Building Bayesian Networks based on DEMATEL for Multiple Criteria Decision Problems: A Supplier Selection Case Study

Rukiye Kaya[a], Barbaros Yet[a*]

[a]Department of Industrial Engineering, Hacettepe University, Ankara 06800, Turkey

E-mail Addresses: rk398@kent.ac.uk (R. Kaya), barbaros.yet@hacettepe.edu.tr (B.Yet)

*Corresponding Author: Dr. Barbaros Yet,
Department of Industrial Engineering, Hacettepe University, 06800, Ankara, Turkey
Tel: +90 312 780 5577, E-mail: barbaros.yet@hacettepe.edu.tr

ABSTRACT

Bayesian Networks (BNs) are effective tools for providing decision support based on expert knowledge in uncertain and complex environments. However, building knowledge-based BNs is still a difficult task that lacks systematic and widely accepted methodologies, especially when knowledge is elicited from multiple experts. We propose a novel method that systematically integrates a widely used Multi Criteria Decision Making (MCDM) approach called Decision Making Trial and Evaluation Laboratory (DEMATEL) in BN construction. Our method elicits causal knowledge from multiple experts based on DEMATEL and transforms it to a BN structure. It then parameterizes the BN by using ranked nodes and evaluates its robustness and consistency by using sensitivity analysis. The

proposed method provides a practical and generic way to build probabilistic decision support models by systematically exploiting expert knowledge. Suitable applications of this method include decision problems with multiple criteria, high uncertainty and limited data. We illustrate our method by applying it to a supplier selection case study in a large automobile manufacturer in Turkey.

Keywords: Bayesian Networks, DEMATEL, Multiple Criteria Decision Making, Supplier Selection

1. INTRODUCTION

In many risk analysis and decision support problems, including supplier selection, the primary source of information is expert knowledge and data is available in limited amounts. Bayesian networks (BNs) offer a powerful framework for making complex probabilistic inferences based on expert knowledge in such domains (Fenton & Neil, 2013). A BN is a Directed Acyclic Graph (DAG) composed of nodes and arcs (Pearl, 1988). This graphical structure is well suited for representing expert knowledge as important causal factors and relations elicited from experts can be encoded as nodes and arcs in the BN. Each node has a Node Probability Table (NPT) that defines its conditional probability distribution. Once a BN is built, efficient algorithms are available to compute the probabilities of the uncertain variables when any subset of BN's variables are instantiated (Lauritzen & Spiegelhalter, 1988; Neil et al., 2007). Despite these benefits, BN construction based on expert knowledge remains to be a difficult task. Domain experts often get confused between modelling direct and indirect causal relations, or between causal and associational relations in the BN (Neil et al., 2000) . These may lead to cycles and inconsistencies. Moreover, when multiple domain experts are present, they may provide conflicting statements but these statements must be consolidated for the decision support model. As a result, systematic approaches are required to build BNs based on expert knowledge but they are not widely available as we discuss in Section 2.

In this paper, our focus is on building BN decision support models for Multiple Criteria Decision Making (MCDM) problems based on knowledge elicited from multiple experts. We investigate how a popular causal modelling approach in the MCDM domain, i.e. Decision Making Trial and Evaluation Laboratory (DEMATEL) in particular (Dalalah et al., 2011; Hayajneh, & Batieha, 2011; Lin & Wu, 2008), could assist BN construction.

We propose a novel and systematic method for building BNs with multiple experts based on DEMATEL. DEMATEL uses surveys to elicit the strength of direct and indirect causal relations from multiple experts. Our method performs a series of operations to transform the results of DEMATEL to a BN model and uses ranked nodes to parameterize the BN. This paper offers several contributions for both DEMATEL and BN domains, including the following:

1) It systematically transforms the DEMATEL results to BN models. This enables the use of DEMATEL for probabilistic decision support.

2) It provides a generic and practical way of integrating knowledge elicited from multiple domain experts into BN construction.

3) It offers a systematic approach to review and evaluate the BN model based on DEMATEL and sensitivity analysis of BNs.

We illustrate our method with a case study of supplier selection in a large automobile manufacturer in Turkey. Supplier selection is a complex MCDM problem that involves a great degree of uncertainty (Dogan & Aydin, 2011). Supplier selection decisions are mostly made based on expert knowledge, as data about new suppliers is often available in limited amounts. In the case study, we conducted surveys with multiple experts from this company, and built a BN decision support model by using the proposed method. The case study shows the use of our method and evaluates the consistency of the resulting model by using sensitivity analysis.

The remainder of this paper is organized as follows: Section 2 gives a recap of expert-driven BN construction and reviews previous studies in this domain. Section 3 describes the steps of DEMATEL, and Section 4 presents the proposed method. Section 5 introduces the supplier selection case study and reviews the previous MCDM and BN studies in this domain. Section 6 applies the proposed method to the case study and demonstrates it with different scenarios, and Section 7 presents our conclusions.

2. BUILDING BAYESIAN NETWORKS

A BN model is built in two steps. Firstly, the graphical structure is built by defining the important variables, and the causal and associational relations between those variables. When two nodes A and B are directly connected, as in A → B, A and B are called the parent and child node respectively. Secondly, the parameters are defined. The parameters of discrete BNs are generally defined in NPTs. A NPT has a probability value for each

combination of the states of a variable and its parents. Therefore, the number of parameters in an NPT is the Cartesian product of the number states of that node and of its parents. This causes the NPT to get infeasibly large to be elicited from the experts if the variable has a large number of parents.

Ranked nodes have been proposed to simplify the elicitation task as they require a fewer number of parameters than usual NPTs and they are able to model a wide variety of shapes (Fenton et al., 2007; Laitila & Virtanen, 2016). A ranked node has ordinal states and an underlying Truncated Normal (TNormal) distribution. It approximates the TNormal distribution to ordinal states by using intervals that have equal widths (Fenton et al., 2007). For example, Figure 1a shows the probability density plot of a TNormal distribution bounded between 0 and 1 with parameters μ: 0.7 and σ^2: 0.1, and Figure 1b shows the 5-state ranked node approximation of this distribution. Since ranked nodes approximate continuous TNormal distributions, they enable the use of weighted functions of parents in the form of regression equations to define the NPT of a child node (Fenton et al., 2007; Laitila & Virtanen, 2016).
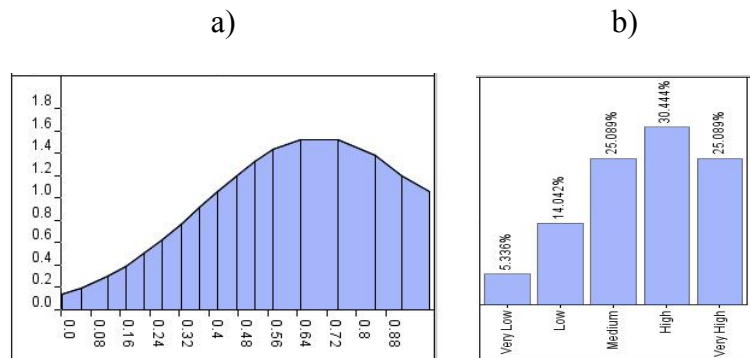
a)   b)

Figure 1. a) Underlying Tnormal distribution and b) ordinal states of a ranked node

In a BN, sensitivity analysis of findings or interventions can be used to examine how instantiating or controlling a variable affect the results respectively. The sensitivity analysis of findings indicates both causal and associational effects of observing a variable, and the sensitivity analysis of interventions can be used to measure only the causal effects (sensitivity analysis of findings and interventions is described in more detail in Section 4).

Earlier studies about expert-driven BN construction focused on providing general guidelines (Henrion, 1988) using BN objects and fragments to define the structure. Laskey and Mahoney (1997) used semantically meaningful BN fragments to build BNs. Similarly, Neil et al. (2000) proposed BN fragments that can be used as building blocks for commonly

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encountered BN modelling tasks. Laskey and Mahoney (2000) proposed a system engineering approach that iteratively builds BNs by using BN fragments. Their approach starts by building simple prototypes and refines those prototypes in each iteration.

BNs have been applied in a wide variety of domains including environmental sciences, reliability analysis and health-care. Several guidelines have been published for expert-driven BN construction in these domains. Przytula and Thompson (2000) presented guidelines for constructing BN structure and elicit parameters for diagnostic systems. They show how to combine the sub-models about specific faults to build a complex diagnostic BN. Sigurdsson et al. (2001) discussed the use of expert-driven BNs in system reliability modelling. Chen and Pollino (2012) discussed the use of BNs in environmental sciences and provides guidelines for good practice BN modelling in this domain. Mkrtchyan et al. (2015) reviewed BN applications for human reliability analysis and presented guidelines and suggestions for building BNs in this domains.

Surveys are suitable resources for BN construction and, expert and data driven approaches have been developed to use this resource. Ishino (2014) proposed a primarily data-driven methodology to construct BNs from survey data. Their approach uses partly expert knowledge when selecting variables to be included in the BN, but the BN construction is largely based on data-driven structure learning algorithms. More recently, Constantinou et al. (2016) proposed a method for building BNs by using health assessment surveys. Their method provides guidelines on how to manage survey data, and modify the BN structure and parameters based on data availability. Constantinou et al. (2016) also discussed the steps of causal analysis and validation of the BN.

