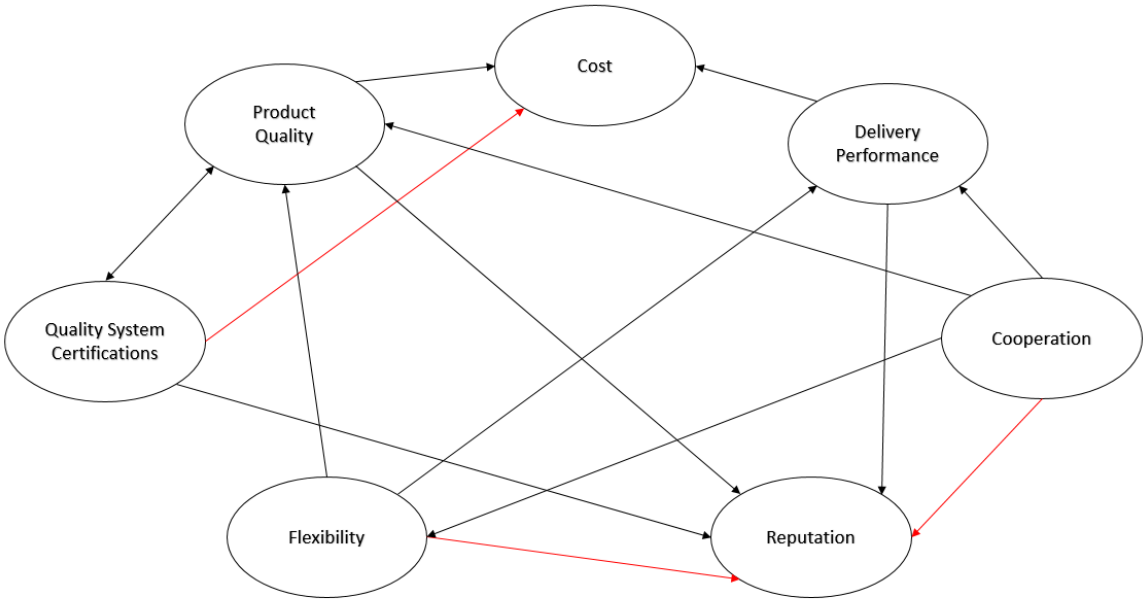

Figure 25. Additional Arc Modifications

In the case study, experts removed some arcs as the causal relations between those variables are mediated through other variables. For example, the arc from flexibility to reputation and the arc from cooperation to reputation are considered to be redundant as the causal relations between these nodes are mediated through delivery performance. In other words, delivery performance summarizes the effect of cooperation and flexibility on reputation in this model. Similarly the arc from quality system certifications to cost is also found redundant as there is a causal link between Quality System Certification → Product Quality → Cost. So these arcs were removed from the causal network to simplify the model (see Figure 25), and the final causal model is shown in Figure 26.

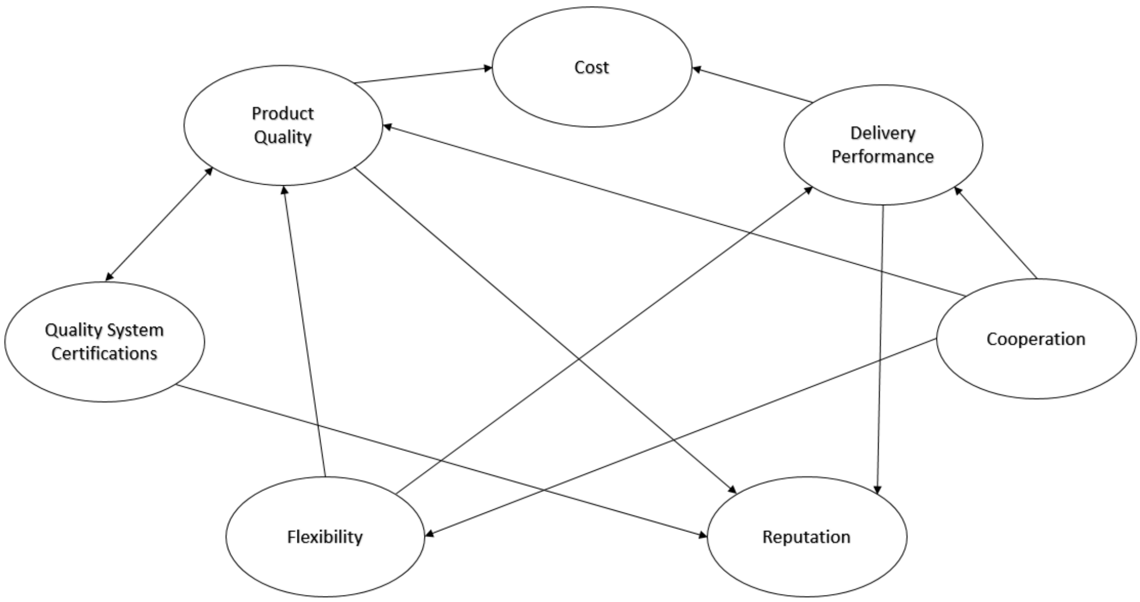

Figure 26. Final Causal Network Model

5.2.1.6. Step 6: Defining the States of the BN

The final causal model in Figure 7 is ready to be used as a BN structure where each node represents a variable and each arc represents a causal relation. However, each variable in a BN must have a set of mutually exclusive and collectively exhaustive states. Therefore, we need to define states for each variable in Figure 26. We defined 5 ordinal states (i.e. very low, low, medium, high and very high) for all variables in our model.

For quality system certifications, very low means supplier has no quality system certifications, low means supplier has ISO 9001 but can not pass buyer's quality inspection, medium means supplier has ISO 9001 and passed supplier's quality inspection test, high means supplier has ISO 9001, passed supplier's quality inspection and test and has additonal quality system certificate which is essential for the buyer's industry such as ISO/TS16949, and finally very high means supplier has extra certifications as OHSAS 18001 addition to possesions in high state.

The definitions of the other variables' states are based on qualitative expert knowledge, and this is discussed in more detail in Section 5.3. We used two different time frames because of cycle between product quality between quality system certifications. The final model divided into two-time frame is shown in Figure 27.

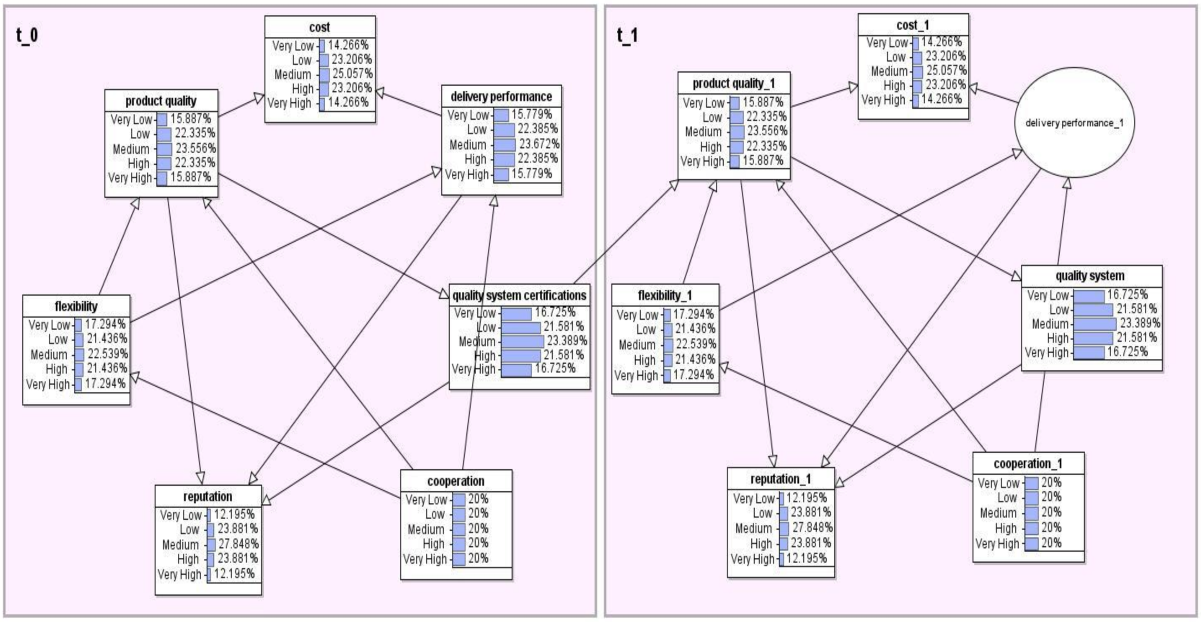

Figure 27. Model with two time frames

5.2.1.7. Step 7: Parameterizing the Causal BN with Ranked Nodes

The parameters of the BN are determined with the ranked nodes method. Ranked nodes approximation reduces the number of parameters required for each variable and simplifies the definition of NPTs for experts (see Section 2.1 for a detailed description of ranked nodes). We preferred to use weighted average (wmean) function for the ranked nodes in the case study. For wmean function, we need to define a coefficient for every parent variable and a variance parameter. We defined weights of each parent based on their coefficient in A matrix from DEMATEL. For example, the parents of product quality is cooperation and flexibility in our model. The weights of these parents were defined from the values in average direct relation matrix in Table 1. The variance values for the ranked nodes was defined by the sum of variances of the survey responses for product quality. However, since the survey matrix is scaled between 0 and 4, and Tnormal distribution of ranked nodes has unit scale, we need to normalize this variance to [0-1] scale. For this normalization, we divide the sum of survey variances associated with the variable to $4P^2$ where P is the number of parents of the variable.

	8. How much does flexibility influence product quality?	10. How much does cooperation influence product quality?
mean	1,86	2,36
variance	0,90	1,32

Table 3. Means and variances of effects of flexibility and cooperation on product quality

The mean and variance of the DEMATEL survey responses associated with parents of product quality are shown in Table 3. The wmean parameters of this variable are shown below:

Mean of product quality = wmean (2.36, cooperation, 1.86, flexibility)

Variance of product quality = (0.90+1,32)/64

Figure 28 shows how these variables were entered in AgenaRisk software. The parameters of the rest of the variables in the model were defined in the same way as this.

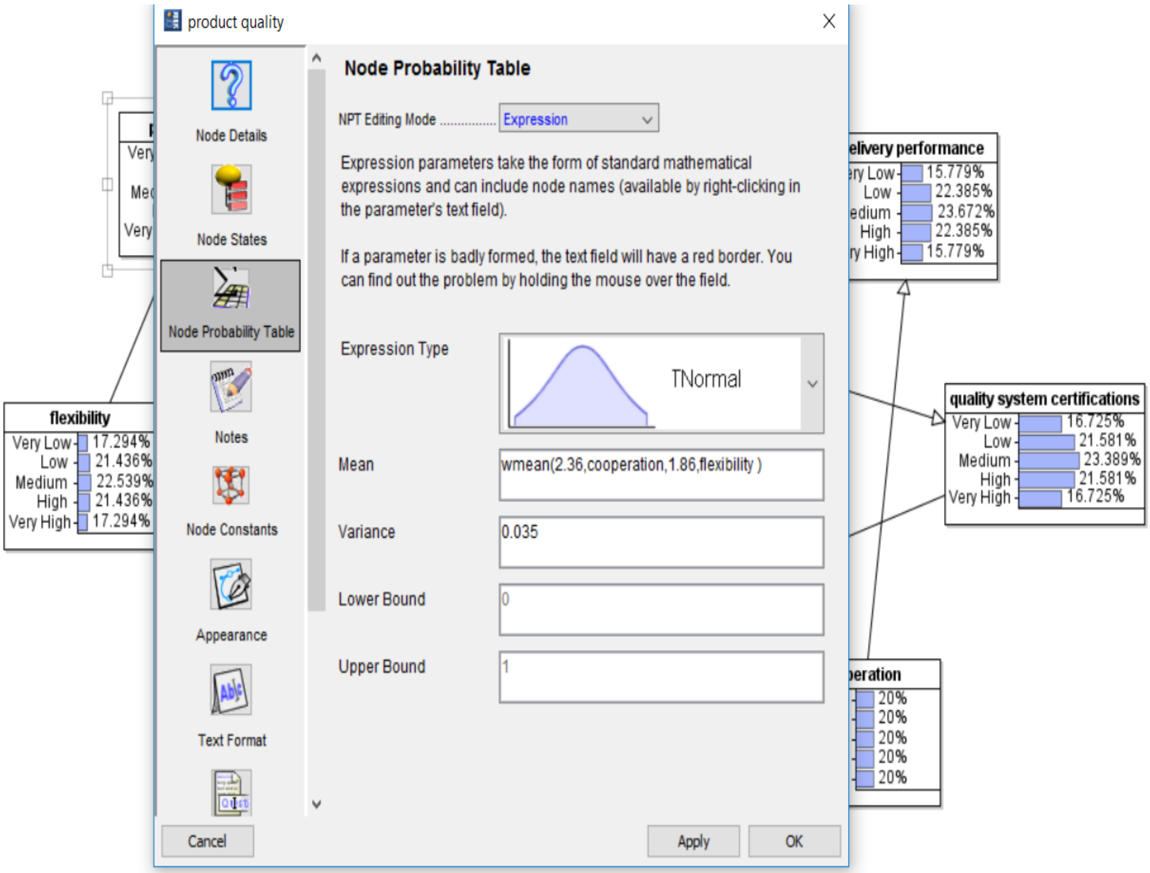

Figure 28 . Weighted average with Ranked Nodes

5.2.1.8. Step 8: Bayesian Network Model

After the parameters of all nodes are defined with ranked nodes technique, the final BN model was computed by using AgenaRisk software. The marginal probailities of all nodes in a single time frame of the model is shown in Figure 29. In the following section, we evaluated our model by using sensitivity and scenario analysis. Evaluations were conducted on a single time frame as time frames are repetitions of the same BN model fragment.

