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Technical Note

# Supply chain diagnostics with dynamic Bayesian networks

Han-Ying Kao[a,*], Chia-Hui Huang[b], Han-Lin Li[b]

[a]Department of Marketing and Distribution Management, Hsuan Chuang University, 48 Hsuan Chuang Road, Hsinchu 300, Taiwan, ROC
[b]Institute of Information Management, National Chiao-Tung University, Ta-Hsueh Road 1001, Hsinchu 300, Taiwan, ROC

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**Abstract**

This paper proposes a dynamic Bayesian network to represent the cause-and-effect relationships in an industrial supply chain. Based on the Quick Scan, a systematic data analysis and synthesis methodology developed by Naim, Childerhouse, Disney, and Towill (2002). [A supply chain diagnostic methodlogy: Determing the vector of change. *Computers and Industrial Engineering*, *43*, 135–157], a dynamic Bayesian network is employed as a more descriptive mechanism to model the causal relationships in the supply chain. Dynamic Bayesian networks can be utilized as a knowledge base of the reasoning systems where the diagnostic tasks are conducted. We finally solve this reasoning problem with stochastic simulation.
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*Keywords:* Dynamic Bayesian networks; Diagnostic reasoning; Supply chain diagnostics; Stochastic simulation

## 1. Introduction

Naim et al. (2002) presented a methodology, Quick Scan, to conduct a supply chain oriented business diagnostics in 20 European automotive supply chain values streams. Quick Scan is a systematic methodology to collect and synthesize quantitative and qualitative data from a supply chain. One of the main outputs of Quick Scan is the cause-and-effect diagram of the supply chain. The contributions of the research mentioned above are:

(1) Data collection and integration. Many important and insightful information were collected and analyzed through the field studies and case studies.

* Corresponding author. Tel.: +886 3 5302255/5227 fax: +886 3 5391236.
*E-mail addresses:* teresak_hk@yahoo.com.tw (H.-Y. Kao), teresak@hcu.edu.tw (H.-Y. Kao), leohuang.iim92g@nctu.edu.tw (C.-H. Huang), hlli@cc.nctu.edu.tw (H.-L. Li).

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(2) Identification of causal relationships in a supply chain. After the thorough analysis and cross-reference, a cause-and-effect diagram was proposed.
(3) Provide a systematic and integrated view of supply chain diagnostics.

At the same time, we also find some interesting issues worth further discussions:

(1) The strength and uncertainty of the causal relationships in supply chain diagnostics are not identified and quantified.
(2) The diagnostic reasoning methods are not provided.

In this study, we propose a dynamic Bayesian network (DBN) (Dagum, Galper, & Horvitz, 1992; Kjærulff, 1992) to elaborate the causal relationships previously extracted by Naim et al. and show how diagnostic reasoning can be conducted on dynamic Bayesian networks. A numerical example is illustrated.

## 2. Dynamic Bayesian networks

A Bayesian network (Castillo, Gutoerrez, & Hadi, 1997; Pearl, 1988) is a probability-based knowledge representation method, which are appropriate for the modeling of causal processes with uncertainty. A Bayesian network is a directed acyclic graph (DAG) whose nodes represent random variables and whose links define probabilistic dependences between variables. These relationships are quantified by associating a conditional probability table with each node, given any possible configuration of values for its parents. Diagnosis or prediction with Bayesian networks consists of fixing the values of the observed variables and computing the posterior probabilities of some of the unobserved variables.

A dynamic model can be constructed from a set of building blocks that capture the instantaneous relationships between domain variables, together with a set of temporal dependencies that capture the dynamic behaviors of the domain variables (Dagum, Galper, & Horvitz, 1992). The building block of a dynamic Bayesian network is a static Bayesian network. We can extend the static Bayesian network to a dynamic Bayesian network model by introducing relevant temporal dependencies between representations of the static network at different times. Two types of dependencies can be distinguished in a dynamic Bayesian network: contemporaneous dependencies and non-contemporaneous dependencies. Contemporaneous dependencies refer to arcs between nodes that represent variables within the same time period. Non-contemporaneous dependencies refer to arcs between nodes that represent variables at different times. We will illustrate how dynamic Bayesian networks can be used to formulate the supply chain diagnostic problems and how the participating enterprises in the supply chain can solve the reasoning problems on the networks.