Although BNs are suitable tools for building models based on expert knowledge, generic and systematic methodologies for this task have not been widely studied. Xiao-xuan et al. (2007) described a method that directly elicits the BN structure by asking domain experts about presence and direction of causal relation between each pair of variables. After defining the structure, they used probability scales with verbal and numerical anchors (Van Der Gaag et al., 1999) to elicit the probabilities. If there are multiple domain experts, they assigned weights to each expert according to factors including their title and familiarity with the domain. They used a weighted average of elicited probabilities for the parameters of the BN. This way of assigning expert weights does not necessarily reflect domain expertise; for example, it may assign a high weight to someone who has an academic title but is not familiar with the domain. Yet and Marsh (2014) proposed a method that uses abstraction operations

to refine and simplify expert built BNs. Nadkarni and Shenoy (2004) proposed a causal mapping approach for building BNs. Causal maps differ from BNs in several aspects as causal maps can contain cycles as their arcs can represent both direct and indirect relations, and absence of an arc between the variables of a causal map does not necessarily mean that they are independent. Nadkarni and Shenoy's method first builds a causal map based on expert knowledge and then transforms it to a BN.

Table 1. Guidelines and Methods for Expert and Survey Driven BN Construction

Study	Proposed Approach	Application/Example
Henrion (1989)	Overall guidelines for BN construction.	Diagnosis of plant disorders
Laskey and Mahoney (1997)	Reusable BN fragments for BN construction (network fragments)	Military intelligence
Neil et al. (2000)	Reusable BN fragments for BN construction (idioms)	Software reliability and testing
Laskey and Mahoney(2000)	System engineering approach for BN building	Military intelligence
Przytula and Thompson (2000)	Guidelines and a method for diagnostic BN construction for engineering systems.	Diagnostics of engineering systems
Sigurdsson et al. (2001)	Guidelines for BN construction in the reliability analysis domain.	System reliability analysis
Nadkarni and Shenoy (2004)	BN construction methodology based on causal mapping.	Product design
Xiao-xuan et al. (2007)	Elicits BN structure by using a simple questionnaire, and parameters by using probability scales.	Demand forecasting
Chen and Pollino (2012)	Guidelines for BN construction in the environmental sciences domain.	Environmental sciences
Yet and Marsh (2014)	Abstraction method for expert built BNs.	Trauma Care
Ishino et al. (2014)	BN construction approach that uses expert assisted variable selection and structure learning algorithm with survey data.	Marketing
Mkrtchyan et al. (2015)	Guidelines for BN construction in the human reliability analysis domain.	Human reliability analysis
Constantinou et al. (2016)	A method that focuses on data management, parameter learning, analysis and validation of BNs by using questionnaire data.	Forensic psychiatry

Table 1 summarizes the methods and applications described in reviewed papers in the chronological order. The contributions of this paper include a generic and systematic methodology that covers all steps of BN construction and evaluation by using judgment of multiple experts. We analyze survey data from multiple experts using DEMATEL and then we systematically transform the results of DEMATEL to a BN structure and parameters together with domain experts. Our method covers construction of BN structure and parameters, sensitivity analysis and evaluation. Although we illustrate our method using a supplier selection case study, the proposed method is not domain-specific. It can be applied to other domains where domain experts are accessible, and DEMATEL surveys can be conducted.

3. DECISION MAKING TRIAL AND EVALUATION LABORATORY (DEMATEL)

Table 2. Example Survey Question

What is the degree of direct causal influence of X on Y?
○ No Influence (0)
○ Low Influence (1)
○ Medium Influence (2)
○ High Influence (3)
○ Very High Influence (4)

Decision Making Trial and Evaluation Laboratory (DEMATEL) is a survey based MCDM method to determine both direct and indirect causal relations between the criteria and the strength of those relations (Dalalah et al., 2011; Lin & Wu, 2008). DEMATEL analysis is based on two matrices that are defined and calculated from the survey results (see Table 2 for a survey question example). The first matrix is called the average direct relation matrix *A* that shows the degree of direct influences between the criteria. The second matrix is called the total relation matrix *T* that represents the sum of direct and indirect influences between the criteria. A causal network is built by using influences that are greater than a threshold value in the total relation matrix *T* (Chang, Chang, & Wu, 2011). The threshold value is defined by the decision analyst. The steps of DEMATEL are as follows:

1. The direct relation matrix *A* is constructed by asking the influence of decision criteria on each other on a 0 to 4 scale (see Table 2). If there are multiple experts and the average of their response for each influence is recorded in the direct relation matrix.

2. A normalized direct relation matrix *M* is obtained by dividing values of the direct relation matrix *A* with the maximum of sum of rows and columns:

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

where a_{ij} is the average direct relation matrix value for row i and column j.

3. The total relation matrix *T* represents the sum of direct and indirect relations:

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

It is calculated as follows:

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

where *I* is the identity matrix.

4. For each criterion, the sum of the associated row *R* and column *C* is calculated. The criterion is classified as a net cause (sender) if $R - C$ is positive, and it is classified as a net effect (receiver) if it is negative. The total relation strength of a criterion is represented by $R + C$.

5. A threshold value is defined by the domain experts and causal network is built by including the causal influences that are above the threshold in the total relation matrix.

Figure 2 shows an example causal graph built by DEMATEL. The vertical and horizontal axes in this figure represents the R-C and R+C values respectively. The arcs between variables represent whether the sum of direct and indirect strength of causal relations were above the threshold in the total relation matrix T. For example, the arc A → E represents that the presence of causal relation between A and E which is the sum of direct and indirect causal relations. This causal representation is quite different than BNs. In a BN, the arc A → E would represent a direct causal relation between A and E, and the indirect relations would be modelled by paths of directed arcs. As a result, DEMATEL results cannot be directly used for building BNs; they need to be systematically transformed. We present a novel method for this task in the following section.
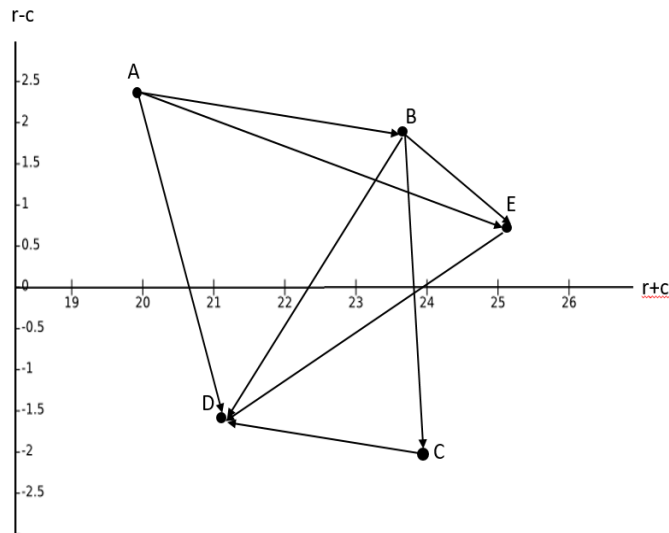

Figure 2. An Example DEMATEL Causal Graph

4. THE PROPOSED METHOD

Figure 3 shows an overview of our method. It is composed of 8 steps: the first three steps apply DEMATEL to the decision problem, fourth, fifth and sixth steps transforms the

DEMATEL results to a BN structure, and the last two steps parameterizes and evaluates the BN.
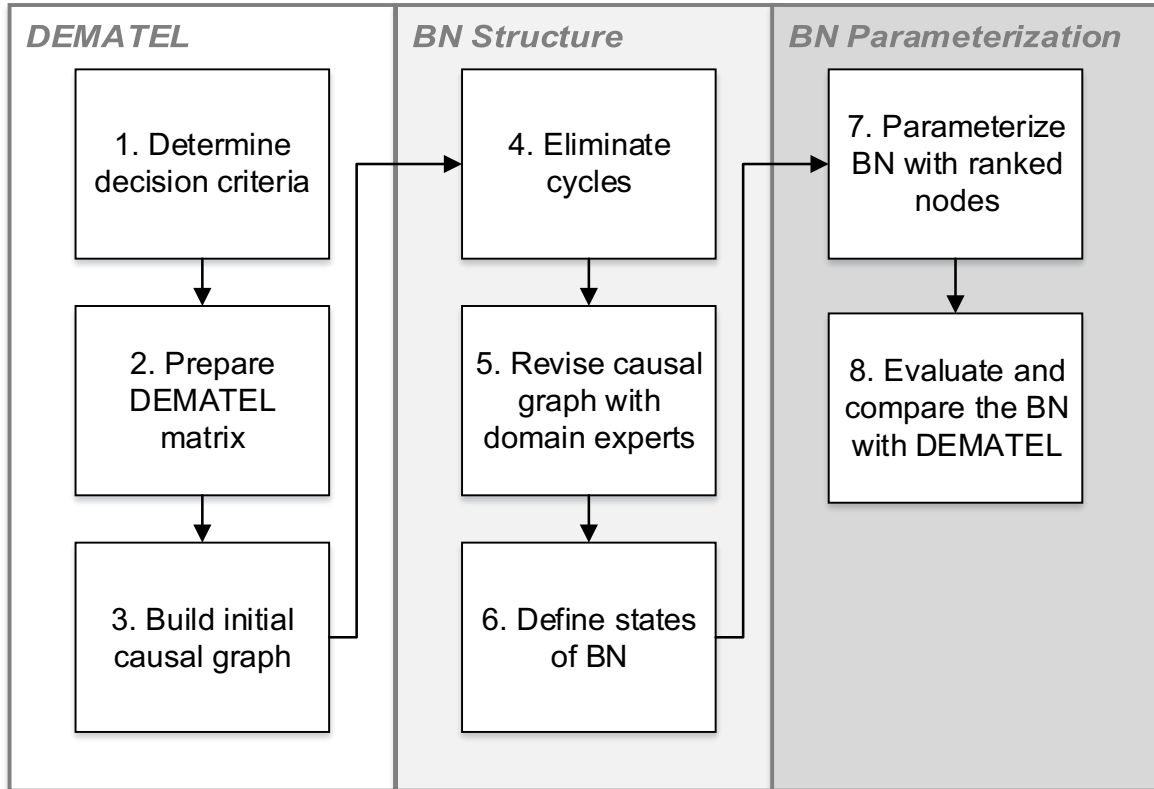

Figure 3. Overview of the Proposed Method

A brief description of each step of our method is shown below. Each step is illustrated in more detail by using the case study in Section 6.