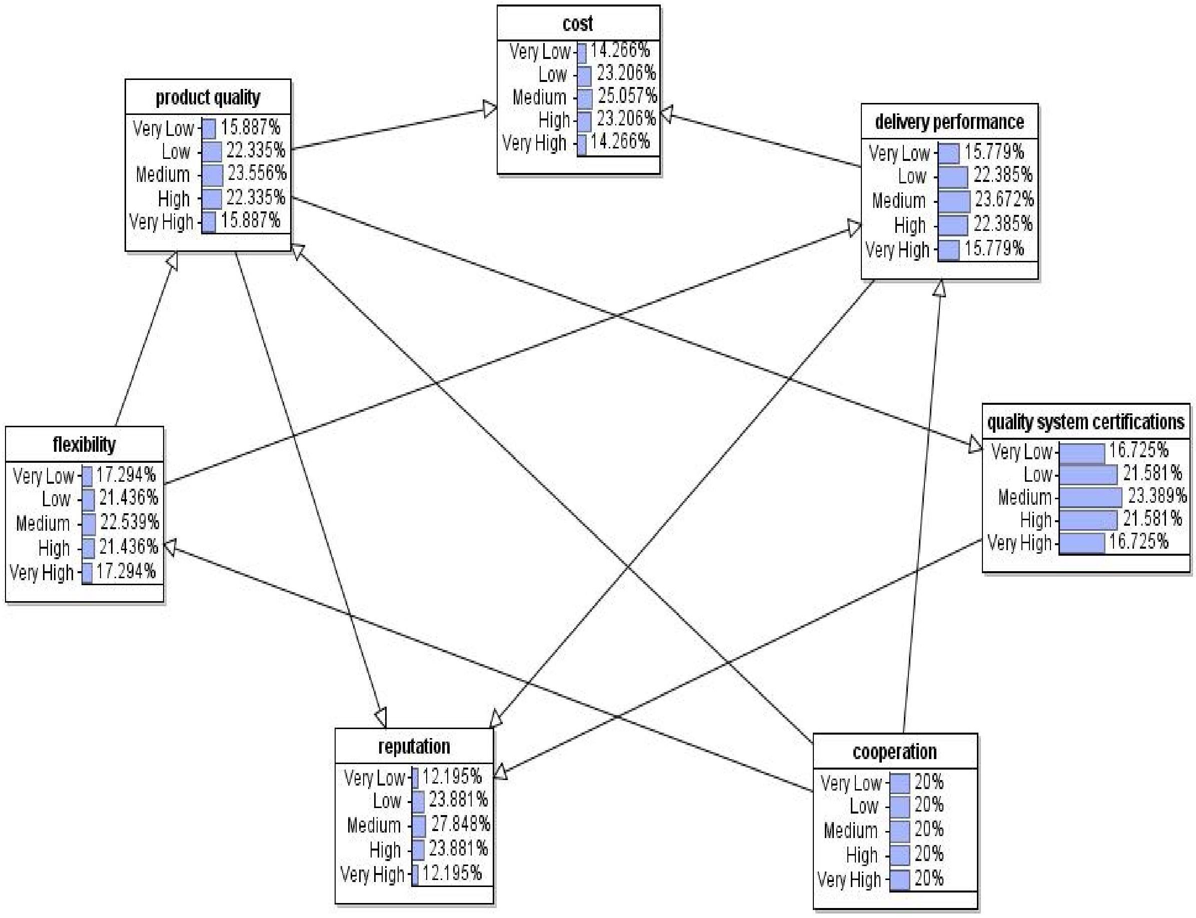

Figure 29. BN Model with one-time frame

6. RESULTS

Since our method builds a BN based on expert knowledge, the evaluation of the model must also be based on expert knowledge. We used sensivitiy analysis of evidence, sensitivity analysis of parameters, and scenario analysis for this task. We evaluated the consistency of our model with DEMATEL results by making a sensitivity analysis of evidence and comparing this with DEMATEL's total relation matrix in section 6.1. A complete consistency between DEMATEL and our method was not expected since we made some modifications on arcs based on expert knowledge. However, our aim was to examine the inconsistencies between these two methods with experts. Sensitivity analysis of parameters was also conducted to measure robustness of the model in Sectoin 6.2. Scenario analyses were conducted to evaluate the inferences of the model based on expert knowledge and to illustrate the use of the model in Section 6.3. Since it is usually not possible to directly observe the decision criteria in Figure 29, we expanded the BN model with indicators that indirectly estimate the state of the decision criteria in scenario analysis in section 6.3.1.

6.1. Sensitivity to Evidence and Consistency with DEMATEL

When a sensitivity analysis of evidence is done for a BN, a target variable is selected, and the effect of entering evidence to other variables on the target variable is measured. We conducted evidence sensitivity analysis on AgenaRisk to see how much each criterion is affected from the variation of the other criteria. We conducted evidence sensitivity analyses for every criterion in the model. This analysis also ranks the total impact of other variables on a particular variable, and helps us to determine the most influential criteria. The results of the sensivity analysis of evidence are shown by tornado diagrams in Figures 30, 31 and 32.

We compared the results of the sensitivity analysis with the total relation matrix of DEMATEL. We did not expect 100% consistency between the sensitivity analysis results and the total relation matrix since our method modifies the initial causal graph from DEMATEL based on expert knowledge. We constructed our model according to the direct relation matrix and we eliminated arcs that are under the threshold value. We also eliminated cyclic and some redundant arcs. As a result, we expect the total relation matrix of DEMATEL and the results of the evidence sensitivity analysis to be different from each other. However, our aim was to identify these differences and review them with domain experts to see if there was any error in the BN model.

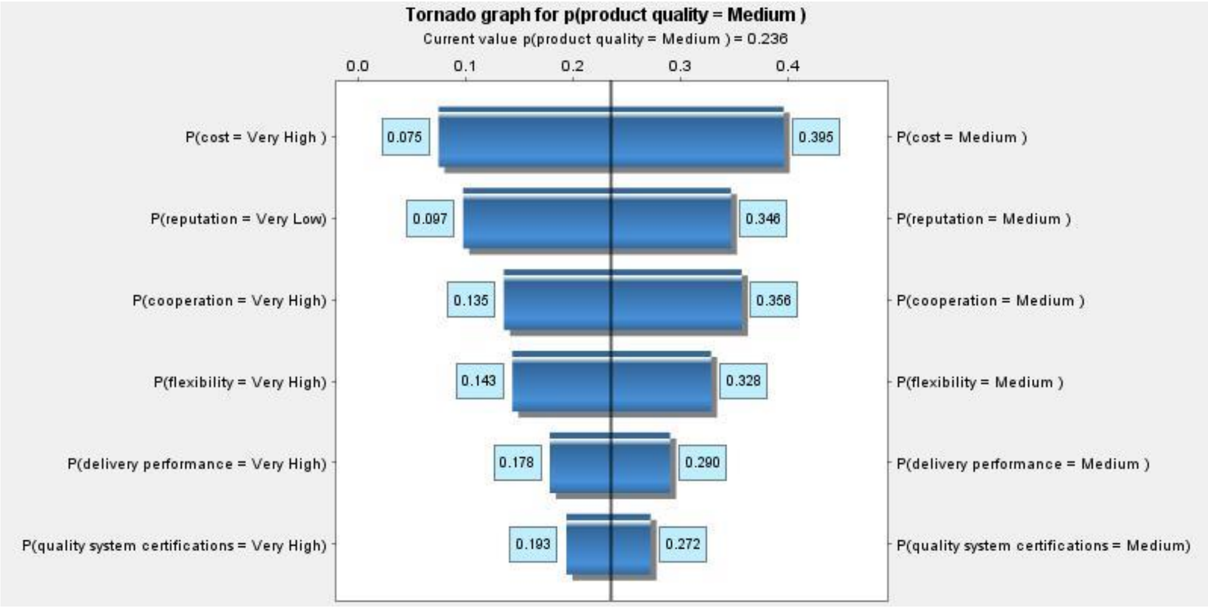

Figure 30. Tornado graph for evidence sensitivity of product quality

Figure 30 shows a tornado graph for the sensitivity analysis where product quality is the target variable as shown at the top of this diagram. The sensitivity of this variable to other variables is shown with the ranking. For example, the variable that has the highest effect on the medium state product quality is cost, and this can change the probabilility of medium product quality from 0.075 to 0.395. According to total relation matrix of DEMATEL in Table 2, impact ranking of criteria for product quality is quality system certifications, cooperation, flexibility, delivery performance, cost and reputation respectively. In our BN model the quality system certification is ranked at the bottom, but cost and reputation are ranking at the top. When we review this difference with domain experts, they also agreed with the BN model that cost and reputation are highly related with product quality so they did not make any changes in this part. The difference about quality system certification is considered to be due to the temporal division of the model. Since we only evaluated one-time frame of the model, the relation between quality system certifications and product quality was underestimated. The ranking between cooperation, flexibility and delivery performance was the same in both DEMATEL and BN.

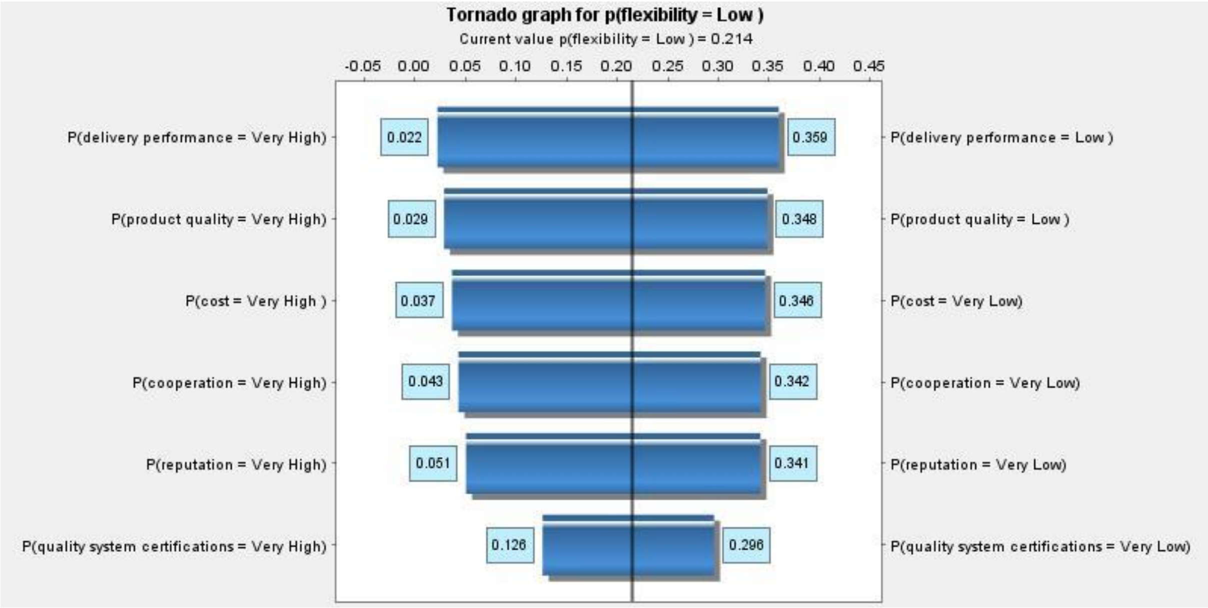

Figure 31. Tornado graph for evidence sensitivity of flexiblity

Figure 31 shows the tornado graph for sensitivity analysis on flexibility. The rankings in the DEMATEL's total relation matrix for flexibility is cooperation, quality system certifications, product quality, cost, delivery performance and reputation. We observe that the total effect of cooperation and quality system certifications was lower in the BN model as we made removed some arcs due to cycles and indirect causal relations of these variables in sections 5.2.1.4 and 5.2.1.5. As a result, the rankings of the rest of the variables increased and all variables except quality system certifications have very similar amount of effects on flexibility.