### 2.1. A dynamic Bayesian network of supply chain

First of all, we represent the key variables in the supply chain with the nodes and translate this cause-and-effect diagram in (Naim et al., 2002) into a dynamic Bayesian network as in Fig. 1. All nodes or variables in this dynamic Bayesian network are defined to be binary. The states and description of

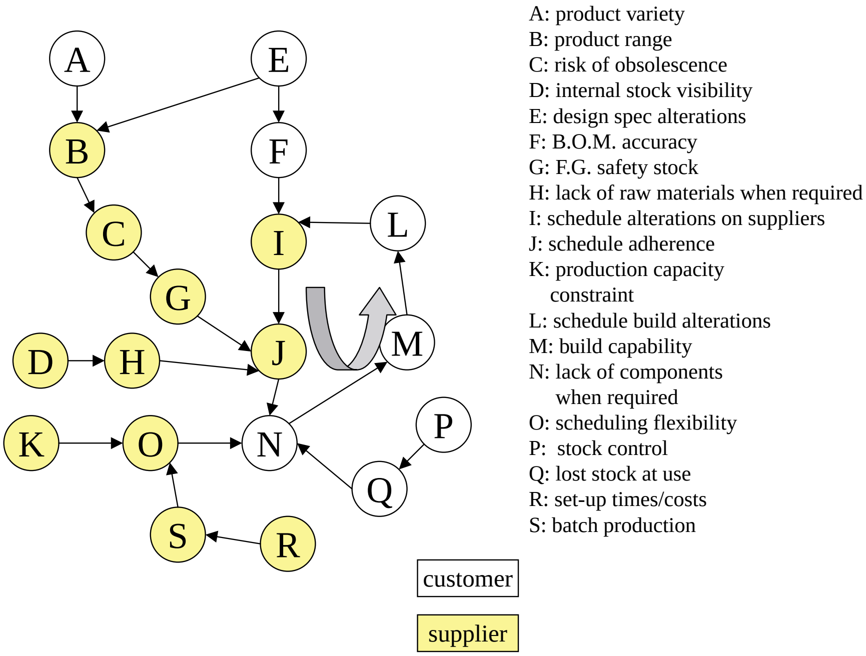


Fig. 1. A dynamic Bayesian network of supply chain diagnostics.

the nodes are listed in Table 1. We use the uppercase letters to represent the variables and lowercase letters for their associated values. For example, $C^t \in \{0, 1\}$ represents the dichotomy between low risk of obsolescence and high risk of obsolescence at time $t$. $+c^t$ stands for $C^t=1$ and $\neg c^t$ stands for the negation of $+c^t$. In this paper, we put little attention on how to learn and estimate the parameters in this dynamic Bayesian network, but concentrate on the diagnostic reasoning methods.

In Fig. 1, a self-enhancing feedback loops exists among **I** (schedule alterations placed on suppliers), **J** (schedule adherence), **N** (lack of components when required), **M** (build capability) and **L** (schedule build alterations). If we take a time expansion aspect, Fig. 1 can be expended as Fig. 2. We assume that the relationship and conditional probability distributions among the nodes are deterministic and unchanged as time varies along, except the relationships between **J** and **N**. The joint probability distribution of this dynamic Bayesian network for time $t=0$ to $n$ can be expressed as (2.1)