1. **Determine decision criteria:** Firstly, we need to determine the important factors for the decision problem. The criteria are determined based on expert knowledge and a review of the relevant literature.

2. **Prepare DEMATEL matrix**: After determining decision criteria, a DEMATEL survey is conducted to ask experts about influences of different criteria on each other. According to the survey results, the steps of DEMATEL are executed, direct relation matrix and total relation matrix are computed.

3. **Build 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 initial causal

network. Threshold value is determined based on expert opinion. The initial causal network is not necessarily a BN structure as it may contain cycles.

4. **Eliminate cycles:** BNs are directed acyclic graphs so we need to eliminate the cycles that may exist in the initial causal graph in order to transform it to a BN. Our method guides the decision analyst to search for the following reasons of cycles and eliminate them:

   - **r1:** In a DEMATEL survey, the domain expert should indicate the degree of causal relations between the variables. Since causal relations are directed, the answers of the expert should reflect the direction of the causal relation. However, some experts, especially those who are not familiar with causal models, may indicate correlation rather than causality in their answers. This will lead them to give symmetric answers in the survey. For example, if there is a strong causal relation such $A \rightarrow B$, the expert should assign high causal impact from A to B and no causal impact from B to A in the DEMATEL survey. If the expert's answers incorrectly reflect correlation rather than causality, they will symmetrically assign high causal impact in both directions in the DEMATEL survey. Our method reviews the model with experts to identify such errors and eliminate them.

   - **r2:** Two variables in the DEMATEL survey may be highly correlated but not causally related in reality. The expert may incorrectly identify this correlation as a direct causal relation in the DEMATEL survey, and this may cause a cycle. In this case, correlation between the variables is confounded through a latent variable or some other variable in the causal network. If it is due to another variable in the network, the causal path between them is identified and the cycle is removed by modifying the network according to this causal path. If the correlation is due to a latent variable, the latent variable and the causal relation should be explicitly represented in the causal network to resolve the cycle.

   - **r3:** Some cycles are caused by temporal relations between the variables. For example, there seems to be a cyclic causal relation between humidity and rain as both of these variables causes each other. This cyclic causal relation, however, happens at different time stages. Humidity causes rain at time t, and rain increases humidity at time $t+1$. This kind of cycles are resolved by using dynamic BNs with multiple time frames.

5. **Revise causal graph with experts**: After cycle eliminations, the causal graph is revised by experts to check if there are any redundant or deficient arcs. For example, some arcs may be redundant as they represent indirect causal relations that are already represented by other causal paths present in the BN. Some arcs about important relations may be missing or accidentally deleted in previous steps. The domain experts review the BN to identify and fix such errors.

6. **Define the states of the BN:** A BN is constructed according to the final causal graph that is obtained after revisions. Mutually exclusive and collectively exhaustive states is determined for each node based on expert knowledge.

7. **Parameterize 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, the details of which is described in Section 6.

8. **Evaluate and compare the BN with DEMATEL:** We use sensitivity analysis to compare the BN model with the DEMATEL results and evaluate its consistency with domain knowledge. We use two different types of sensitivity analysis approaches for this task:

   - **Sensitivity to Findings:** This is a common type of sensitivity analysis that is implemented in most BN software. In this approach, we select a target variable, and measure the effect of observing other variables on the target variable by instantiating those variables in the BN and assessing the change in the posterior of the target variable. We quantify the results of the sensitivity analysis by using the mutual information criterion metric. Mutual information between two variables represents the entropy reduction in one variable when the other variable is observed. In BNs, mutual information criterion can represent the amount of information gain for the target variable when the other variable is instantiated. The mutual information between two variables X and Y can be calculated as follows:

$$I(X;Y) = \sum_{x \in X} \sum_{y \in Y} P(x,y) \log \frac{P(x,y)}{P(x)P(y)}$$

   The results of sensitivity analysis of findings represent the total information gain which may propagate through forward or backward inference. The information gain is not necessarily causal; it may include the information from the effects of the target variables. Since the values in the total relation matrix T represents the total causal effect from one variable to another, it is not suitable to compare them with these

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results. We use a symmetric *T** matrix that offers a suitable medium for comparing the DEMATEL results with the BN's sensitivity to findings. Each value in *T** represents the total effect between two variables that is the sum of total causal effect in both directions. We assume that the total effect of a variable on itself is zero. *T** matrix is calculated as follows:

$$t_{ij}^* = t_{ij} + t_{ji} \quad \forall\, i \neq j$$

$$t_{ij}^* = 0 \quad \forall\, i = j$$

We compare the sensitivity of BN to findings with the corresponding values in the *T** matrix.

- **Sensitivity Analysis to Interventions:** The *T* matrix in DEMATEL represents the sum of direct and indirect causal effect between two variables. In a BN, such effect can be represented by interventions. While the effects of an observation can be propagated through forward, backward or inter-causal reasoning, the effect of an intervention is only propagated through causal paths in a BN. Therefore, sensitivity analysis of interventions is compatible with the *T* matrix and offers us a suitable medium to evaluate the similarities and differences between the BN model and DEMATEL results. An intervention is modelled by 1) removing the incoming arcs on the intervened variable 2) instantiating the variable 3) propagating the BN to update the posteriors of other variables (Pearl, 2009). The results of sensitivity analysis of interventions are also quantified by mutual information criterion.

5. SUPPLIER SELECTION CASE STUDY

We used a case study of supplier selection for a major automobile manufacturing in Turkey to illustrate the application of our method. Automobile manufacturers often work with a large number of suppliers. When selecting a supplier, they need to consider multiple criteria including cost, flexibility, reputation and quality but they usually have limited data about these criteria especially for new supplier alternatives. Moreover, the decision criteria are often related to each other and a great deal of uncertainty is associated with them. DEMATEL and BNs respectively offer a powerful framework for understanding the causal relations between criteria from expert knowledge and providing decision support in such circumstances. In this section, we review previous studies that used MCDM approaches (Section 5.1), including DEMATEL, and BNs (Section 5.2) for supplier selection (see Table

3 for an overview of the reviewed papers). In the following section, we illustrate how the proposed method is applied to the case study.

Table 3. DEMATEL and BNs applications for Supplier Selection

Study	Method
Chang et al. (2011)	Fuzzy DEMATEL
Dalalah et al. (2011)	Fuzzy DEMATEL and TOPSIS
Dogan and Aydin (2011)	BN based on Total Cost of Ownership
Büyüközkan and Çiftçi (2012)	Fuzzy DEMATEL, ANP and TOPSIS
Dey et al. (2012)	DEMATEL and QFD
Ferreira and Borenstein (2012)	Influence Diagrams and Fuzzy Logic
Lockamy and McCormack (2012)	BN based on Survey Data
Hsu et al. (2013)	DEMATEL
Badurdeen et al. (2014)	BN based on Risk Taxonomy
Liu et al. (2018)	ANP, DEMATEL and Game Theory

5.1. MCDM techniques in Supplier Selection

Commonly used MCDM methods in supplier selection include Analytic Hierarchy Process (AHP) (Levary, 2008), Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) (Yoon & Hwang, 1995; Samvedi et al., 2013; Ramanathan, 2007) and DEMATEL (Chang et al., 2011; Hsu et al., 2013; Liu et al., 2018). In uncertain and dynamic problems, MCDM techniques are often combined with mathematical programming and artificial intelligence techniques (Çarman & Tuncer Şakar, 2018; Dalalah et al., 2011; Dogan & Aydin, 2011; Ramanathan, 2007; Wang et al., 2009). This section will review the recent studies in this domain primarily focusing on the DEMATEL applications. The readers are referred to Chai et al. (2013) for a systematic review of this subject.

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. (Büyüközkan & Ciftci, 2012; Dey et al., 2012). Hsu et al. (2013) use DEMATEL to evaluate the performances of suppliers with regards to carbon management. They determine the causal relationship between criteria for the supplier selection based on the carbon management and identify the significant criteria for this decision. Liu et al. (2018) integrate ANP, entropy weight, game theory, DEMATEL and evidence theory for supplier selection problem. ANP and entropy weight methods determine the weights of criteria. Game theory and DEMATEL adjust the weights of criteria. Evidence theory deals with the uncertainty of the problem. Integration of DEMATEL and BN meet these aspects in more efficient way. Chang et al. (2011) used fuzzy DEMATEL method to determine the most important supplier selection criteria for evaluation of supplier performance. Büyüközkan and Çiftçi (2012) integrated fuzzy DEMATEL, fuzzy ANP and fuzzy TOPSIS methods to evaluate green suppliers for an automobile manufacturer

in Turkey. They visualized the causal relations using DEMATEL, conduct pairwise comparisons by ANP, and calculate the distance to the ideal solution by using TOPSIS. Fuzzy logic was used to elicit human judgement in all three approaches.

Previous approaches have not combined DEMATEL with a probabilistic modelling and inference approach to deal with uncertainty. Integration of DEMATEL and BNs enables us to evaluate the uncertainty and to compute the posterior probability distribution of the criteria under different scenarios. Therefore, unlike previous approaches, our method can use DEMATEL results for making risk analysis under different scenarios.