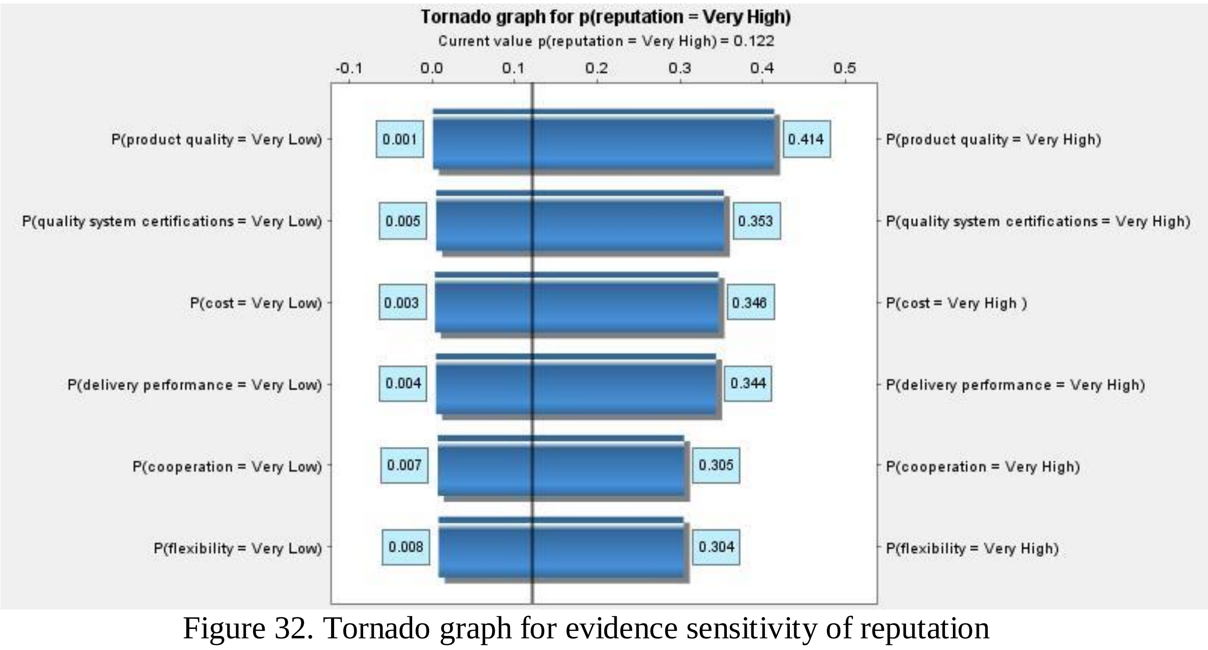

Figure 32. Tornado graph for evidence sensitivity of reputation

Figure 32 shows the tornado graph for reputation. Total relation matrix rankings for reputation is, product quality, quality system certifications, cooperation, flexibility, delivery performance and cost respectively. Since we eliminated arcs between cooperation-reputation and flexibility-reputation, the rank of cost and delivery performance increased compared to the DEMATEL's results.

We also evaluated the sensitivity of all other variables in the BN model with experts. All differences between the DEMATEL's and BN's results were found to be caused by the arc removals done when building the BN, and the results of the BN were considered to be reasonable by experts. The senstivity anaylsis of evidence technique allowed us to review the model in a systematic way.

6.2. Sensitivity to Parameters

In sensitivity analysis for parameters, a target variable is chosen and the impact of changing the parameters of other variables on the target variable is analysed. Each parameter in the model is varied within defined bounds, and the amount of change on the targert variable's probability distribution is measured [31]. We use sensitivity analysis of parameters to evaluate the robustness of the model for the changes in its parameters. We used Genie software to conduct sensitivity analysis of parameters.

We first set the medium state of product quality as the target node and run the sensitivity analysis of parameters. The results are shown in the tornado graph in Figure 33. We changed the probabilities of all other nodes by 10% and observed how much change occured in the probability of medium product quality. The initial probability of product quality in medium state, before any change, is 0,235559. By changing the other parameters 10%, this probability value can be changed between 0,232537 and 0,23858. In other words, this variable is not sensitive to changes in other variables.

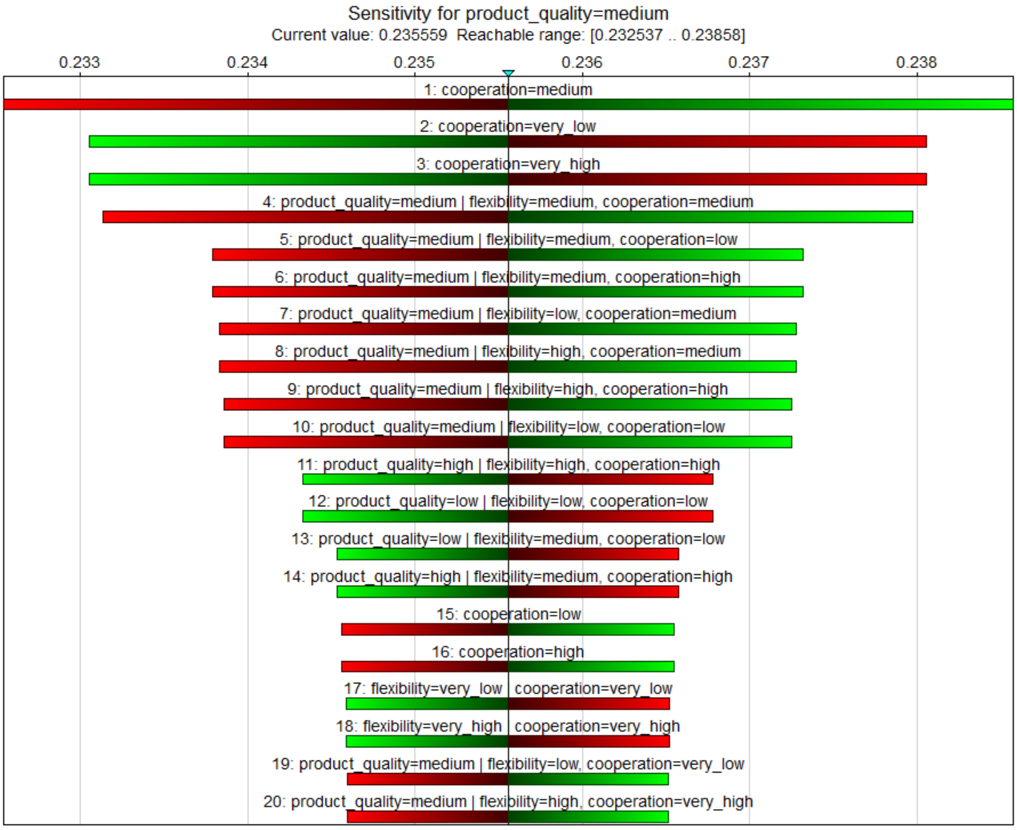

Figure 33. Tornado graph for parameter sensitivity of product quality

Figures 34 and 35 show the results of parameter sensitivity analyses for cost and delivery performance respectively. When the other parameters are changed by 10%, the probability of cost changes maximum between 0,247177 and 0,253957, and the probability of delivery performance is 0.233943 and 0.239493. The sensitivity analysis of other parameters were also done and the results were similar. In summary, the changes in individual parameters do not significantly change the results of our model.

Parameter sensitivity analysis is a useful approach to evaluate the BN models developed by our proposed method. The model developers can assess the robustness of their model and prioritize the most sensitive variables so that they can define more accurate values for their parameters.

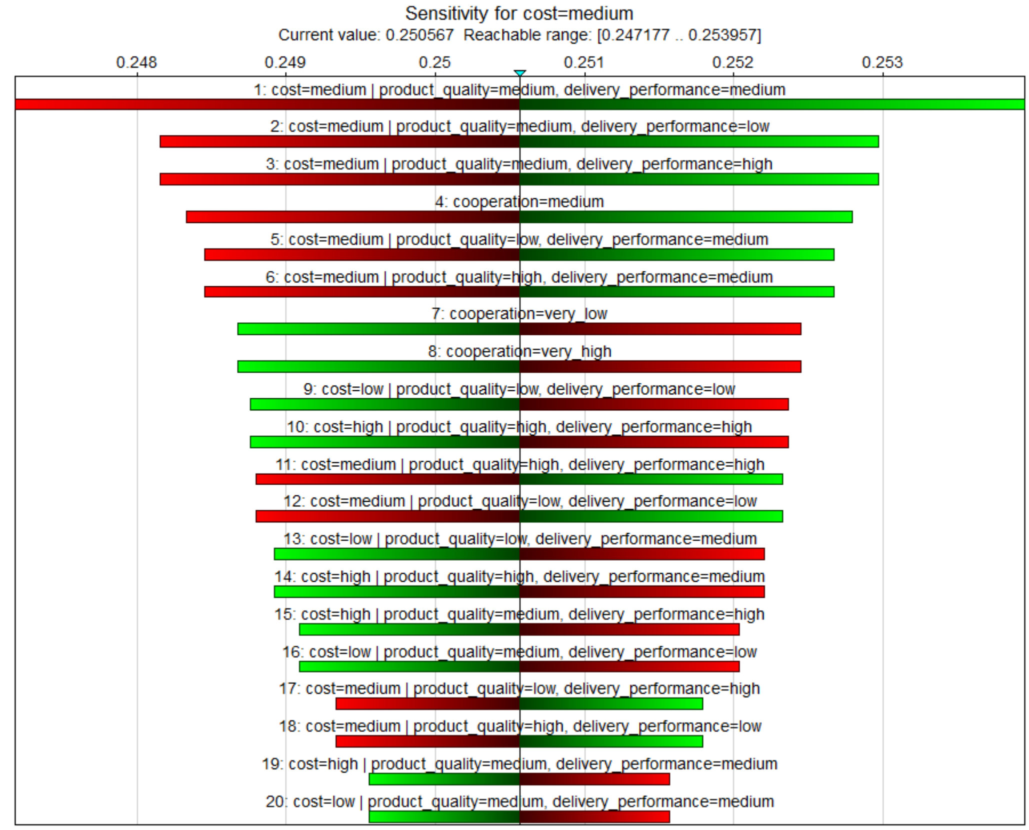

Figure 34. Tornado graph for parameter sensitivity of cost

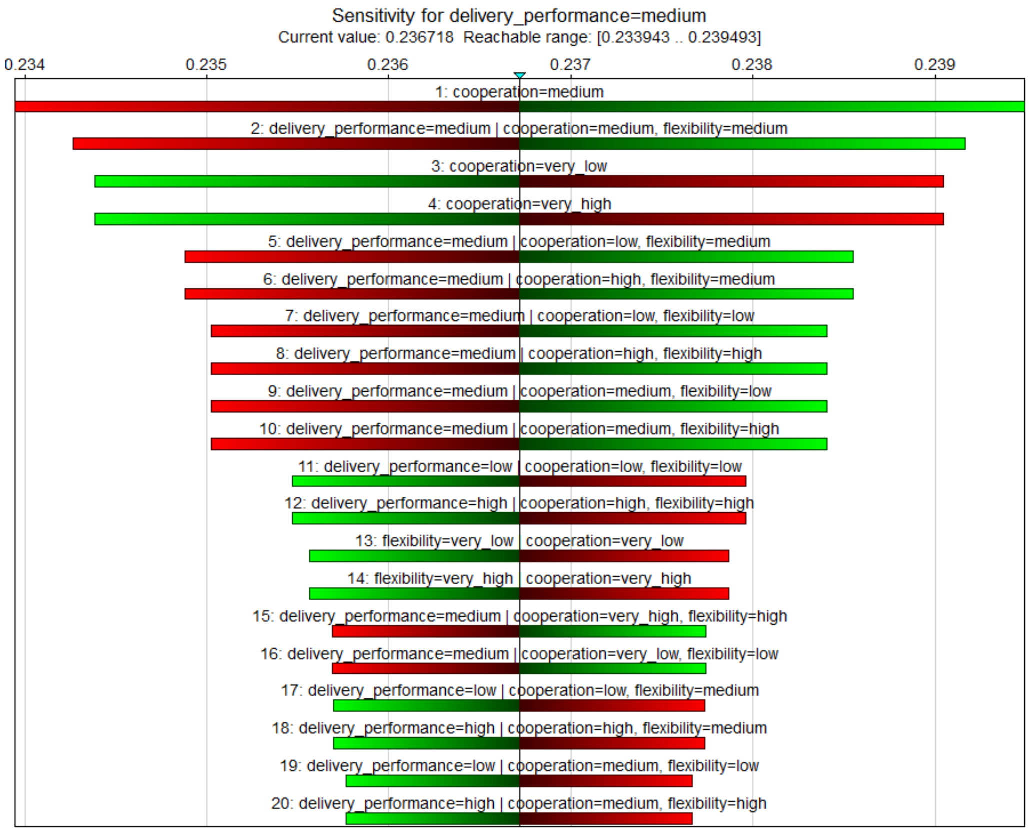

Figure 35. Tornado graph for parameter sensitivity of delivery performance

6.3. Scenario Analysis and Use of the Model

In this section, we explained how our supplier selection BN model can be used as a decision support tool. Supplier selection BN model in Figure 29 identifies the relations between the main supplier selection criteria. However, we often can not directly observe these criteria. We can indirectly measure them through indicators. In this section, we first expanded our model by adding indicators in section 6.3.1,we carried out some scenario analyses on our model in section 6.3.2 and we evaluated two alternative suppliers for the component of the product of automotive manufacturer in section 6.3.3

6.3.1. Expanding the BN Model with Indicators

Our model aims to provide decision support and risk assessment for supplier selection. Among the variables in our model, only cost and quality system certifications can be directly observed due to the definition of their states. The other variables in our model can only be observed through indirect indicators. For example, product quality cannot be directly observed but it can be indirectly estimated through the specifications of its raw materials, dimensions and other compliances. These types of variables like product quality are also called latent variables in BNs and causal modelling literature. The indicator variables of a latent variable are added as its children in the BN structure. We added indicators to latent variables in our model i.e. product quality, delivery performance, flexibility, cooperation and reputation by expert knowledge. Indicators of these variables and their states are described below:

Product Quality Indicators:

The product quality is measured through raw material, dimensional specification and other compliances.