$$
\begin{aligned}
&P(a^0, a^1, \ldots, a^n, b^0, b^1, \ldots, b^n, \ldots, s^0, s^1, \ldots, s^n) \\
&\quad = P(a^0)P(b^0|a^0, e^0)P(c^0|b^0)P(d^0)P(e^0)P(f^0|e^0)P(g^0|c^0)P(h^0|d^0)P(i^0|f^0, l^0)P(j^0|i^0, g^0, h^0) \\
&\qquad \times P(k^0)P(l^0|m^0)P(m^0|n^0)P(n^0|o^0, q^0)P(o^0|s^0, k^0)P(p^0)P(q^0|p^0)P(r^0)P(s^0|r^0) \\
&\qquad \times \prod_{t=1}^{n}[P(a^t)P(b^t|a^t, e^t)P(c^t|b^t)P(d^t)P(e^t)P(f^t|e^t)P(g^t|c^t)P(h^t|d^t)P(i^t|f^t, l^t)P(j^t|i^t, g^t, h^t) \\
&\qquad \times P(k^t)P(l^t|m^t)P(m^t|n^t)P(n^t|j^{t-1}, o^t, q^t) \times P(o^t|s^t, k^t)P(p^t)P(q^t|p^t)P(r^t)P(s^t|r^t)]. \qquad (2.1)
\end{aligned}
$$

Table 1
The description of nodes in the dynamic Bayesian network in Fig. 1

| Node | Description | State |
|---|---|---|
| A[a] | Product variety | 1: large; 0: small |
| B[b] | Product range | 1: large; 0: small |
| C[b] | Risk of obsolescence | 1: high; 0: low |
| D[b] | Internal stock visibility | 1: good; 0: poor |
| E[a] | Design specification alterations | 1: often; 0: not often |
| F[a] | BOM accuracy | 1: high; 0: low |
| G[b] | Finished goods safety stock | 1: high; 0: low |
| H[b] | Lack of raw materials when required | 1: high; 0: low |
| I[b] | Schedule alterations on suppliers | 1: often; 0: not often |
| J[b] | Schedule adherence | 1: high; 0: low |
| K[b] | Production capacity constraint | 1: high; 0: low |
| L[a] | Schedule build alterations | 1: often; 0: not often |
| M[a] | Build capability | 1: high; 0: low |
| N[a] | Lack of components when required | 1: high; 0: low |
| O[b] | Scheduling flexibility | 1: high; 0: low |
| P[a] | Stock control | 1: good; 0: poor |
| Q[a] | Lost stock at use | 1: high; 0: low |
| R[b] | Set-up times/costs | 1: large; 0: small |
| S[b] | Batch production | 1: large; 0: small |

[a] Customer.
[b] Supplier.

The term $P(n^t|j^{t-1},o^t,q^t)$ embraces contemporaneous dependencies at time $t$ and non-contemporaneous dependencies at $t-1$. We will adopt a commonly used parametric decomposition in time-series analysis: the additive decomposition (Dagum et al., 1992). The additive decomposition is used commonly in time-series analysis for integrating predictions based on current observations with predictions based on historical observations. Additive decompositions are an integral aspect of models

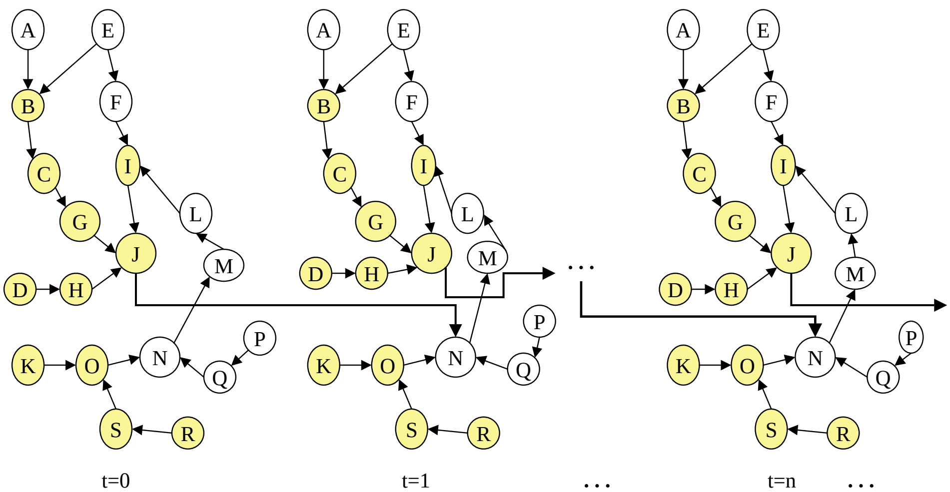


Fig. 2. A series of connected Bayesian networks of supply chain diagnostics with time expansion.