5.2. Bayesian Networks in Supplier Selection

BNs has been widely used in different uncertain domains (Darwiche, 2010; Ferreira & Borenstein, 2012; Yet et al., 2016) including supplier selection. Dogan and Aydin (2011) integrated BNs and the Total Cost of Ownership method by using financial data and domain knowledge. Their model integrated different cost types related with suppliers to provide decision support for supplier selection. Ferreira and Borenstein (2012) combined fuzzy logic and a derivation of BNs extended with decision and utility nodes, called influence diagrams, for analyzing supplier selection decision. They illustrated their model by using a supplier selection for biodiesel production. Lockamy and McCormack (2012) analyzed supply chain risks of casting suppliers by using BNs. They considered factors including the external and operational risks and potential revenue impact on the buyer. This enabled them to prioritize the risk factors according to their effect on revenue and probability of occurrence. Badurdeen et al. (2014) used a supply chain risk taxonomy to build a BN.

Although these BN models have been successfully used for different supplier problems, considerable effort and modelling expertise is required to adapt these BN models for different applications (e.g. different companies or industries) as they have been specifically designed for a problem. Our method, however, offers a generic way for developing a causal BN model for practically any supplier selection or MCDM problem where data is limited and expert knowledge is available,

6. BUILDING A BN FOR SUPPLIER SELECTION

We made interviews and surveys with 14 experts from a major automobile manufacturer in Turkey to develop and evaluate the BN model. This section demonstrates how the proposed method is applied to the supplier selection case study, and describes each step in more detail.

1. **Determine decision criteria**

In the supplier selection case study, we first reviewed previous studies (see Section 5) and prepared a list of potential decision criteria for our problem. Afterwards, we made interviews with the experts from the automobile manufacturer to select the criteria. The criteria used for our model is as follows:

- **Product Quality** refers to supplier's ability of producing quality products to meet raw material, dimension and other requirements requested by customer (Dogan & Aydin, 2011).
- **Cost** includes product price and other costs related with the supply process.
- **Delivery Performance** includes factors such as delivery duration, packaging and transportation conditions, discrepancies between the ordered and delivered quantity, and satisfactory documentation regarding the delivery (Badurdeen et al., 2014; Dogan & Aydin, 2011; Lockamy & McCormack, 2012).
- **Quality System Certifications** such as ISO 9001 and ISO/TS16949 are taken into account when selectiong suppliers (Dogan & Aydin, 2011).
- **Flexibility** represents the supplier's ability to adapt to changes and needs of customers, and it is considered to a crucial factor for supplier selection (Oly et al., 2005). Flexibility criteria can be examined under three categories: i.e. product flexibility, volume flexibility and delivery flexibility (Dogan & Aydin, 2011).
- **Cooperation** represents the degree of communication and collaboration with the supplier (Lockamy & McCormack, 2012).
- **Reputation** of the supplier (i.e. national and international) is an important factor for the experts from the car manufacturer company.

2. **Prepare DEMATEL matrix**

DEMATEL has two essential matrices; the average direct relation matrix and the total relation matrix. We compute both of these matrices, and use the average direct relation matrix for building a causal graph and the total direct relation matrix for evaluating the model. In our case study, after determining supplier selection criteria, we conducted an online survey with 14 experts from the automobile manufacturer. We asked the experts the degree of direct causal influences of supplier selection criteria on each other by using a scale between 0 (No Influence) and 4 (Very High Influence). According to the survey results, we

computed the DEMATEL matrices. The direct and total relation matrices are shown in Tables 4 and 5 respectively.

Table 4. Average Direct Relation Matrix of DEMATEL

D	Product Quality	Cost	Delivery Performance	Quality System Certifications	Flexibility	Cooperation	Reputation
Product Quality	0	3	1	2.2857	1.4286	1.2857	3.1429
Cost	1.7143	0	1.2857	1.0714	1.9286	1.5714	2.3077
Delivery Performance	1.7143	2.0714	0	1.5	1.3571	1.4286	2.3571
Quality System Certifications	2.6429	2.1429	1.5714	0	1.5	1.3571	2.7857
Flexibility	1.8571	2.2143	2.3571	1	0	2.0714	1.8571
Cooperation	2.3571	1.7143	2.2857	1.2143	2.2857	0	2.2143
Reputation	1.7857	2.3077	1.2143	1.2143	1.2857	1.4286	0

Table 5 Total 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	0.431	0.4936	0.2639	0.3299	0.3585	0.3469	0.5336
Quality System Certifications	0.5262	0.5508	0.3949	0.2722	0.403	0.378	0.6127
Flexibility	0.4655	0.5312	0.4293	0.322	0.2983	0.4053	0.5391
Cooperation	0.5136	0.5303	0.4421	0.3505	0.45	0.2978	0.5841
Reputation	0.4029	0.4702	0.3153	0.2908	0.3291	0.322	0.3566

3. Build initial causal graph

We used the direct relation matrix of DEMATEL to construct a causal graph basis for a BN as BN arcs represent direct causal relations. We determined a threshold value of 1.75 with the experts and modelled the relations above this value in the BN structure. The threshold value is determined by building a causal graph with several different thresholds and reviewing them with experts. The initial causal network built is shown in Figure 4.
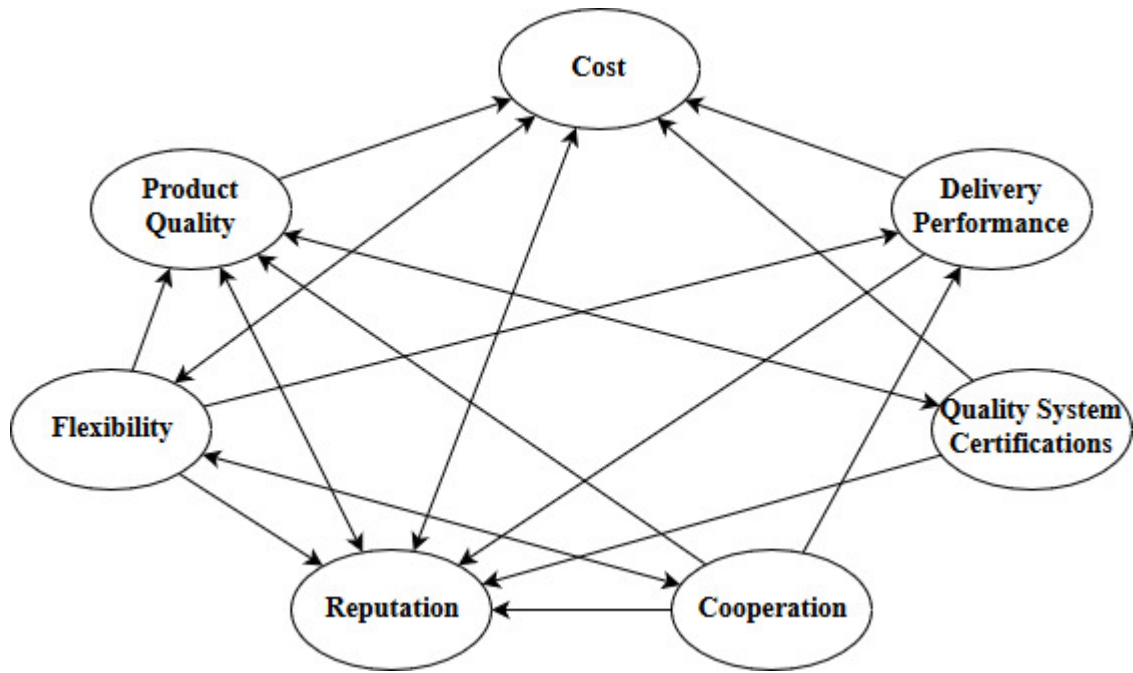
Figure 4. Initial Direct Causal Relation Network

The initial causal network in this step contains cycles and is densely connected. In the following two steps, we eliminate the cycles to transform the causal network into a causal BN structure and simplify it.
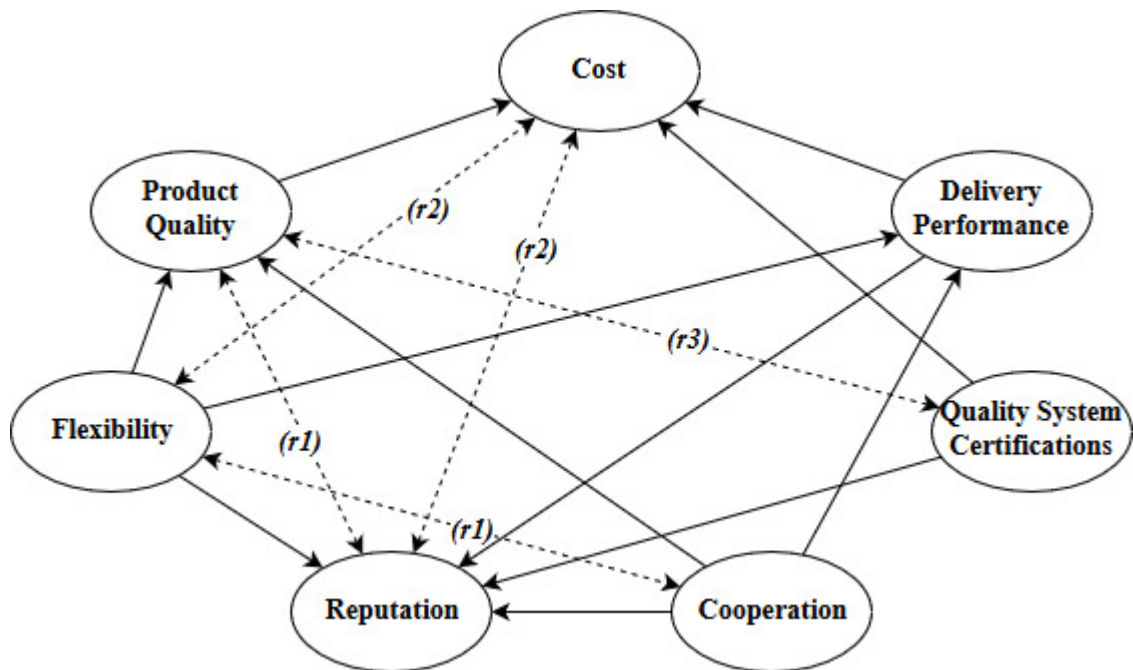
4. Eliminate cycles

Figure 5. Cycles on Initial Causal Network

Our method eliminates three types of cycles as described in Section 4. We examined the cycles in the initial casual network with domain experts. Figure 5 shows the cycles due to each of these types by dashed arcs respectively denoted by r1, r2 and r3.