- **Raw Material**: Is used raw material suitable for the product specifications?
  States (Yes, No)
- **Dimensional Compliance**: Do the dimensions of the product meet the dimension specifications of the product?
  States (Yes, No)
    - If we have past data, specify a threshold percentage for the quantity of parts which have dimension inconvenience in last year shipments. Check last year shipments, if the quantity of parts defected under the threshold, dimensional compliance state is yes, otherwise being no.

- If we have no past data, check the dimensions of sample part. If all sample parts have dimensional convenience, state of the node is yes, otherwise being no.

- **Other Compliances**: Do the products meet other requirements via other operations on the products as painting, coating etc?
  States (low, medium, high)

Delivery Performance Indicators:

The delivery performance variable has six indicators which are described below.

- **On-time Delivery**: If we work with the supplier before, check last year shipments. If we didn't work before, check the supplier's shipments to before buyers.
  States:
  - Low: If late shipments' percentage over 10% of total shipments in last year.
  - Medium: If late shipments' percentage is between 5% and 10% of total shipments in last year.
  - High: If late shipments' percentage is under 5% of total shipments in last year.
- **Right Quantity**: Does supplier ship the parts on requested quantity?
  States (Yes, No)
- **Packaging Conditions**: Some products are needed to pack in special conditions. For instance, some parts are needed to cover rust-preventive oil or packaging papers.
  Is packaging conditions proper?
  States (Yes, No)
- **Handling Conditions**: Are the parts loaded and discharged in convenient conditions and with the proper handling equipments without any damage?
  States (Yes, No)
- **Transportation Conditions**: Transportation way of the products changes according to product and also distance from the supplier to buyer as road, air or sea transportation. And property of transportation vehicles is also important to deliver the products in safe as in weatherproof conditions. If buyer conducts the shipments in their own, the state of the node is selected as yes.
  States (Yes, No)
- **Documents**: Buyers wait for many document with the shipment of the parts as invoice, dispatch note and quality control reports. If supplier sends all these documents with the shipment, the state of node is yes.
  States (Yes, No)

Flexibility Indicators

Flexibility variable is estimated by product, volume and delivery flexibility. These variables and their states are described below.

- **Product flexibility**: Does supplier response to requested changes on product?
  States:
  - Low: Supplier doesn't meet the requested changes on products or meets the changes in low level.
  - Medium: Supplier meets the changes on the product in medium level.
  - High: Supplier meets all requested changes on product.
- **Volume flexibility:** Does supplier response to requested change on quantity?
  States:
  - Low: Supplier meets the quantity increase up to 10%.
  - Medium: Supplier meets the quantity increase from 10% to 25%.
  - High: Supplier meets the quantity increase over 25%.
- **Delivery Flexibility:** Does supplier response to backdate to delivery date?
  States:
  - Low: Supplier responses to backdates up to 1 week.
  - Medium: Supplier responses to backdates from 1-4 week.
  - High: Supplier responses to backdates over 4 weeks.

Cooperation Indicators

The degree of cooperation is estimated by three variables in our model as described below.

- **Data Sharing:** Does supplier share data as production and quality control reports?
  States (Yes, No)
- **Communication:** Is supplier willing to communicate?
  States (Yes, No)
- **Problem Solving:** Is supplier good at problem solving?
  States (Yes, No)

Reputation Indicators

Reputation of a supplier is estimated by three variables as described below.

- **Working with Competitors:** Does supplier work with my competitors?
  States (Yes, No)

- **Annual Production volume:** How much is the annual production volume of the supplier?

  States (Low, Medium, High)

- **International Export:** Does supplier make international export?

  States (Yes, No)

The BN model expanded with indicators is shown in Figure 36. In the following section, we illustrated the use of this model with different scenarios.

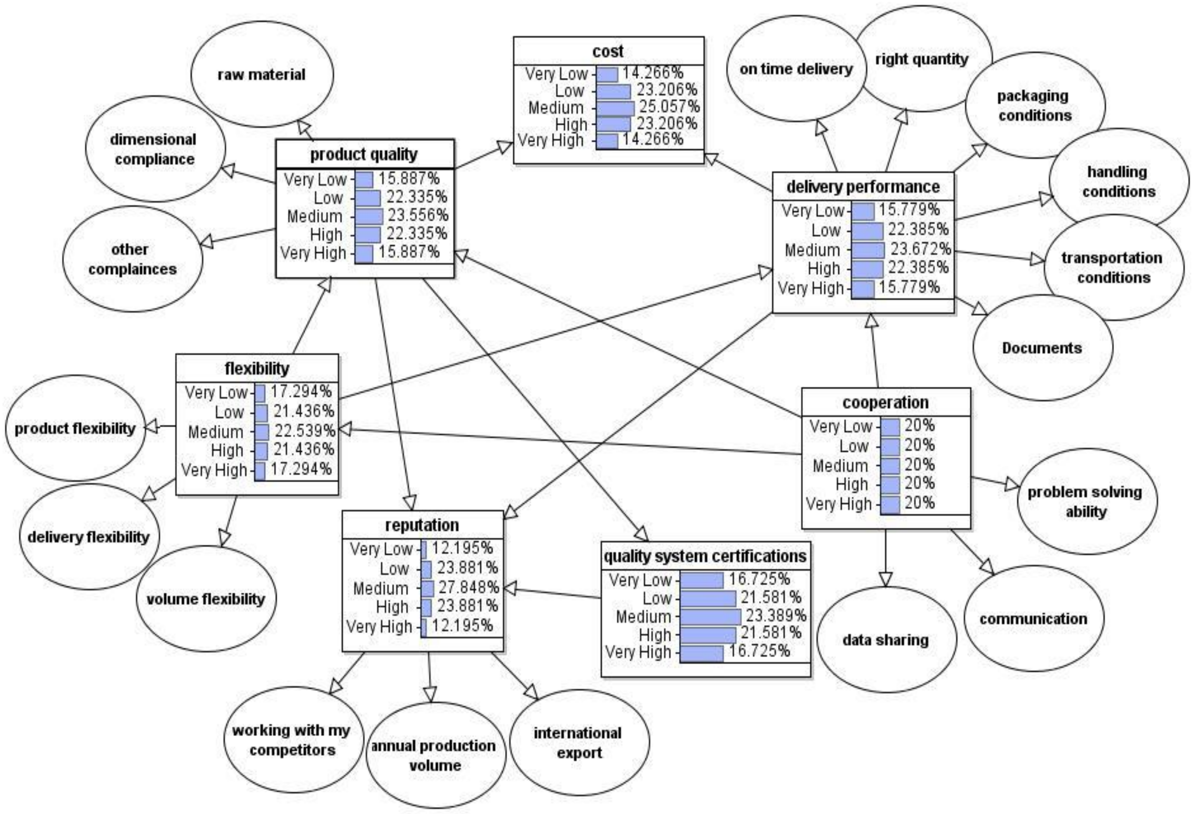

Figure 36. Model with indicators

6.3.2. Scenario Analysis

In this section, we illustrated the use of our model under different scenarios. We examined how the posterior probabilities of the supplier selection criteria change when different evidence is entered to the model. We started with a simple scenario where we only know that the supplier has proper raw material, dimensional and other compliances. Figure 37 shows the updated probabilities based on this information.

Note that increased product quality also affects all other decision criteria in the model and increases their expected values. This is because product quality has direct or indirect relations with all other criteria in the model and there is no other information entered to the model. The least affected critera from this information is the delivery performance.

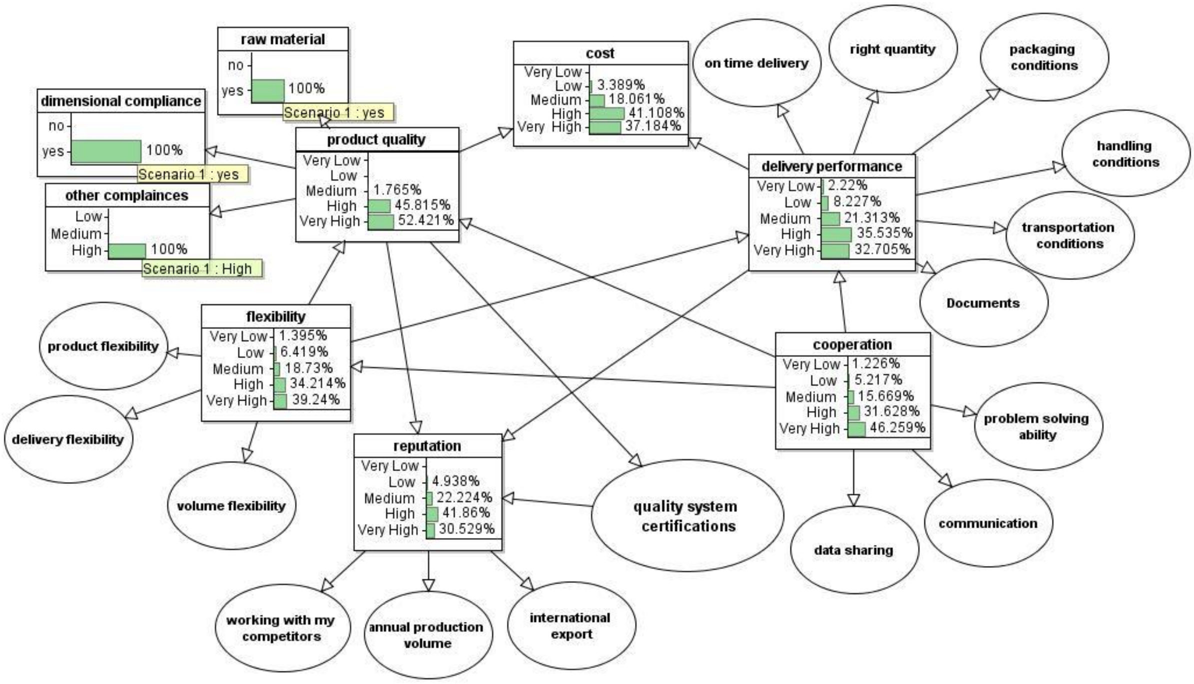

Figure 37. Scenario 1: High Product Quality

In Scenario 2 we have information about high level of cooperation and flexibility from the indicators of these variables as shown in Table 4.

Indicator	Value	Indicator	Value
Product Flexibility	High	Data Sharing	Yes
Delivery Flexibility	High	Problem Solving	High
Volume Flexibility	High	Communication	High

Table 4. Known indicators for Scenario 2

We can see that with increasing of fexibility and cooperation, considerable improvement is seen on all other criteria as shown in Figure 38.

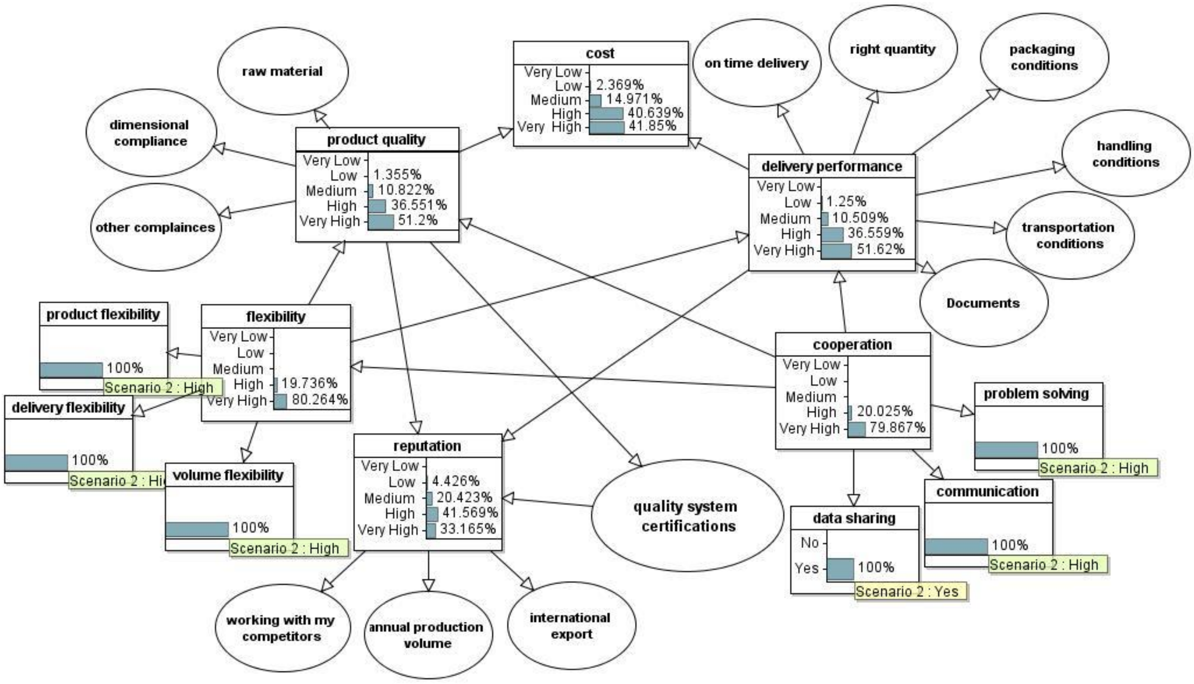

Figure 38. Scenario 2: High Flexibility and Cooperation

In Scenario 3, we evaluated the effect of having positive evidence about product quality and negative evidence about delivery performance. We assumed there are no information about the indicators of other criteria. Known indicators for scenario 3 are as shown in Table 5.