that purport to forecast future values of time-series. Using likelihood weighting, an expert can specify the weight of the past versus the present easily. The term $P(n^t|j^{t-1},o^t,q^t)$ can be decomposed as follows

$$P(n^t|j^{t-1}, o^t, q^t) = \omega P(n^t|o^t, q^t) + (1-\omega)P(n^t|j^{t-1}), \quad (2.2)$$

where $\omega$ denotes the likelihood that $n^t$ predicted from the information at period $t$, and $(1-\omega)$ denotes the likelihood that $n^t$ predicted from the information prior to time $t$. The likelihood weight $\omega$ can be learned and estimated from the historical data.

## 3. Diagnostic reasoning in the dynamic Bayesian network of supply chain

The diagnostic problems in a supply chain can be regarded from the supplier's aspect, the customer's aspects, the central planner's aspects, or any other possible roles concerning the supply chain. Now, we hypothesize a case and show how the supplier conducts diagnostic reasoning tasks on this dynamic Bayesian network of supply chain diagnostics. We assume that all the conditional probabilities have been learned and given in Table 2. In a living expert diagnostic system, these parameters for the dependency relationships can be learned and maintained by the knowledge engineers.

Table 2
The conditional probabilities of the DBN in Fig. 1

| | |
|---|---|
| $P(+a^t)=0.7$ | |
| $P(+d^t)=0.7$ | |
| $P(+e^t)=0.4$ | |
| $P(+k^t)=0.5$ | |
| $P(+p^t)=0.3$ | |
| $P(+r^t)=0.5$ | |
| $P(+c^t\|+b^t)=0.85$ | $P(+c^t\|\neg b^t)=0.2$ |
| $P(+f^t\|+e^t)=0.15$ | $P(+f^t\|\neg e^t)=0.9$ |
| $P(+g^t\|+c^t)=0.1$ | $P(+g^t\|\neg c^t)=0.8$ |
| $P(+h^t\|+d^t)=0.05$ | $P(+h^t\|\neg d^t)=0.9$ |
| $P(+l^t\|+m^t)=0.1$ | $P(+l^t\|\neg m^t)=0.9$ |
| $P(+m^t\|+n^t)=0.1$ | $P(+m^t\|\neg n^t)=0.95$ |
| $P(+n^t\|+j^{t-1})=0.1$ | $P(+n^t\|\neg j^{t-1})=0.5$ |
| $P(+q^t\|+p^t)=0.1$ | $P(+q^t\|\neg p^t)=0.5$ |
| $P(+s^t\|+r^t)=0.7$ | $P(+s^t\|\neg r^t)=0.3$ |
| $P(+b^t\|+a^t,+e^t)=0.9$ | $P(+b^t\|\neg a^t,+e^t)=0.6$ |
| $P(+b^t\|+a^t,\neg e^t)=0.8$ | $P(+b^t\|\neg a^t,\neg e^t)=0.2$ |
| $P(+i^t\|+f^t,+l^t)=0.8$ | $P(+i^t\|\neg f^t,+l^t)=1.0$ |
| $P(+i^t\|+f^t,\neg l^t)=0.01$ | $P(+i^t\|\neg f^t,\neg l^t)=0.5$ |
| $P(+n^t\|+o^t,+g^t)=0.01$ | $P(+n^t\|\neg o^t,+g^t)=0.1$ |
| $P(+n^t\|+o^t,\neg g^t)=0.2$ | $P(+n^t\|\neg o^t,\neg g^t)=0.6$ |
| $P(+o^t\|+k^t,+s^t)=0$ | $P(+o^t\|\neg k^t,+s^t)=0.7$ |
| $P(+o^t\|+k^t,\neg s^t)=0.6$ | $P(+o^t\|\neg k^t,\neg s^t)=0.95$ |
| $P(+j^t\|+g^t,+h^t,+i^t)=0.2$ | $P(+j^t\|+g^t,\neg h^t,+i^t)=0.5$ |
| $P(+j^t\|+g^t,+h^t,+i^t)=0.6$ | $P(+j^t\|+g^t,\neg h^t,\neg i^t)=0.99$ |
| $P(+j^t\|\neg g^t,+h^t,+i^t)=0$ | $P(+j^t\|\neg g^t,\neg h^t,+i^t)=0.5$ |
| $P(+j^t\|\neg g^t,+h^t,\neg i^t)=0.6$ | $P(+j^t\|\neg g^t,\neg h^t,\neg i^t)=0.8$ |