- **r1:** The cycles between Product Quality ↔ Reputation, and Cooperation ↔ Flexibility are possibly caused due to a confusion of correlation and causation from the survey respondents. In the review, the domain experts indicated that there is a clear causal relation from product quality to reputation, and from flexibility to cooperation. The cycles were eliminated accordingly.

- **r2:** The cycles between Cost ↔ Flexibility, and Cost ↔ Reputation are considered to represent correlation that is confounded through some other variables. The domain experts indicated that the correlation between cost and reputation could be due to the fact that both of these factors are affected by the product quality. The correlation between cost and flexibility is considered to be mediated through product characteristics and delivery performance

- **r3:** The cyclic relation between Product Quality ↔ Quality System Certifications are considered to be caused by a temporal relation. 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 is eliminated by using multiple time frames in the BN.

The causal graph where the cycles due to r1 and r2 are eliminated is shown in Figure 6. The cycle due to third reason is eliminated by using dynamic BNs with multiple time frames (see Figure 9).
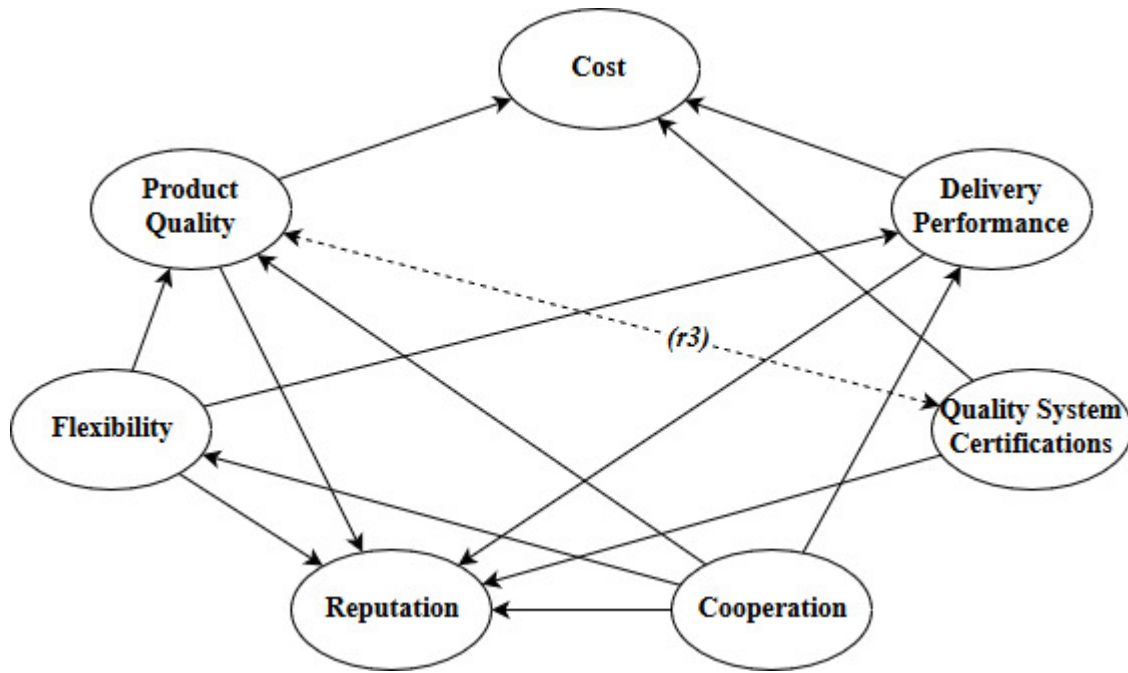
Figure 6. Initial causal graph with eliminated cycles due to r1 and r2

5. Revise causal graph with experts

After the cycle elimination step, we reviewed the causal graph with experts to respectively add or remove any missing or redundant arcs that were incorrectly identified by DEMATEL. The domain experts removed some arcs as they indicated that these arcs represent indirect causal relations, and the causal effect is mediated through some other variable in the BN. 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 path: Quality System Certifications → Product Quality → Cost. So these arcs were removed from the causal network to simplify the model, and the final causal model is shown in Figure 7.
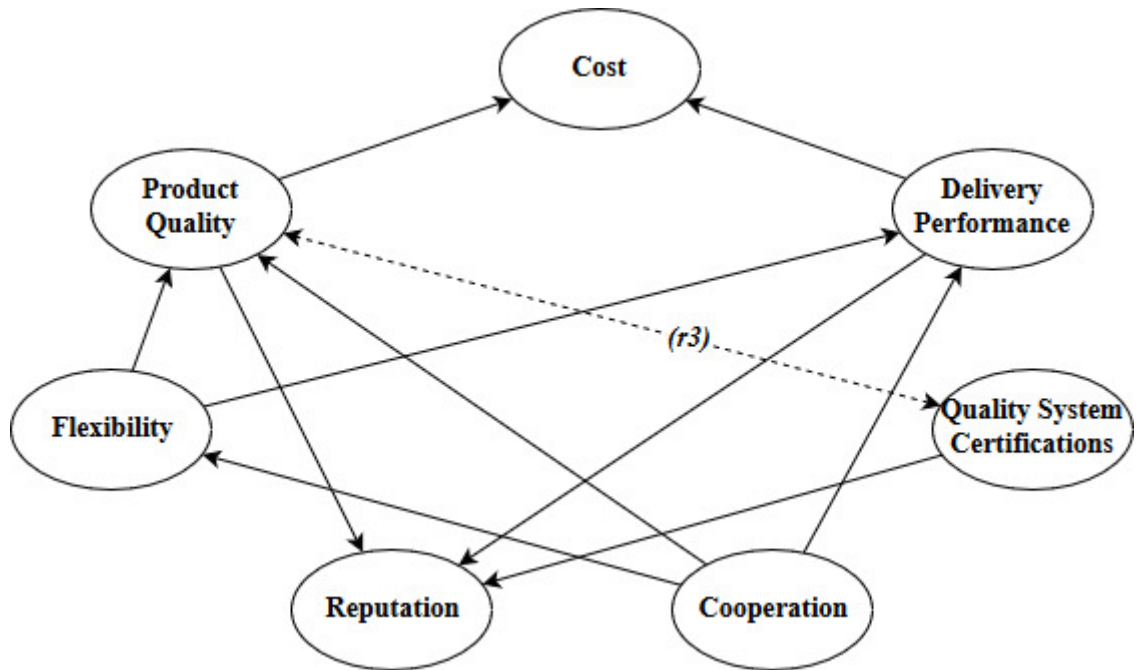
Figure 7. Final Causal Network Model

6. Define states of the BN

Each variable in a BN have a set of mutually exclusive and collectively exhaustive states. We defined 5 ordinal states (i.e. very low, low, medium, high and very high) for all variables in our model.

7. Parameterize BN with ranked nodes

The ranked nodes approach was used to simplify the parameter elicitation task with the expert (see Section 2 for a description of ranked nodes). We used the weighted mean (WMEAN) function for the ranked nodes. A ranked node defined with WMEAN requires a weight parameter for each parent and a variance parameter to define the central tendency and uncertainty of its conditional probability distribution respectively. We used the average direct relation matrix of DEMATEL to define the weights of each parent. For example, the parents of product quality are cooperation and flexibility in our model. The weights of these parents were defined from the *A* matrix in Table 4. The variance values for the ranked nodes was defined by the sum of variances of the survey responses for product quality, and it was normalized to the unit scale for the TNormal distribution.