Indicator	Value	Indicator	Value
Raw Material	Yes	On-time Delivery	Low
Dimensional Compliance	Yes	Right Quantity	No
Other Compliances	High	Packaging Conditions	No
		Handling Conditions	No
		Transportation Conditions	No
		Documents	No

Table 5. Known Indicators for Scenario 3

In this case, the predictions on the other critera in model was quite uncertain with an expected value of ‘medium’ level as shown in Figure 39. This was because both product quality and delivery performance were important variables and they had similar influences on the other variables.

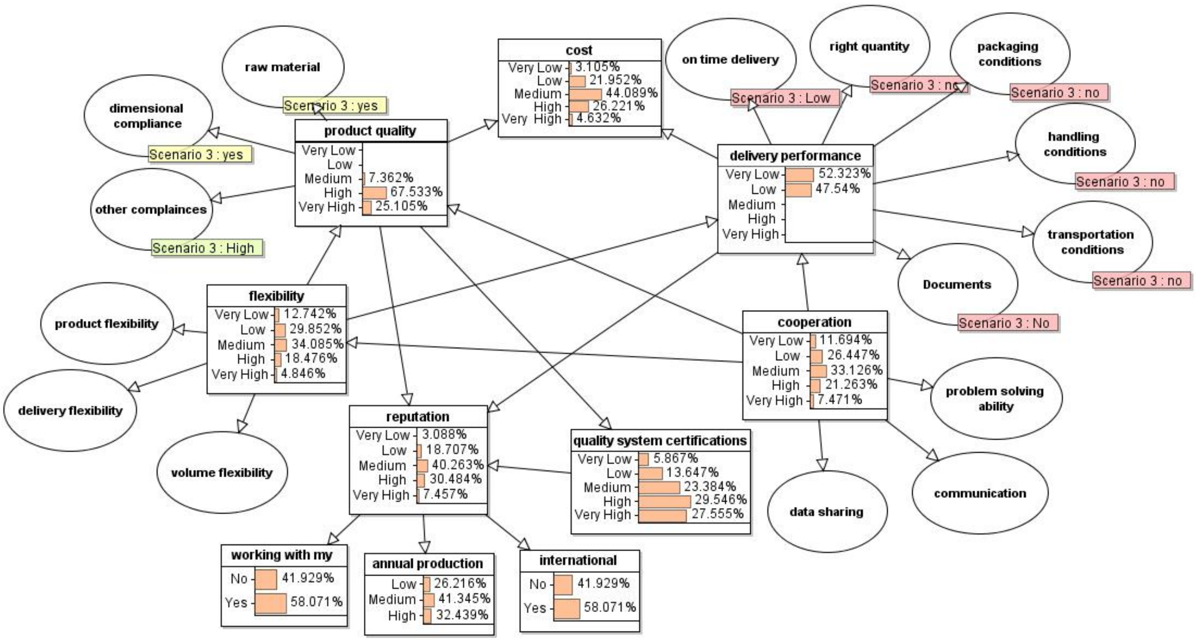

Figure 39. Scenario 3: High Product Quality and Low Delivery Performance

In Scenario 4, we have no information about the delivery performance indicators and cost of a supplier. However, we have information about its quality system certifications, product quality indicators, flexibility, cooperation and reputation. This information is summarized in Table 6. Based on this information our model predicts a low level of flexibility, cooperation and delivery performance and medium level of product quality from this supplier as shown in Figure 40. The cost is likely to be low or medium, and the delivery performance is likely to be very low or low. Our model classifies this supplier as a low cost supplier with insufficient delivery performance. The decision about selecting this supplier will be based on the importance given to these criteria by the decision makers. However, apart from having a low cost, the supplier does not seem to be advantageous in any criteria.

Indicator	**Value**	**Indicator**	**Value**
Working with Competitors	No	Volume Flexibility	Medium
Annual Production	Low	Delivery Flexibility	Medium
International Export	No	Product Flexibility	Low
Data Sharing	No	Raw Material	Yes
Problem Solving	Low	Dimensional Compliance	No
Communication	Medium	Other Compliances	Medium

Table 6. Known Indicators for scenario 4

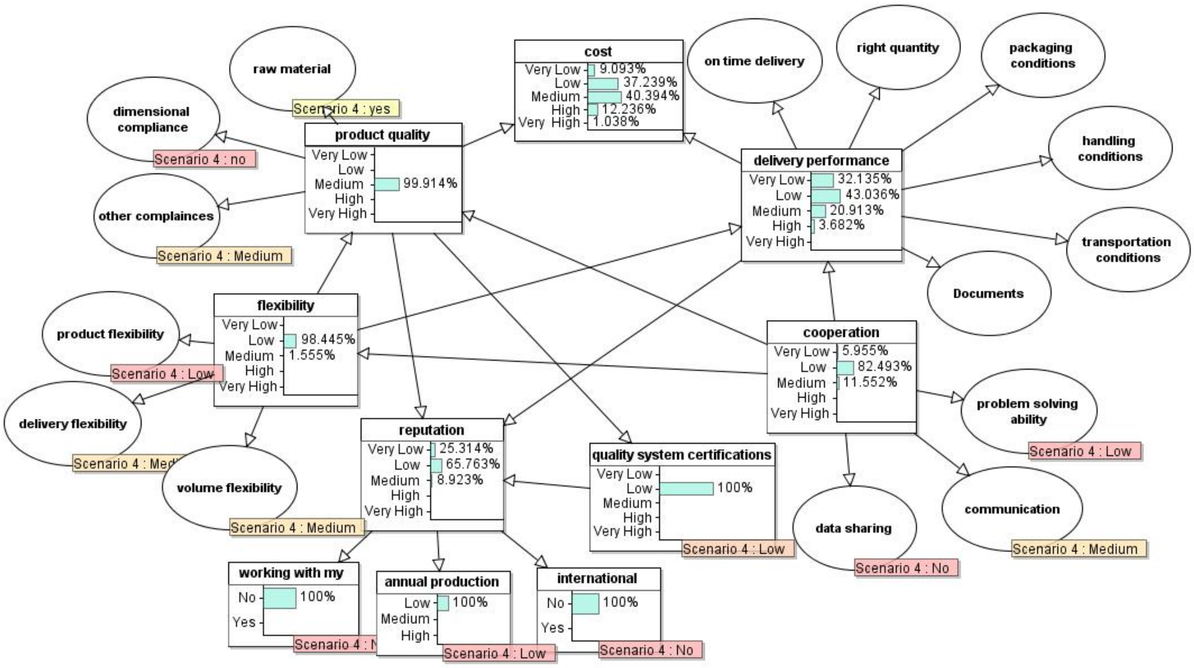

Figure 40. Scenario 4: Unkown Cost and Delivery Performance Indicators

Suppose we collect more information about this supplier and learn that this supplier has satisfactory delivery performance indicators. Figure 41 shows the updated probabilities after information about delivery performance indicators are added. Note that the delivery performance criteria is now expected to be medium rather than low. However, this information did not have much effect on the other variables in the model. Moreover, although the delivery performance indicators were mostly positive, the delivery performance did not increase to high or very high states because the parents of delivery performance (i.e. flexibility and cooperation) have poor indicators in this scenario. We also expect cost to increase slightly due to increased delivery performance in this scenario. The BN model offers us a powerful mechanism to revise our predictions with new information as shown in this scenario.

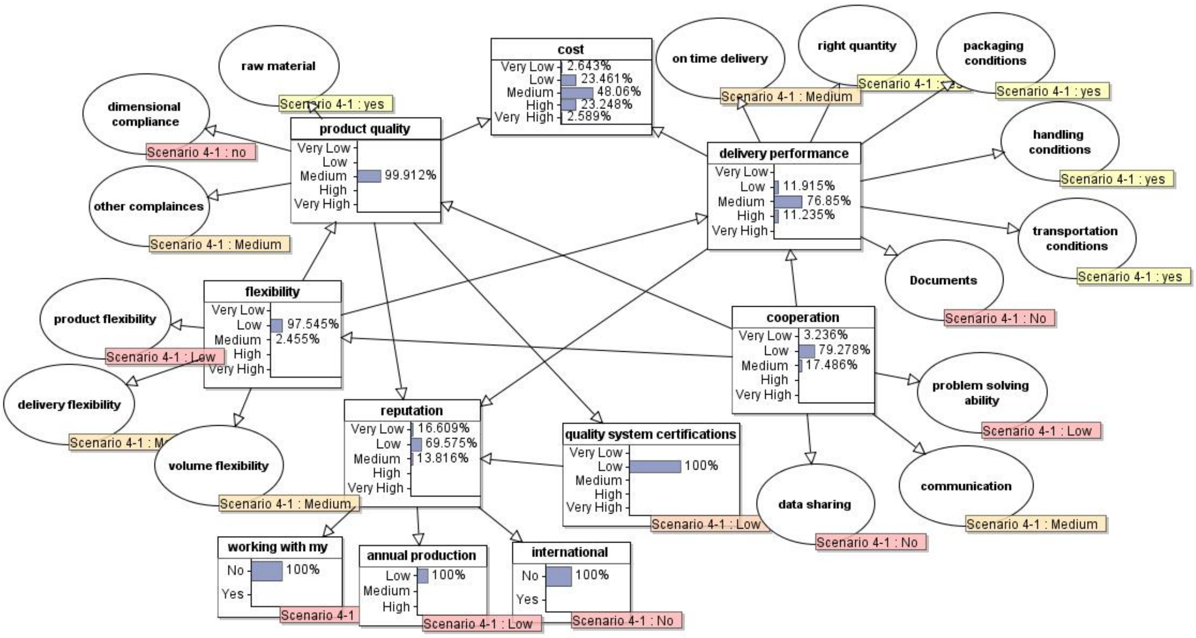

Figure 41. Scenario 4 with additional information about delivery performance

In Scenario 5, we have limited information about a supplier who is known to have high costs, and high quality system certifications (i.e. ISO 9001 and another certificate important in that domain). We also know that the supplier has a high production volume and works with a competitor of our company. The supplier is a national producer and does not make exports. Based on this limited information, our model predicts a high level of expected cooperation, quality and delivery performance from this supplier as shown in Figure 42. However, the uncertainty regarding the supplier selection criteria is higher as there is considerable unknown information about the supplier.

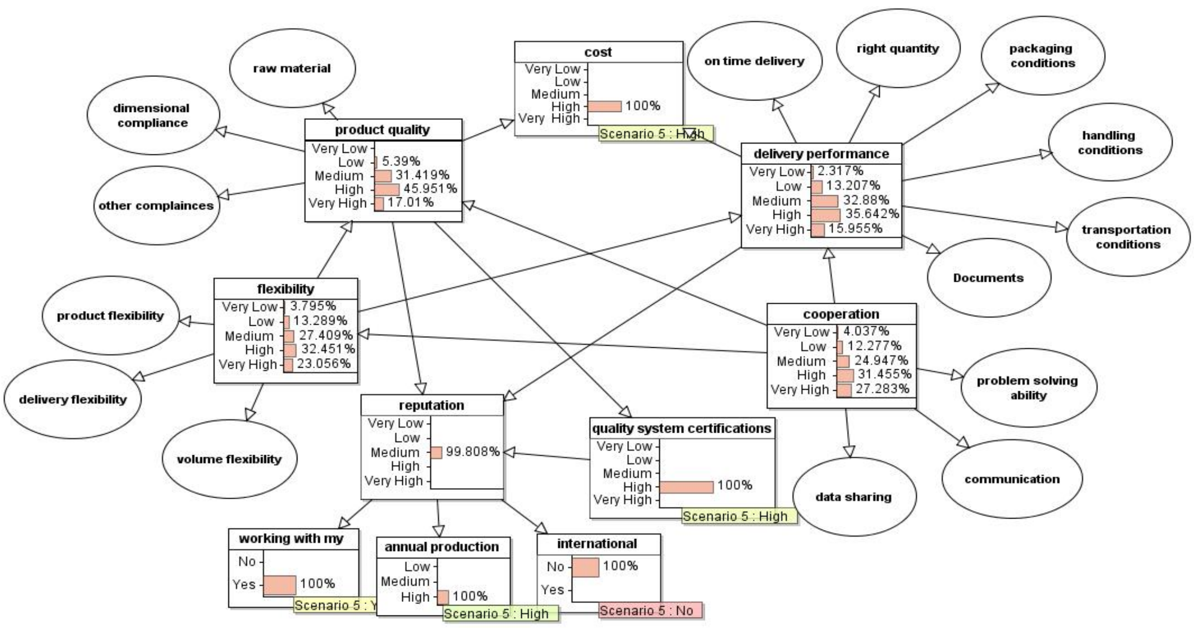

Figure 42. Scenario 5: High Cost and Quality Certification, Medium Reputation

In summary, the model developed by our method enables us to do a wide variety of scenario analysis with incomplete information. The information about supplier criteria can be conflicting, and the analyses could be revised when more information becomes available.