*Case* (Supplier's viewpoint): The supplier finds some symptoms internal to his company, which might result from some segments in the supply chain. The supplier observed that, for the preceding periods, the customer puts large schedule alterations ($I^t=1$), and as a result, the schedule adherence has been poor ($J^t=0$). The supplier starts to investigate and collect relevant data inside the company for problem diagnosis. The supplier itself has a large product range ($B^t=1$) and high risk of obsolescence ($C^t=1$), and hence keeps limited finished goods ($G^t=0$). The supplier has maintained good internal stock visibility ($D^t=1$), and the raw materials are available when required ($H^t=0$). The production capacity constraint is high ($K^t=1$) and the scheduling flexibility is low ($O^t=0$). Also, the supplier bears large set-up times/costs ($R^t=1$) and has large batch production ($S^t=1$). On the customer side, the supplier has no extra information in addition to the data shown in Table 2. Given the information on hand, the supplier wants to compute the posterior probability distributions of every proposition in the system backward for a few periods, given the evidence set $\mathbf{e}=\{B^t=1, C^t=1, D^t=1, G^t=0, H^t=0, I^t=1, J^t=0, K^t=1, O^t=0, R^t=1, S^t=1|0\le t\le n\}$.

The case is a typical diagnostic reasoning problem in a dynamic environment. There are many methods to conduct diagnostic reasoning (Castill, Gutoerrez, & Hadi, 1996; Castillo et al., 1997; Pearl, 1988). We will use stochastic simulation (Pearl, 1988) to solve this problem.

First of all, we denote by $w_X$ the state of all variables except $X$, then the value of $X$ will be chosen by tossing a coin that favors 1 over 0 by a ratio of $P(+x|w_X)$ to $P(x|w_X)$. We will show that $P(x|w_X)$, the distribution of each variable $X$ conditioned on the values $w_X$ of all other variables in the system, can be calculate by purely local computations. The distributions of $P(x|w_X)$ in this network at time $t$ are as follow

$$P(a^t|w_{A^t}) = \alpha P(a^t)P(b^t|a^t, e^t), \tag{2.3}$$

$$P(e^t|w_{E^t}) = \alpha P(e^t)P(b^t|a^t, e^t)P(f^t|e^t), \tag{2.4}$$

$$P(f^t|w_{F^t}) = \alpha P(f^t|e^t)P(i^t|f^t, l^t), \tag{2.5}$$

$$P(l^t|w_{L^t}) = \alpha P(l^t|m^t)P(i^t|f^t, l^t), \tag{2.6}$$

$$P(m^t|w_{M^t}) = \alpha P(m^t|n^t)P(l^t|m^t), \tag{2.7}$$

$$P(n^t|w_{N^t}) = \alpha[\omega P(n^t|o^t, q^t) + (1-\omega)P(n^t|j^{t-1})]P(m^t|n^t), \tag{2.8}$$

$$P(p^t|w_{P^t}) = \alpha P(p^t)P(q^t|p^t), \tag{2.9}$$

$$P(q^t|w_{Q^t}) = \alpha P(q^t|p^t)[\omega P(n^t|o^t, q^t) + (1-\omega)P(n^t|j^{t-1})], \tag{2.10}$$

where $\alpha$ is the normalizing constant.