After the parameters of all nodes are defined using ranked nodes, the final BN model was computed by AgenaRisk (Agena, 2018) as ranked nodes are readily implemented in this software. Figure 8 shows the dynamic BN version of the model divided into different time

frames. Multiple time frames were required in order to remove the cycle between product quality and quality system certifications as described in Step 4.
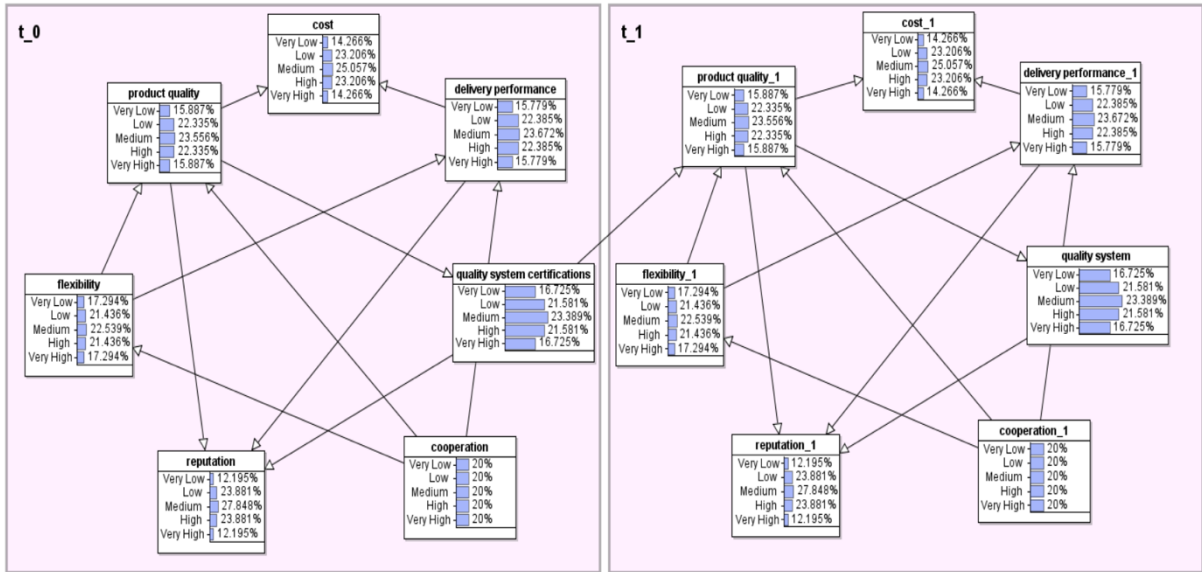

Figure 8. Model with multiple time frames

8. Evaluate and compare the BN with DEMATEL

In this step, we analyze the sensitivity of the BN to interventions and findings and compare them with T and T^* matrices of DEMATEL as described in Section 4.

Sensitivity to Interventions

Figure 9 shows the sensitivity of each variable to the interventions on other variables. Each bar in Figure 9 shows the information gain (mutual information) on the target variable when there is an intervention on the variable. For example, cooperation has causal effect on all other variables while no variable has causal effect on cooperation in Figure 9. Figure 10 shows the causal effects that are over the threshold value in T matrix. In DEMATEL, the final causal graph is built by defining a threshold value for the T matrix and including the causal effects that are over this value. We used the average of the T matrix values as the threshold value.

In our review with domain experts, the effects of interventions in the BN (Figure 9) and the total causal relations in the T matrix (Figure 10) are found to be compatible with each other. For example, in both BN and T matrix, cooperation is a major cause variable that affects all variables but is not causally affected by other variables. Cost is a major effect variable that is causally affected by all other variables, but it does not have causal effect on any other variables in the BN, and it only affects reputation in the T matrix.

The first main difference between the sensitivity analysis and *T* matrix is the causal effects on quality certifications. While no other variable has notable causal effect on quality certifications in the *T* matrix, product quality and cooperation has causal effects on this variable in the BN. This is considered to be due to the temporal modification on the BN structure (see Step 4). The domain experts preferred the BN's results in this case, as cooperation with the supplier can lead to improved product quality and this enables getting quality certifications. The second main difference is in the degree of causal effects of cooperation. This variable has causal effects on other variables in both BN and DEMATEL, but the magnitude of this effect seems to be higher in the BN model. The domain experts also preferred the BN's result in this case, as they consider cooperation as a major factor in supplier selection that can improve the state of all other variables in medium or long term.
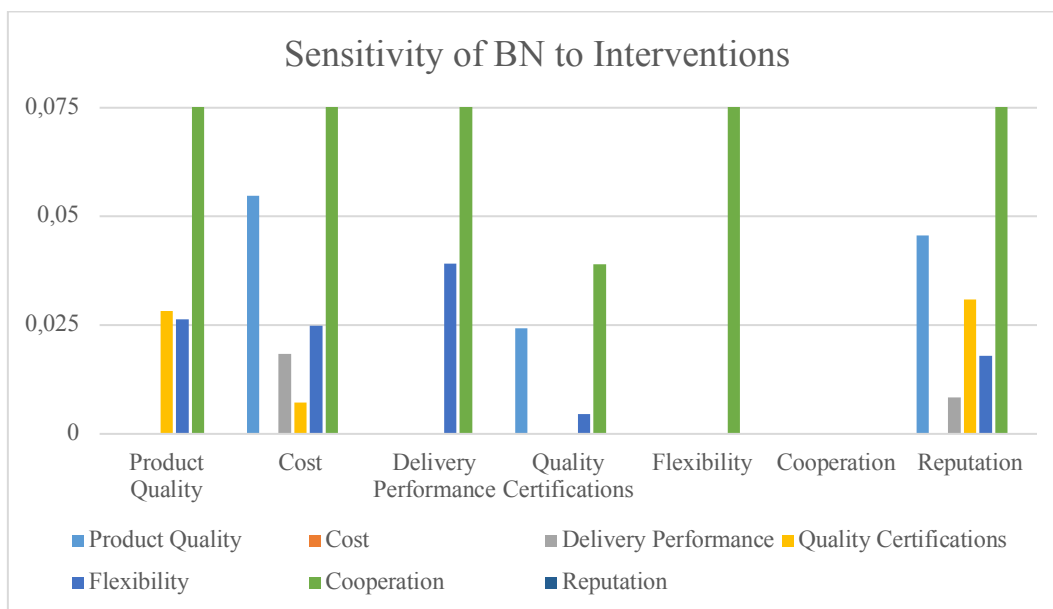

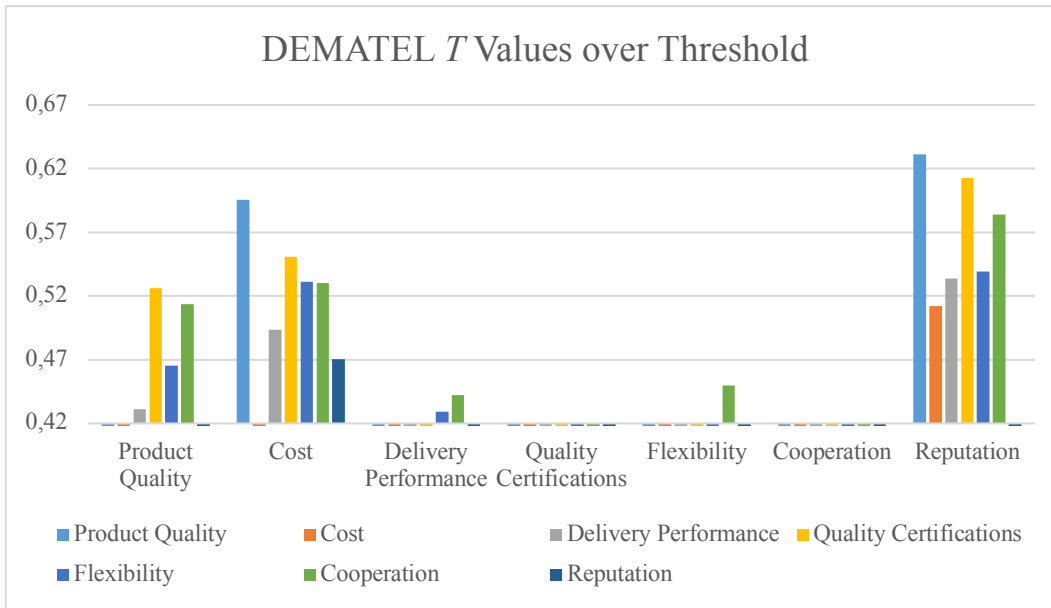Figure 9. Sensitivity of BN to Interventions

Figure 10. *T* Matrix Values over the Threshold Value

Sensitivity to Findings

We compared the sensitivity analysis of evidence for BN with the *T** matrix computed from the DEMATEL results. *T** is a symmetric matrix that represents the sum of total causal effect between each pair of variables in both directions (see Section 4 for a description of *T**). Table 6 shows *T** for the case study. We set the threshold value for *T** as the average of all values in *T**.

Table 6. *T** Matrix

T*	Product Quality	Cost	Delivery Performance	Quality System Certifications	Flexibility	Cooperation	Reputation
Product Quality	0.0000	1.0119	0.7956	0.9317	0.8667	0.8890	1.0340
Cost	1.0119	0.0000	0.8293	0.8457	0.9097	0.8752	0.9825
Delivery Performance	0.7956	0.8293	0.0000	0.7248	0.7878	0.7890	0.8489
Quality System Certifications	0.9317	0.8457	0.7248	0.0000	0.7250	0.7285	0.9035
Flexibility	0.8667	0.9097	0.7878	0.7250	0.0000	0.8553	0.8683
Cooperation	0.8890	0.8752	0.7890	0.7285	0.8553	0.0000	0.9061
Reputation	1.0340	0.9825	0.8489	0.9035	0.8683	0.9061	0.0000