6.3.3. Evaluation of Two Alternative Suppliers in Automotive Manufacturer

We evaluated two alternative suppliers for the component of an automotive product in our automotive manufacturer with the experts. We denoted alternative suppliers as A and B. The automotive manufacturer worked with supplier A before and they have some information from the past experience. However, they didn’t work with supplier B and they have only limited information about it from the market. Experts requested sample parts for the component from the suppliers. According to sample parts, supplier B couldn’t meet the other compliances of the sample parts due to improper heat treatment operation. However, they are willing to communicate and share data. After shipment of samples, they set a meeting and offered solutions for the heat treatment problem. Offered price for the component by supplier B is medium. The supplier works with competitors of the manufacturer; annual production volume is high but national supplier. They have ISO 9001, passed quality inspection of the automotive manufacturer and they have ISO/TS16949.

Transportation conditions for both suppliers are suitable since the automotive manufacturer transport the parts by its trucks. On the other hand, supplier A met all specifications about the sample parts but offered high price.

They don’t work with competitors, annual production volume is medium and national supplier. Quality system certifications is at high level as supplier A. There were some problems about on-time delivery and communication of the supplier due to past experience. According to experts, communication of the supplier is low, they share data but problem solving ability is low. On-time delivery performance of the supplier is medium. Experts only know about delivey flexibility as low but they don’t know about product and volume flexibility since they didn’t ask before. Indicators of criteria due to suppliers are summarized in Table 7.

	Supplier A	**Supplier B**
Product Quality	-	-
Raw Material	Yes	Yes
Dimensional Compliance	Yes	Yes
Other Compliances	High	Medium
Cost	High	Medium
Delivery Performance	-	-
On-time Delivery	Medium	Unknown
Right Quantity	Yes	Unknown
Packaging Conditions	Yes	Unknown
Handling Conditions	Yes	Unknown
Transportation Conditions	Yes	Yes
Documents	Yes	Unknown
Flexibility	-	-
Product Flexibility	Unknown	Unknown
Delivery Flexibility	Low	Unknown
Volume Flexibility	Unknown	Unknown
Cooperation	-	-
Problem Solving Ability	Low	Medium
Communication	Low	High
Data Sharing	Yes	Yes
Quality System Certifications	High	High
Reputation	-	-
Working with Competitors	No	Yes
Annual Production Volume	Medium	High
International Export	No	No

Table 7. Indicators of Suppliers A and B

When we entered evidences to known indicators, BN model results for supplier A and B were illustrated as in Figure 43 and 44.

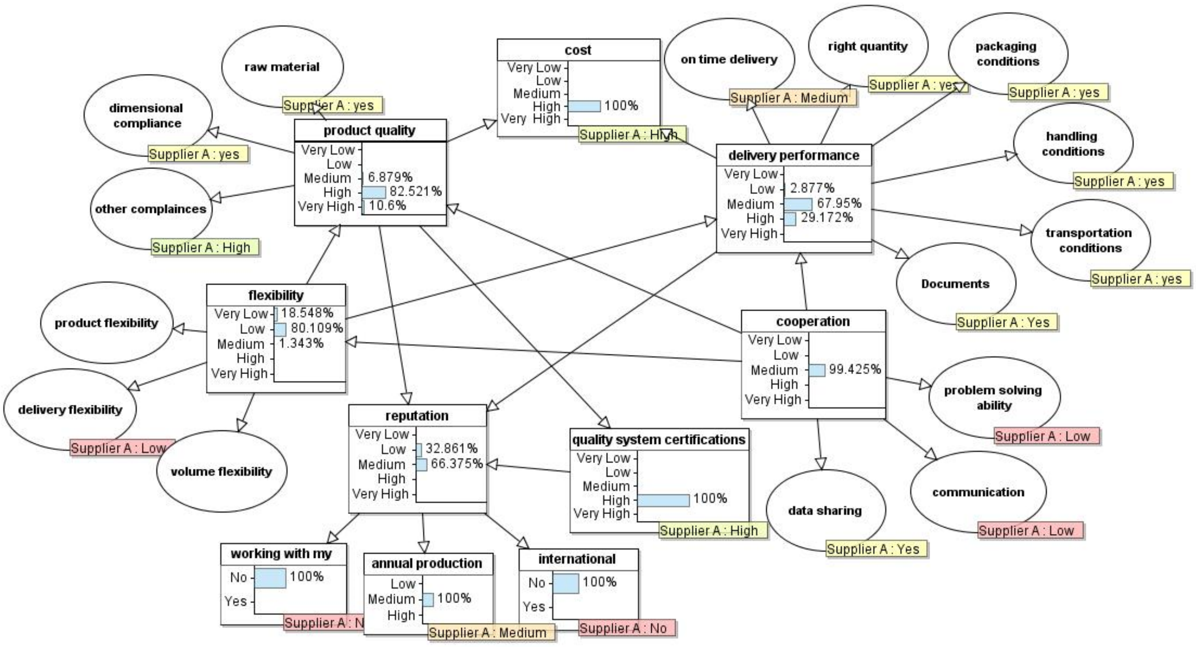

Figure 43 . BN model for Supplier A

Based on the evidences from past experience of supplier A, BN model predicts high level of product quality, medium level of cooperation but low level of flexibility. And delivery performance of supplier tends to be medium or high. According to experts, delivery performance value is not sufficient due to high cost of it.

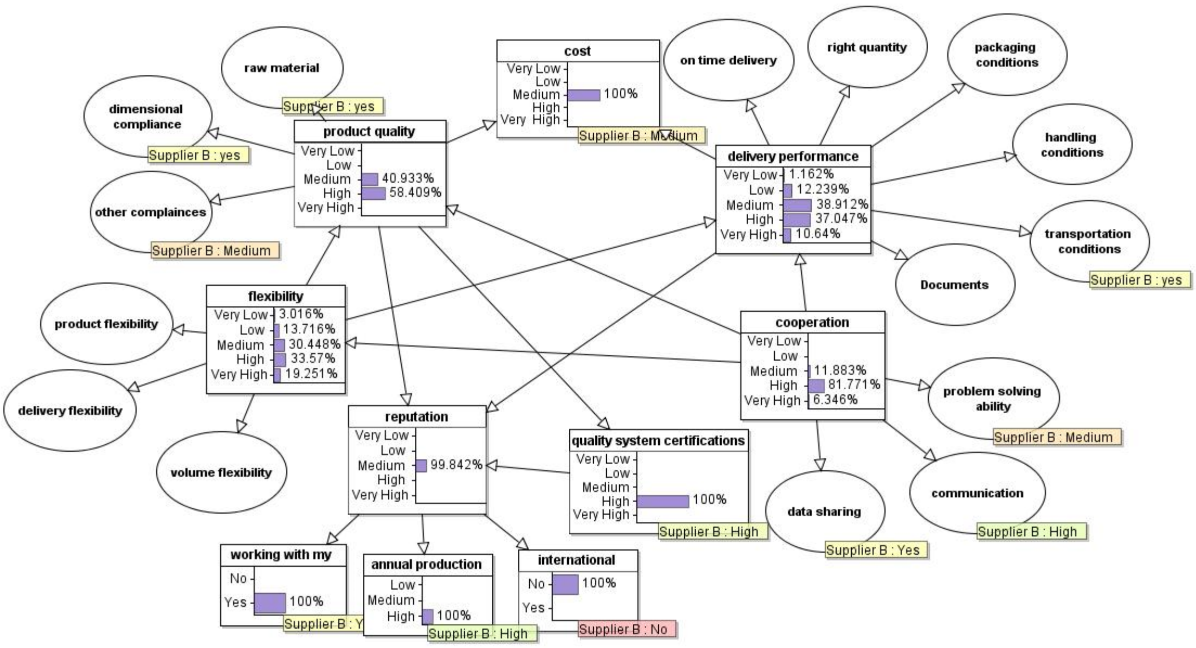

Figure 44 . BN model for Supplier B

Based on the limited information of experts about supplier B, delivery performance of it is likely to be medium. However, there is high uncertainty regarding the delivery performance and the other criteria due to lack of information. The model predicts high level of cooperation for supplier B. Experts think that they can work with this supplier. Delivery performance and product quality criteria may be improved by the time. However, they decided to search new alternatives.

The BN models developed by our method estimated risks and uncertainities regarding criteria and enabled experts to evaluate supplier alternatives with limited information. By the time, based on observed information, models will be revised and experts can see the updated values of selection criteria

7. CONCLUSION

In this thesis, we proposed a novel method that integrates DEMATEL and BNs to build probabilistic decision support models based on expert knowledge. The proposed method uses DEMATEL to elicit the structure of BN from expert knowledge. Up to now, there hasn't been a generally accepted method to determine the causal structure of a BN from expert knowledge. With our proposed method, in a multiple criteria decision making problem, the influences of criteria on each other are asked to multiple experts via DEMATEL survey and a causal BN is constructed based on the average direct relation matrix of DEMATEL. Our method parameterizes the BN by using ranked nodes; the weights of parent nodes and the variance values of child nodes are calculated by using DEMATEL's results instead of eliciting large NPTs from experts. With this integrated method causal relationship between multiple criteria can be constructed systematically and the causal BN built from this method can be used for decision analysis under uncertainty and risk analysis even if there is partial information. We applied our method to a supplier selection decision problem in a large automotive manufacturer. We determined supplier selection criteria based on previous studies and expert knowledge, and we conducted a DEMATEL survey with 14 experts from the manufacturer. The causal relations between the supplier selection criteria were determined based on the survey results. Our method eliminates cycles in the initial causal structure and revises it by expert opinion. The revised causal graph was used as the causal structure of our BN model. Next, we used ranked nodes to parameterize the BN model. Weighted mean function was used as a ranked node function, and the weights of parent nodes and variances of child nodes were obtained from the survey results. The BN model we developed was used to analyze the relations and uncertainty between supplier selection criteria. Robustness of the BN model was evaluated by sensitivity analyses of parameters, and sensitivity analysis of evidence was conducted to compare the BN model with total relation matrix of DEMATEL for validation of the model. Inconsistencies were reviewed by experts, and the final model was prepared. The experts indicated that it's difficult to directly enter values about some of the decision criteria such as reputation and cooperation. Therefore, before using the model for scenario analysis, indicators that can indirectly measure the decision criteria were added to the BN model. For example, rather than entering a value to reputation, a decision maker can enter information about foreign exports, production volume, and other clients of the supplier company, and our model estimates reputation level from these indicators. Different scenario analyses were conducted by entering evidences to some criteria and indicators, and estimating the values of the other criteria. Two potential suppliers of automotive manufacturer were evaluated according to limited information of experts about the suppliers. The model built by our method were considered to be useful for the supplier selection problem as the problem has a high amount of uncertainty and low amount of data, and BN models can deal with these issues.

The first contribution of this study is providing a way to construct BN structure and parameters from multiple experts in a quantitative way by using DEMATEL. In traditional way of building structure of BNs with experts, causal relationship between criteria is usually defined by experts in a qualitative way. They usually present their opinion related to causal relationship as direction of arcs between criteria without necessarily stating the degree of these relations. However, DEMATEL survey asks experts pairwise causal influence degrees of criteria in a score from 0 to 4, and this enables us to both quantify the strength of causal relations and the uncertainty around different expert's statements. In addition to this contribution, our method also makes it easier to consider multiple experts' opinions when building the BN structure. When a BN structure is built without any systematic approach, different experts can submit different opinion related to direction of arcs between criteria, and determining a single BN structure is difficult in this way. However, in our proposed method, opinion of multiple experts' can be considered systematically based on DEMATEL surveys and the following steps to transform the DEMATEL results into a BN model.