We will simulate for period $t=0$–5 and set $\omega=0.5$ for all periods except the starting period ($t=0$) where $\omega$ is set 1. The value of $\omega$ can be estimated from the historical data (Dagum et al., 1992). For the convenience to illustrate, we assume that the evidence set remains unchanged during the simulation. However, in a real case, the behaviors or symptoms observed in a supply chain may vary in different period, which result in various evidence sets for different periods. So this assumption can be released as applied to the real complex cases. The algorithm of the stochastic simulation is described as follow.

**Algorithm 1**: (Stochastic simulation)
**Loop** while simulation not terminated:
Set $t=0$, all nodes$=0$.
**Loop** while $t$ is not greater than **LastT**:
$B(t)=1,\ C(t)=1,\ D(t)=1,\ G(t)=0,\ H(t)=0,\ I(t)=1,\ J(t)=0,\ K(t)=1,\ O(t)=0,\ R(t)=1,\ S(t)=1$
**Node Set**$=\{$A, E, F, L, M, N, P, Q$\}$
$X=$**First Node In Node Set**.
**Loop** while $X$ is not **End Of Node Set**
S1: $X$ inspects its neighbors, finding their values.
S2: Compute $P(X(t)=1|w_{X(t)})/P(X(t)=0|w_{X(t)})$.
S3: Set $X(t)$ from a random number generator favoring 1 by the ratio $P(X(t)=1|w_{X(t)})/P(X(t)=0|w_{X(t)})$.
S4: $X$ moves to **NextNodeInNodeSet**.
**EndLoop**.
SET $t=t+1$.
**EndLoop**.
**EndLoop**.
Compute the proportion of 1 of every element of every node in **NodeSet**.
**End of Algorithm 1**.

This study takes the numbers of iterating runs for 100, 1000 and 10,000. The results of the stochastic simulation are listed in Tables 3a–c. In Tables 3a–c, the beliefs or posterior probabilities of the unknown nodes to be true during the simulated horizon ($t=0$–5) are computed. As the industrial engineer inspects these results, he can see clearly the probability distributions of the potential causes of the supply chain symptoms. Subsequently, the industrial engineer can determine which items need further actions. From Table 3c, there are three most possible origins of the supply chain inefficiency: $A^t=1$ (with belief around 0.83), $E^t=1$ (with belief around 0.60) and $L^t=1$ (with belief around 0.75). The results imply that

Table 3a
The results of stochastic simulation: $P(x^t=1|e)$: 100 runs

| X | t= | | | | | |
|---|---|---|---|---|---|---|
| | 0 | 1 | 2 | 3 | 4 | 5 |
| A | 0.86 | 0.85 | 0.79 | 0.90 | 0.86 | 0.77 |
| E | 0.52 | 0.64 | 0.69 | 0.52 | 0.50 | 0.61 |
| F | 0.43 | 0.28 | 0.23 | 0.50 | 0.50 | 0.39 |
| L | 0.73 | 0.60 | 0.88 | 0.92 | 0.82 | 0.93 |
| M | 0.46 | 0.53 | 0.13 | 0.21 | 0.28 | 0.10 |
| N | 0.45 | 0.47 | 0.87 | 0.75 | 0.29 | 0.84 |
| P | 0.26 | 0.29 | 0.34 | 0.40 | 0.37 | 0.29 |
| Q | 0.41 | 0.36 | 0.29 | 0.23 | 0.28 | 0.28 |

Table 3b
The results of stochastic simulation: $P(x^t=1|e)$: 1000 runs

| X | t= | | | | | |
|---|---|---|---|---|---|---|
| | 0 | 1 | 2 | 3 | 4 | 5 |
| A | 0.836 | 0.848 | 0.828 | 0.811 | 0.815 | 0.818 |
| E | 0.630 | 0.604 | 0.613 | 0.629 | 0.635 | 0.589 |
| F | 0.345 | 0.373 | 0.368 | 0.345 | 0.332 | 0.397 |
| L | 0.753 | 0.736 | 0.792 | 0.718 | 0.650 | 0.817 |
| M | 0.325 | 0.337 | 0.256 | 0.330 | 0.476 | 0.262 |
| N | 0.644 | 0.653 | 0.721 | 0.645 | 0.513 | 0.729 |
| P | 0.332 | 0.321 | 0.316 | 0.293 | 0.302 | 0.352 |
| Q | 0.269 | 0.339 | 0.316 | 0.351 | 0.374 | 0.285 |

the customer needs to review and control its large product variety ($A^t=1$) and frequent design specification alterations ($E^t=1$). Also, the analyst believes that those two causes are influential to the large schedule build alterations ($L^t=1$) from the customer, which consequently amplifies the poor schedule adherence of the supplier.