Figures 11 and 12 show the mutual information criterion values from the sensitivity analysis and the *T** matrix values that are above the threshold value respectively. We reviewed these results with domain experts and the sensitivity of each variable in the BN model is found to be consistent with the total effect in the *T** matrix. The following section illustrates the use of our model for decision support.
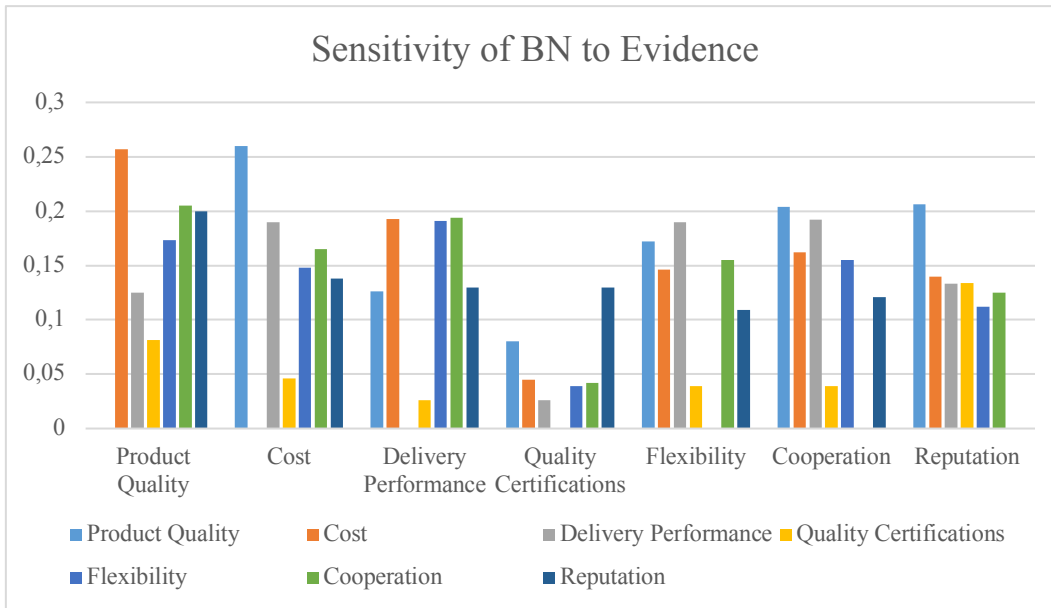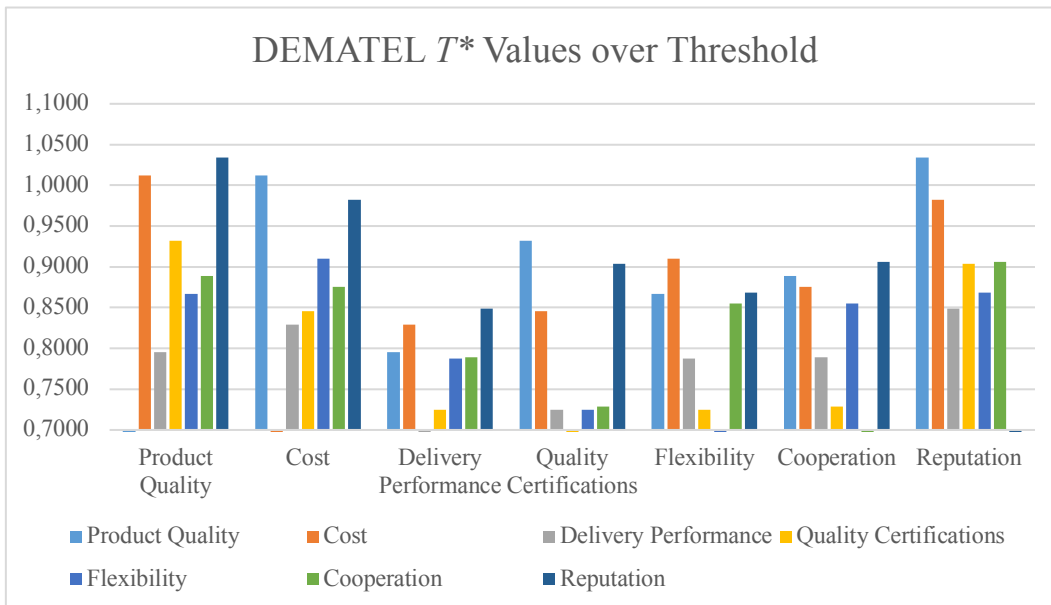
Figure 11 Sensitivity of BN to Findings

Figure 12. *T** Matrix Values over the Threshold Value

6.1. Expanding the BN Model with Indicators

In this section, we expand our model by adding indicators for estimating latent variables that cannot be directly observed and illustrate the use of the model for supplier selection, monitoring and comparison scenarios. Among the variables in our model, only cost and quality system certifications can be directly observed. The other variables in our model are latent variables that can only be estimated through indirect indicators. For example, product quality is a latent variable that can be estimated through indicators including the specifications of its raw materials, dimensions and other compliances. Measurements and indicators of a latent variable are modelled as its children in the BN structure. When the BN

model is used for decision support, the user instantiates these indicators rather than directly instantiating the latent variable.

Table 7. Criteria with Indicators

Criteria	Indicators
Product Quality	Raw Material Compliance
	Dimensional Compliance
	Other Compliances
Cost	-
Delivery Performance	On-time Delivery
	Right Quantity
	Packaging Conditions
	Handling Conditions
	Transportation Conditions
	Documents
Quality System Certifications	-
Flexibility	Product Flexibility
	Delivery Flexibility
	Volume Flexibility
Cooperation	Problem Solving Ability
	Communication
	Data Sharing
Reputation	Works with the Competitors
	Annual Production Volume
	International Export

Table 7 shows the indicators we included for each variable in our BN. These variables either has ordinal states (i.e. low, medium high) or binary states (i.e. no, yes). Figure 13 shows the BN model expanded with indicators. In the remainder of this section, we illustrate the use of this model with two scenarios.

Scenario 1: Selecting and Monitoring Suppliers

The first scenario demonstrates selection and online monitoring of a supplier by using our BN model. There is often uncertainty regarding the performance of a new supplier, and this uncertainty decreases as the customer starts to work with the supplier and collects more data and information. The BN model can revise the belief about the performance criteria dynamically as more information is collected.
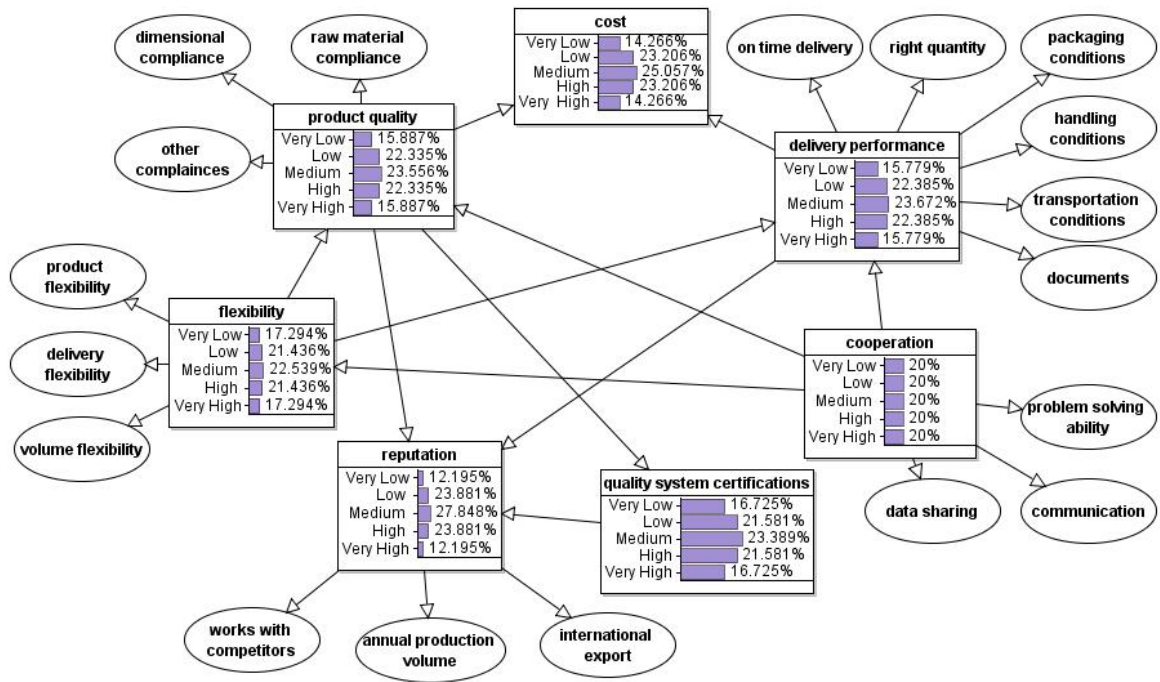
Figure 13. Model with indicators

The automobile manufacturer company evaluates and monitors a new supplier that also works with several other major automobile manufacturers. The supplier is willing to share information regarding their production. The first batch of samples from the supplier met the requirements regarding material, dimensions and transportation conditions. However, the surface requirements of some samples, and the packaging conditions of the delivery were not completely satisfactory. Based on this initial information, the BN model is instantiated (see Table 8), and the probabilities of unobserved variables are updated. Figure 14 shows the posteriors of the selection criteria for this initial evaluation. Note that, the uncertainty regarding flexibility and delivery performance posteriors is relatively high due to lack of information about these properties.

The company agrees to work with the supplier and collects more information about it in the first three months after the agreement. The supplier has improved the packaging conditions, and requirements regarding surface treatment of their products after initial requests from the customer. However, there were delayed deliveries, some products were damaged during transportation in this duration, and the supplier was also found to be slow in responding to changes requested by the company. They update the BN model with this information from the 3rd month evaluation (see Table 8), and the posteriors of the selection criteria is also shown in Figure 14.