The second contribution of this study is a novel application of BNs and DEMATEL with the proposed methodology to a supplier selection case study in a large automotive manufacturer in Turkey. By determination of causal relationship between supplier selection criteria via DEMATEL and analysis of the causal network via BN, risks and uncertainty among the relationship between supplier selection criteria were estimated. Even if decision makers have limited information about the suppliers, the BN we developed estimates unknown criteria based on it. The proposed model can also be used in other supplier selection risk analysis problems.

In future studies, the proposed method could be integrated with other MCDM methods such as TOPSIS and Elimination and Choice corresponding to Reality (ELECTRE). Currently, the BN model developed from our method estimates the values and uncertainty of decision criteria based on observed information and relations between these criteria.

Decision makers can use this information to support their decisions. However, the model does not recommend a decision to decision makers. By integrating our method with MCDM method such as TOPSIS and ELECTRE, we can also use our model for recommending a decision. Another future study could be to expand our method with data learning algorithms. Currently, our method uses expert knowledge supplied by DEMATEL. In case of available data, the data can then be used to support expert knowledge in our method.

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APPENDIX

SORULAR YANITLAR 14

Bölüm 1/2

Tedarikçi Seçim Kriterlerinin birbirleri üzerindeki Etkilerini Değerlendirme Anketi

Bu anket, uzman bilgisine dayalı olarak, 'tedarikçi seçimi kararı' üzerinde etkili olduğu düşünülen kriterlerin arasındaki sebep sonuç ilişkilerini gösteren bir ağ ortaya çıkarmak amacıyla hazırlanmıştır.

Aşağıda tedarikçi seçimi kararı üzerinde etkili olduğu düşünülen 7 kriter ve tanımlamaları yer almaktadır.

Kriterler:

1. ÜRÜN KALİTESİ : Tedarikçi firmanın, müşterinin talep ettiği tüm isteklere cevap verebilecek şekilde kaliteli ürün üretebilme kabiliyetidir.

2. MALİYET : Maliyet kriteri, ürün fiyatı ve tedarik sürecine ilişkin taşıma maliyeti, kalite problemlerinden kaynaklanan maliyet, üretimde aksaklık, kesintiden kaynaklanan maliyet gibi maliyetleri içeren kriterdir.

3. SEVKİYAT PERFORMANSI : Sevkiyat performansı, ürünlerin zamanında, doğru miktarda, beklenen paketleme ve taşıma koşullarında , hasarsız ve ilgili tüm irsaliye, fatura ve kalite kontrol raporları gibi dökümanlarla sevkiyatının gerçekleştirilmesidir.

4. KALİTE SİSTEM SERTİFİKALARINA SAHİP OLMA : Tedarikçi firmanın ISO 9001, ISO/TS16949 gibi kalite belgelerine sahip olma kriteridir.

5. ESNEKLİK : Tedarikçi firmanın müşterinin talep ettiği değişikliklere cevap verebilme kabiliyetidir. Esneklik kriteri, süreç esnekliği, hacim esnekliği ve sevkiyat esnekliklerini içermektedir. Süreç esnekliği, ürün üzerinde yapılması talep edilen değişikliklere tedarikçi firmanın cevap verebilme, adapte olabilme kabiliyeti ve üretim hattında bir üründen diğerine kolayca geçiş yapabilme kabiliyetidir. Hacim esnekliği, tedarikçi firmanın müşterinin talep ettiği adet değişikliği taleplerine cevap verebilme kabiliyetidir. Sevkiyat esnekliği ise, tedarikçinin müşterinin talep ettiği teslimat süresi değişikliklerine uyum sağlayabilme kabiliyetidir.

6. İŞBİRLİĞİ : Tedarikçi firmanın, müşteri ilişkilerinde uyum içinde çalışabilme, iletişim içerisinde olma ve destek olma konularında istekliliğidir.

7. TEDARİKÇİNİN TANINMIŞLIĞI : Tedarikçinin daha önce çalışmış olduğu müşterilerle deneyimlerine dayalı olarak piyasadaki bilinirliğidir.

Anketimiz, bu kriterlerin birbirleri üzerindeki etki derecesine ve genel tedarikçi seçim kararı üzerindeki etki derecesine ilişkin çoktan seçmeli sorulardan oluşmaktadır.

SORULAR YANITLAR 14

Sorular aşağıdaki gibi olacaktır.

Ürün kalitesi, maliyeti ne kadar etkiler?

- Hiç etkisi yoktur.
- Az etkisi vardır.
- Orta derecede etkisi vardır.
- Yüksek etkisi vardır.
- Çok yüksek etkisi vardır.

Maliyet, ürün kalitesini ne kadar etkiler?

- Hiç etkisi yoktur.
- Az etkisi vardır.
- Orta derecede etkisi vardır.
- Yüksek etkisi vardır.
- Çok yüksek etkisi vardır.

Nedensellik(Sebep-Sonuç) İlişkisi

Sorularda kriterlerin birbirlerine etkisi ile "nedensellik" ifade edilmektedir. İki kriter arasında bir "ilişki" olmasına rağmen okun yönüne bağlı olarak "nedensellik" ilişkisi olmayabilir yada etki büyüklükleri farklı olabilir.

Tüm kriterler için her iki yönlü olarak kriterler arasındaki "nedensellik" etki büyüklüğü sorulacaktır.

"Ürün Kalitesi --> Maliyet" şeklinde ürün kalitesinin, maliyet üzerindeki etki derecesini seçmeniz istenecektir.
Tam ters yönde;
"Ürün Kalitesi <-- Maliyet" şeklinde maliyetin, ürün kalitesi üzerindeki etki derecesini seçmeniz istenecektir.

Nedensellik ilişkisine ve okun yönüne bağlı olarak etki büyüklüklerinin değişimine örnek olması amacıyla aşağıdaki örnek soru-cevap hazırlanmıştır.

Örnek Soru-Cevap

Yaş, kalp hastalığını ne kadar etkiler?

- Hiç etkisi yok.
- Az etkisi vardır.
- Orta derecede etkisi vardır.
- Yüksek etkisi vardır.
- Çok yüksek etkisi vardır.

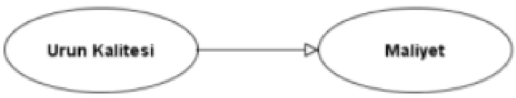
Kalp hastalığı, yaşı ne kadar etkiler?

- Hiç etkisi yoktur.
- Az etkisi vardır.
- Orta derecede etkisi vardır.
- Yüksek etkisi vardır.
- Çok yüksek etkisi vardır.

SORULAR YANITLAR 14

Bölüm 2/2

SORULAR



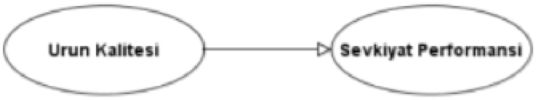
1. Ürün kalitesi, maliyeti ne kadar etkiler?

- ◯ Hiç etkisi yoktur.
- ◯ Az etkisi vardır.
- ◯ Orta derecede etkisi vardır.
- ◯ Yüksek etkisi vardır.
- ◯ Çok yüksek etkisi vardır.

SORULAR YANITLAR 14

2. Maliyet, ürün kalitesini ne kadar etkiler?

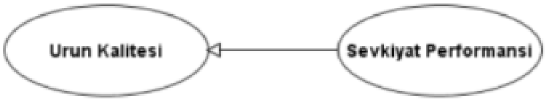
- Hiç etkisi yoktur.
- Az etkisi vardır.
- Orta derecede etkisi vardır.
- Yüksek etkisi vardır.
- Çok yüksek etkisi vardır.



3. Ürün kalitesi, sevkiyat performansını ne kadar etkiler?

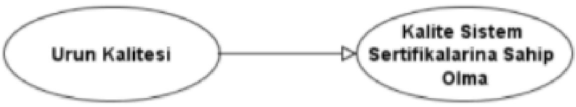
- Hiç etkisi yoktur.
- Az etkisi vardır.
- Orta derecede etkisi vardır.
- Yüksek etkisi vardır.
- Çok yüksek etkisi vardır.

SORULAR YANITLAR 14



4. Sevkiyat performansı , ürün kalitesini ne kadar etkiler?

- Hiç etkisi yoktur.
- Az etkisi vardır.
- Orta derecede etkisi vardır.
- Yüksek etkisi vardır.
- Çok yüksek etkisi vardır.



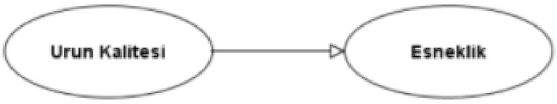
5. Ürün kalitesi, kalite sistem sertifikalarına sahip olmayı ne kadar etkiler?

- Hiç etkisi yoktur.
- Az etkisi vardır.
- Orta derecede etkisi vardır.
- Yüksek etkisi vardır.
- Çok yüksek etkisi vardır.

SORULAR YANITLAR 14

6. Kalite sistem sertifikalarına sahip olma, ürün kalitesini ne kadar etkiler?

- Hiç etkisi yoktur.
- Az etkisi vardır.
- Orta derecede etkisi vardır.
- Yüksek etkisi vardır.
- Çok yüksek etkisi vardır.



7. Ürün kalitesi, esnekliği ne kadar etkiler?

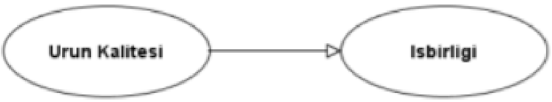
- Hiç etkisi yoktur.
- Az etkisi vardır.
- Orta derecede etkisi vardır.
- Yüksek etkisi vardır.
- Çok yüksek etkisi vardır.

SORULAR YANITLAR 14

8. Esneklik, ürün kalitesini ne kadar etkiler?

- Hiç etkisi yoktur.
- Az etkisi vardır.
- Orta derecede etkisi vardır.
- Yüksek etkisi vardır.
- Çok yüksek etkisi vardır.

Resim başlığı



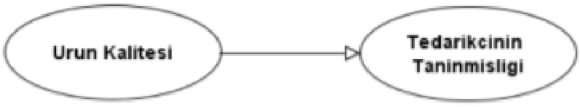
9. Ürün kalitesi, işbirliğini ne kadar etkiler?

- Hiç etkisi yoktur.
- Az etkisi vardır.
- Orta derecede etkisi vardır.
- Yüksek etkisi vardır.
- Çok yüksek etkisi vardır.

SORULAR YANITLAR 14

10. İşbirliği, ürün kalitesini ne kadar etkiler?

- Hiç etkisi yoktur.
- Az etkisi vardır.
- Orta derecede etkisi vardır.
- Yüksek etkisi vardır.
- Çok yüksek etkisi vardır.



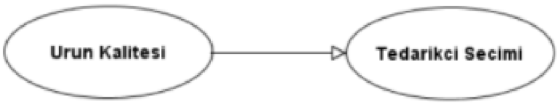
11. Ürün kalitesi, tedarikçinin tanınmışlığını ne kadar etkiler?

- Hiç etkisi yoktur.
- Az etkisi vardır.
- Orta derecede etkisi vardır.
- Yüksek etkisi vardır.
- Çok yüksek etkisi vardır.

SORULAR YANITLAR 14

12. Tedarikçinin tanınmışlığı, ürün kalitesini ne kadar etkiler?

- Hiç etkisi yoktur.
- Az etkisi vardır.
- Orta derecede etkisi vardır.
- Yüksek etkisi vardır.
- Çok yüksek etkisi vardır.



13. Ürün kalitesi, tedarikçi seçimini ne kadar etkiler?

- Hiç etkisi yoktur.
- Az etkisi vardır.
- Orta derecede etkisi vardır.
- Yüksek etkisi vardır.
- Çok yüksek etkisi vardır.

SORULAR YANITLAR 14

14. Maliyet, sevkiyat performansını ne kadar etkiler?

- Hiç etkisi yoktur.
- Az etkisi vardır.
- Orta derecede etkisi vardır.
- Yüksek etkisi vardır.
- Çok yüksek etkisi vardır.

15. Sevkiyat performansı, maliyeti ne kadar etkiler?

- Hiç etkisi yoktur.
- Az etkisi vardır.
- Orta derecede etkisi vardır.
- Yüksek etkisi vardır.
- Çok yüksek etkisi vardır.

SORULAR YANITLAR 14

16. Maliyet, kalite sistem sertifikalarına sahip olmayı ne kadar etkiler?

- Hiç etkisi yoktur.
- Az etkisi vardır.
- Orta derecede etkisi vardır.
- Yüksek etkisi vardır.
- Çok yüksek etkisi vardır.

17. Kalite sistem sertifikalarına sahip olma, maliyeti ne kadar etkiler?

- Hiç etkisi yoktur.
- Az etkisi vardır.
- Orta derecede etkisi vardır.
- Yüksek etkisi vardır.
- Çok yüksek etkisi vardır.

SORULAR YANITLAR 14

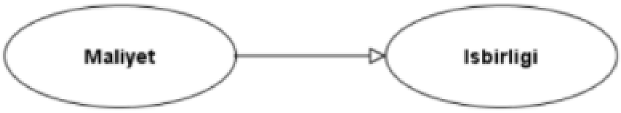
18. Maliyet , esnekliği ne kadar etkiler?