This simplified scenario shows how the participants in the supply chain make proper inference or judgment of the problems in a supply chain on dynamic Bayesian networks. More complex and realistic cases can be extended and solved in a similar way.

## 4. Discussions and conclusions

This study elaborates the cause-and-effect diagram proposed by Naim et al. into a dynamic Bayesian network. We illustrate how the diagnostic reasoning is conducted on this network. The dynamic Bayesian network can be used as the knowledge base of the reasoning systems for the supply chain diagnostics and prediction, vendor appraisal, customer assessment, evaluation of strategic or technical alliance, and so on. A diagnostic or decision support system is composed of the data management subsystem, the model management subsystem, the knowledge engine, the user-interface, and the knowledge workers (Marakas, 2003; Turban & Aronson, 2001). This paper provides a foundation for

Table 3c
The results of stochastic simulation: $P(x^t=1|e)$: 10,000 runs

| X | t= | | | | | |
|---|---|---|---|---|---|---|
| | 0 | 1 | 2 | 3 | 4 | 5 |
| A | 0.8311 | 0.8208 | 0.8211 | 0.8288 | 0.8325 | 0.8237 |
| E | 0.5943 | 0.6016 | 0.5975 | 0.5951 | 0.5947 | 0.5870 |
| F | 0.3823 | 0.3739 | 0.3750 | 0.3798 | 0.3843 | 0.3880 |
| L | 0.7540 | 0.7563 | 0.7537 | 0.7504 | 0.7782 | 0.7639 |
| M | 0.3280 | 0.3267 | 0.3155 | 0.3314 | 0.2918 | 0.3138 |
| N | 0.6506 | 0.6549 | 0.6680 | 0.6467 | 0.6879 | 0.6654 |
| P | 0.3400 | 0.3218 | 0.3141 | 0.3250 | 0.3287 | 0.3085 |
| Q | 0.2567 | 0.3256 | 0.3365 | 0.3271 | 0.3217 | 0.3297 |

the knowledge bases and computation schema in a reasoning system. When the other subsystems are designed and the real-world data are available, it is ready for further development of a practical application of a supply chain diagnostic system.

## References


Castill, E., Gutoerre, J. M., & Hadi, A. S. (1996). A new method for symbolic inference in Bayesian networks. *Networks*, *28*, 31–43.

Castillo, E., Gutoerrez, J. M., & Hadi, A. S. (1997). *Expert systems and probabilistic network models*. New York, Inc: Spinger.

Dagum, P., Galper, A., & Horvitz, E. (1992). *Dynamic network models for forecasting Proceedings of the 8th conference on uncertainty in artificial intelligence (UAI' 92)*. San Francisco (CA), Morgan Kaufmann: Stanford University pp. 41–48.

Kjærulff, U. (1992). *A computational scheme for reasoning in dynamic probabilistic networks Proceedings of the 8th conference on uncertainty in artificial intelligence (UAI' 92)*. San Francisco (CA), Morgan Kaufmann: Stanford University pp. 121–129.

Marakas, G. M. (2003). *Decision support systems in the 21st century*. Pearson Education, Inc.

Naim, M. M., Childerhouse, P., Disney, S. M., & Towill, D. R. (2002). A supply chain diagnostic methodlogy: Determing the vector of change. *Computers and Industrial Engineering*, *43*, 135–157.

Pearl, J. (1988). *Probabilistic reasoning in intelligent systems: Networks of plausible inference*. Morgan Kaufmann Publishers, Inc.

Turban, E., & Aronson, J. E. (2001). *Decision support systems and intelligent systems*. Prentice Hall international, Inc.