Table 8. Information available at the Initial and 3rd Month Evaluation

| Indicators	Initial Evaluation	3 Month Evaluation
Raw Material Compliance	True	True
Dimensional Compliance	True	True
Other Compliances	Low	Medium
Cost	Medium	Medium
On-time Delivery	-	Low
Right Quantity	-	True
Packaging Conditions	Satisfactory	Satisfactory
Handling Conditions	Satisfactory	Unsatisfactory
Transportation Conditions	Satisfactory	Unsatisfactory
Documents	Satisfactory	Satisfactory
Quality System Certifications	Medium	Medium
Product Flexibility	-	Medium
Delivery Flexibility	-	Low
Volume Flexibility	-	Low
Problem Solving Ability	-	Medium
Communication	High	Medium
Data Sharing	True	True
Works with the Competitors	True	True
Annual Production Volume	-	Medium
International Export	True	True
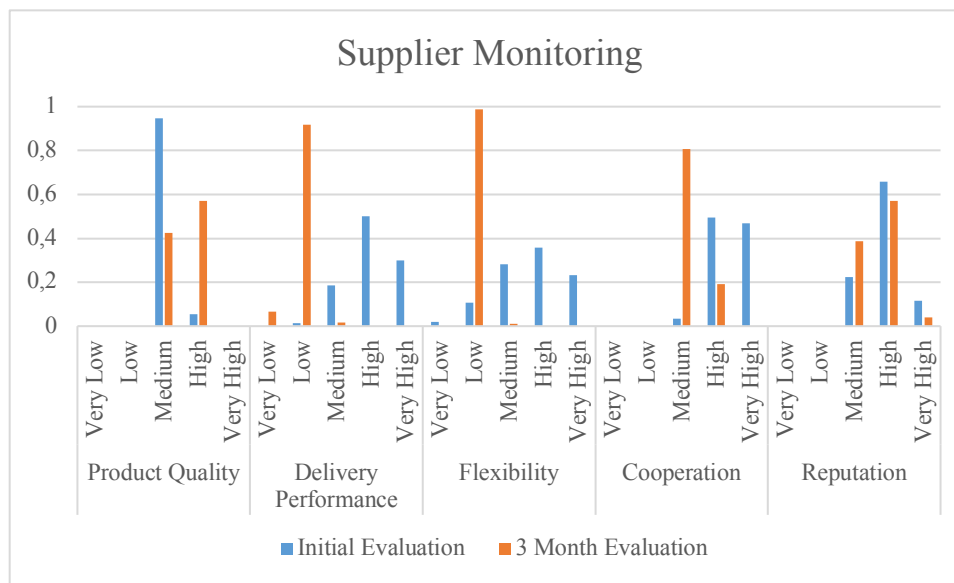
Figure 14. Posteriors of Selection Criteria at the Initial and 3rd Month Evaluation

The uncertainty regarding the decision criteria is lower than the first case as the company has collected more information about the supplier. The BN model estimates higher product quality but lower delivery performance, flexibility and cooperation for the supplier compared to the initial evaluation.

Scenario 2: Comparing Alternative Suppliers

In the second scenario, we compare two local suppliers, i.e. Suppliers A and B, with similar quality certifications for procuring a component for the automobile manufacturer company.

The company has previously worked with Supplier A and is satisfied with the quality of products delivered by supplier. However, the company has experienced some communication and delivery issues with this supplier. Supplier B has not worked with the company before but it works with one of its competitors and has similar quality certifications. Supplier B quoted a lower price for the component but the initial samples from Supplier B did not meet all specifications due to a problem with a heat treatment operation. However, Supplier B immediately arranged a meeting to present their manufacturing procedures, and offered possible solutions for this problem. Table 9 shows the information about Suppliers A and B that is instantiated in the BN model.

Table 9. Information about Supplier A and B

Indicators	Supplier A	Supplier B
Raw Material Compliance	True	True
Dimensional Compliance	True	True
Other Compliances	High	-
Cost	High	Medium
On-time Delivery	Medium	-
Right Quantity	True	-
Packaging Conditions	Satisfactory	-
Handling Conditions	Satisfactory	-
Transportation Conditions	Satisfactory	Satisfactory
Documents	Satisfactory	-
Quality System Certifications	High	High
Product Flexibility	-	-
Delivery Flexibility	Low	-
Volume Flexibility	-	-
Problem Solving Ability	Low	Medium
Communication	Low	High
Data Sharing	True	True
Works with the Competitors	False	True
Annual Production Volume	Medium	High
International Export	False	False

Figure 15 shows the posteriors of the selection criteria for Supplier A and B. Based on past experience with Supplier A, the BN model predicts a high level of product quality, a medium level of cooperation but a low level of flexibility from this supplier. The delivery performance of both suppliers tends to be between medium and high. The product quality of Supplier B is likely to be lower than Supplier A. However, cooperation level with Supplier B is expected to be high and this can enable them to improve the delivery performance and product quality over time. There is higher uncertainty regarding the decision criteria estimates for Supplier B due to lack of previous experience with this supplier.
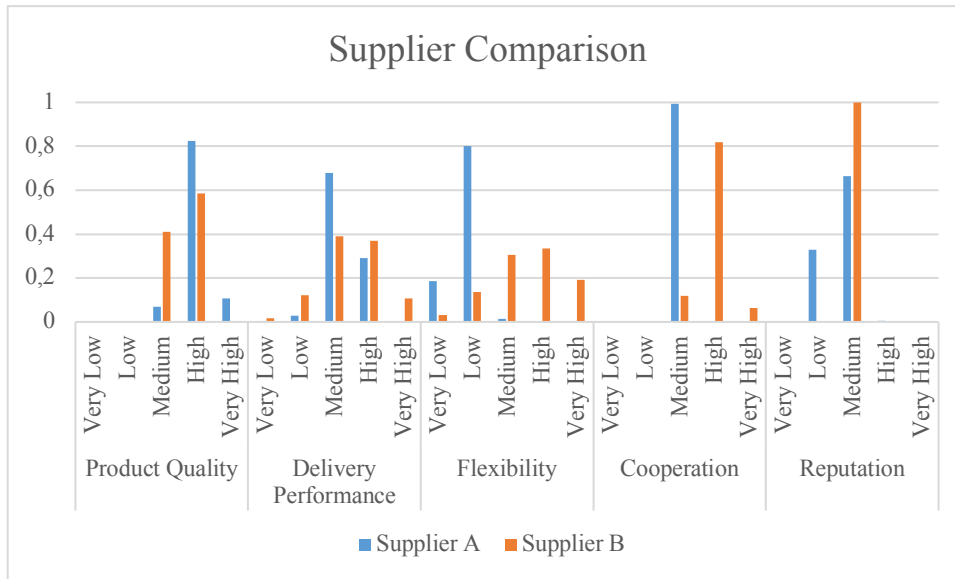
Figure 15 Posteriors of Supplier Selection Criteria for Suppliers A and B

In summary, the posteriors computed by the BN reflect the knowledge elicited by using DEMATEL and expert elicitation sessions. It also reflects the uncertainty of the selection criteria, and offers the flexibility to work with partial information. It refines the probability distributions of the criteria dynamically when more information is available. The BN aims to provide decision support but it is not designed to make automated supplier selection decisions as preference information about the criteria is not encoded in the BN.

7. CONCLUSIONS

This paper proposed a novel method that integrates DEMATEL and BNs to build probabilistic decision support models based on domain knowledge. The proposed method uses DEMATEL to elicit the structure of a BN, and uses ranked nodes to define its NPTs. The parameters required for ranked nodes are also obtained from the results of DEMATEL. The consistency of the BN model with DEMATEL and domain knowledge was evaluated by using sensitivity analysis of findings and interventions. We applied our method to a supplier selection decision problem in a large automobile manufacturer in Turkey. We conducted DEMATEL surveys and interviews with 14 domain experts from this company to build and review the BN model. We also expanded the BN model with indirect indicators and measurements and used it for analyzing different suppliers. Our approach successfully developed a working BN model for this complex problem and analyzed different case studies with this model. In expert reviews, the reasoning mechanism of the model was found to be consistent with domain knowledge.

The proposed method overcomes several limitations of DEMATEL and previous BN construction methodologies as:

1. It provides a systematic way to construct BN structure and parameters based on a widely used and accepted MCDM method,
2. It can use judgements of multiple experts to construct the BN,
3. It is able to make probabilistic inference and provide decision support in uncertain environments based on DEMATEL,
4. It offers a systematic way of reviewing the different aspects of the model with experts based on sensitivity analysis,
5. It demonstrates how to modify and expand the decision support model with additional measurements and indicators.

Limitations of our approach include its dependence to the clarity of the DEMATEL survey and, absence of automated recommendation and ranking features. The DEMATEL survey questions must be designed to elicit direct causal relations. If the aim of the questions or elicited causal relations are not clear, the resulting causal graph can have a large number of cycles which needs to be eliminated in order to build the BN. Eliminating these cycles can be cognitively difficult and time-consuming for domain experts.

BNs developed by the proposed approach provides decision support by computing and presenting the posterior distribution of the decision criteria for each alternative. However, they cannot be used for automated decision making as the current approach do not recommend or rank decision alternatives. This can be a limitation when a large number of decision alternatives are available and manually ranking them is difficult for the decision maker.

In future studies, we firstly plan to integrate the proposed method with TOPSIS and weighted utility functions to provide automated recommendations from the model. The proposed method can be expanded to incorporate decision and utility nodes (i.e. influence diagrams) in the resulting model. Secondly, the use of value of information analysis with our approach can also be investigated. The BN model developed by our approach can have many observable nodes, and collecting information about all of these nodes can be costly for the decision maker. BNs can compute posteriors when a part of their variables are unknown but, currently, the supplier selection BN does not recommend which variable the decision maker should observe next. Expanding our approach with decision and utility nodes will enable us

to analyze value of information by computing the additional value of observing different variables. Thirdly, we plan to investigate the use of hierarchical parameter learning algorithms with our approach. The proposed approach is purely based on expert knowledge. Supplier data, especially about new suppliers, can be scarce, hence traditional data-driven approaches may not be suitable to be used with our approach. Hierarchical Bayesian learning approaches, however, can be used to exploit the similarity between different suppliers when learning parameters from small datasets.

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