- Hiç etkisi yoktur.
- Az etkisi vardır.
- Orta derecede etkisi vardır.
- Yüksek etkisi vardır.
- Çok yüksek etkisi vardır.

19. Esneklik, maliyeti ne kadar etkiler?

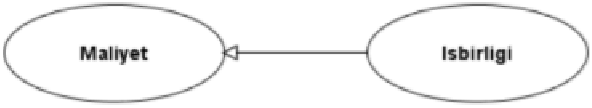
- Hiç etkisi yoktur.
- Az etkisi vardır.
- Orta derecede etkisi vardır.
- Yüksek etkisi vardır.
- Çok yüksek etkisi vardır.

SORULAR YANITLAR 14



20. Maliyet, işbirliğini ne kadar etkiler?

- Hiç etkisi yoktur.
- Az etkisi vardır.
- Orta derecede etkisi vardır.
- Yüksek etkisi vardır.
- Çok yüksek etkisi vardır.



21. İşbirliği, maliyeti ne kadar etkiler?

- Hiç etkisi yoktur.
- Az etkisi vardır.
- Orta derecede etkisi vardır.
- Yüksek etkisi vardır.
- Çok yüksek etkisi vardır.

SORULAR YANITLAR 14

22. Maliyet, tedarikçinin tanınmışlığını ne kadar etkiler?

- Hiç etkisi yoktur.
- Az etkisi vardır.
- Orta derecede etkisi vardır.
- Yüksek etkisi vardır.
- Çok yüksek etkisi vardır.

23. Tedarikçinin tanınmışlığı, maliyeti ne kadar etkiler?

- Hiç etkisi yoktur.
- Az etkisi vardır.
- Orta derecede etkisi vardır.
- Yüksek etkisi vardır.
- Çok yüksek etkisi vardır.

SORULAR YANITLAR 14

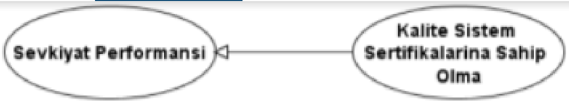
24. Maliyet, tedarikçi seçimini ne kadar etkiler?

- Hiç etkisi yoktur.
- Az etkisi vardır.
- Orta derecede etkisi vardır.
- Yüksek etkisi vardır.
- Çok yüksek etkisi vardır.

25. Sevkiyat performansı, kalite sistem sertifikalarına sahip olmayı ne kadar etkiler?

- Hiç etkisi yoktur.
- Az etkisi vardır.
- Orta derecede etkisi vardır.
- Yüksek etkisi vardır.
- Çok yüksek etkisi vardır.

SORULAR YANITLAR 14



26. Kalite sistem sertifikalarına sahip olma, sevkiyat performansını ne kadar etkiler?

- Hiç etkisi yoktur.
- Az etkisi vardır.
- Orta derecede etkisi vardır.
- Yüksek etkisi vardır.
- Çok yüksek etkisi vardır.

27. Sevkiyat performansı, esnekliği ne kadar etkiler?

- Hiç etkisi yoktur.
- Az etkisi vardır.
- Orta derecede etkisi vardır.
- Yüksek etkisi vardır.
- Çok yüksek etkisi vardır.

SORULAR YANITLAR 14

28. Esneklik, sevkiyat performansını ne kadar etkiler?

- Hiç etkisi yoktur.
- Az etkisi vardır.
- Orta derecede etkisi vardır.
- Yüksek etkisi vardır.
- Çok yüksek etkisi vardır.

Resim başlığı

29. Sevkiyat performansı, işbirliğini ne kadar etkiler?

- Hiç etkisi yoktur.
- Az etkisi vardır.
- Orta derecede etkisi vardır.
- Yüksek etkisi vardır.
- Çok yüksek etkisi vardır.

SORULAR YANITLAR 14

28. Esneklik, sevkiyat performansını ne kadar etkiler?

- ○ Hiç etkisi yoktur.
- ○ Az etkisi vardır.
- ○ Orta derecede etkisi vardır.
- ○ Yüksek etkisi vardır.
- ○ Çok yüksek etkisi vardır.

Resim başlığı

29. Sevkiyat performansı, işbirliğini ne kadar etkiler?

- ○ Hiç etkisi yoktur.
- ○ Az etkisi vardır.
- ○ Orta derecede etkisi vardır.
- ○ Yüksek etkisi vardır.
- ○ Çok yüksek etkisi vardır.

SORULAR YANITLAR 14

30. İşbirliği, sevkiyat performansını ne kadar etkiler?

- Hiç etkisi yoktur.
- Az etkisi vardır.
- Orta derecede etkisi vardır.
- Yüksek etkisi vardır.
- Çok yüksek etkisi vardır.

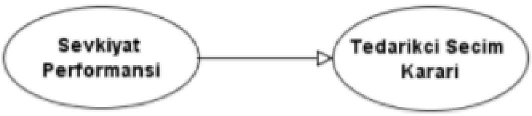
31. Sevkiyat performansı, tedarikçinin tanınmışlığını ne kadar etkiler?

- Hiç etkisi yoktur.
- Az etkisi vardır.
- Orta derecede etkisi vardır.
- Yüksek etkisi vardır.
- Çok yüksek etkisi vardır.

SORULAR YANITLAR 14

32. Tedarikçinin tanınmışlığı, sevkiyat performansını ne kadar etkiler?

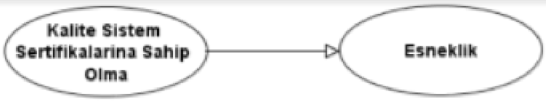
- Hiç etkisi yoktur.
- Az etkisi vardır.
- Orta derecede etkisi vardır.
- Yüksek etkisi vardır.
- Çok yüksek etkisi vardır.



33. Sevkiyat performansı, tedarikçi seçimini ne kadar etkiler?

- Hiç etkisi yoktur.
- Az etkisi vardır.
- Orta derecede etkisi vardır.
- Yüksek etkisi vardır.
- Çok yüksek etkisi vardır.

SORULAR YANITLAR 14



34. Kalite sistem sertifikalarına sahip olma, esnekliği ne kadar etkiler?

- Hiç etkisi yoktur.
- Az etkisi vardır.
- Orta derecede etkisi vardır.
- Yüksek etkisi vardır.
- Çok yüksek etkisi vardır.

35. Esneklik, kalite sistem sertifikalarına sahip olmayı ne kadar etkiler?

- Hiç etkisi yoktur.
- Az etkisi vardır.
- Orta derecede etkisi vardır.
- Yüksek etkisi vardır.
- Çok yüksek etkisi vardır.

SORULAR YANITLAR 14

36. Kalite sistem sertifikalarına sahip olma, işbirliğini ne kadar etkiler?

- Hiç etkisi yoktur.
- Az etkisi vardır.
- Orta derecede etkisi vardır.
- Yüksek etkisi vardır.
- Çok yüksek etkisi vardır.

37. İşbirliği, kalite sistem sertifikalarına sahip olmayı ne kadar etkiler?

- Hiç etkisi yoktur.
- Az etkisi vardır.
- Orta derecede etkisi vardır.
- Yüksek etkisi vardır.
- Çok yüksek etkisi vardır.

SORULAR YANITLAR 14

38. Kalite sistem sertifikalarına sahip olma, tedarikçinin tanınmışlığını ne kadar etkiler?

- Hiç etkisi yoktur.
- Az etkisi vardır.
- Orta derecede etkisi vardır.
- Yüksek etkisi vardır.
- Çok yüksek etkisi vardır.

39. Tedarikçinin tanınmışlığı, kalite sistem sertifikalarına sahip olmayı ne kadar etkiler?

- Hiç etkisi yoktur.
- Az etkisi vardır.
- Orta derecede etkisi vardır.
- Yüksek etkisi vardır.
- Çok yüksek etkisi vardır.

SORULAR YANITLAR 14

40. Kalite sistem sertifikalarına sahip olma, tedarikçi seçimini ne kadar etkiler?

- Hiç etkisi yoktur.
- Az etkisi vardır.
- Orta derecede etkisi vardır.
- Yüksek etkisi vardır.
- Çok yüksek etkisi vardır.

41. Esneklik, işbirliğini ne kadar etkiler?

- Hiç etkisi yoktur.
- Az etkisi vardır.
- Orta derecede etkisi vardır.
- Yüksek etkisi vardır.
- Çok yüksek etkisi vardır.

SORULAR YANITLAR 14

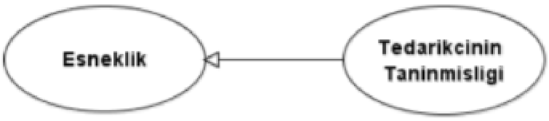
42. İşbirliği, esnekliği ne kadar etkiler?

- Hiç etkisi yoktur.
- Az etkisi vardır.
- Orta derecede etkisi vardır.
- Yüksek etkisi vardır.
- Çok yüksek etkisi vardır.

43. Esneklik, tedarikçinin tanınmışlığını ne kadar etkiler?

- Hiç etkisi yoktur.
- Az etkisi vardır.
- Orta derecede etkisi vardır.
- Yüksek etkisi vardır.
- Çok yüksek etkisi vardır.

SORULAR YANITLAR 14



44. Tedarikçinin tanınmışlığı, esnekliği ne kadar etkiler?

- Hiç etkisi yoktur.
- Az etkisi vardır.
- Orta derecede etkisi vardır.
- Yüksek etkisi vardır.
- Çok yüksek etkisi vardır.

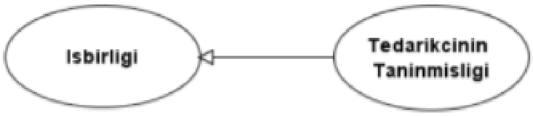
45. Esneklik, tedarikçi seçimini ne kadar etkiler?

- Hiç etkisi yoktur.
- Az etkisi vardır.
- Orta derecede etkisi vardır.
- Yüksek etkisi vardır.
- Çok yüksek etkisi vardır.

SORULAR YANITLAR 14

46. İşbirliği, tedarikçinin tanınmışlığını ne kadar etkiler?

- Hiç etkisi yoktur.
- Az etkisi vardır.
- Orta derecede etkisi vardır.
- Yüksek etkisi vardır.
- Çok yüksek etkisi vardır.



47. Tedarikçinin tanınmışlığı, işbirliğini ne kadar etkiler?

- Hiç etkisi yoktur.
- Az etkisi vardır.
- Orta derecede etkisi vardır.
- Yüksek etkisi vardır.
- Çok yüksek etkisi vardır.

SORULAR YANITLAR 14

48. İşbirliği, tedarikçi seçimini ne kadar etkiler?

- Hiç etkisi yoktur.
- Az etkisi vardır.
- Orta derecede etkisi vardır.
- Yüksek etkisi vardır.
- Çok yüksek etkisi vardır.

49. Tedarikçinin tanınmışlığı, tedarikçi seçimini ne kadar etkiler?

- Hiç etkisi yoktur.
- Az etkisi vardır.
- Orta derecede etkisi vardır.
- Yüksek etkisi vardır.
- Çok yüksek etkisi vardır.

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- YDS: 70 (April, 2014)

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-

Publications

-

Oral and Poster Presentations

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HACETTEPE ÜNİVERSİTESİ
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HACETTEPE ÜNİVERSİTESİ
FEN BİLİMLER ENSTİTÜSÜ
ENDÜSTRİ MÜHENDİSLİĞİ ANABİLİM DALI BAŞKANLIĞI'NA

Tarih: 13/07/2017

Tez Başlığı: SEBEPSEL RİSK ANALİZİ İÇİN BÜTÜNLEŞİK BAYES AĞLARI VE DEMATEL YÖNTEMİ: OTOMOTİV ENDÜSTRİSİNDE TEDARİKÇİ SEÇİMİ VAKA ÇALIŞMASI

Yukarıda başlığı gösterilen tez çalışmamın a) Kapak sayfası, b) Giriş, c) Ana bölümler d) Sonuç kısımlarından oluşan toplam 95 sayfalık kısmına ilişkin, 13/07/2017 tarihinde tez danışmanım tarafından *Turnitin* adlı intihal tespit programından aşağıda belirtilen filtrelemeler uygulanarak alınmış olan orijinallik raporuna göre, tezimin benzerlik oranı % 9 'dur.

Uygulanan filtrelemeler:
1- Kaynakça hariç
2- Alıntılar hariç
3- 5 kelimeden daha az örtüşme içeren metin kısımları hariç

Hacettepe Üniversitesi Fen Bilimleri Enstitüsü Tez Çalışması Orjinallik Raporu Alınması ve Kullanılması Uygulama Esasları'nı inceledim ve bu Uygulama Esasları'nda belirtilen azami benzerlik oranlarına göre tez çalışmamın herhangi bir intihal içermediğini; aksinin tespit edileceği muhtemel durumda doğabilecek her türlü hukuki sorumluluğu kabul ettiğimi ve yukarıda vermiş olduğum bilgilerin doğru olduğunu beyan ederim.

Gereğini saygılarımla arz ederim.

13/07/2017

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