An Extended Bayesian Belief Network Model of Multi-agent Systems for Supply Chain Management

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Abstract. In this paper, we describe our on-going research on uncertainty analysis in Multi-agent Systems for Supply Chain Management (MASCM). In a MASCM, an agent consists of automation processes within a legal entity in the specific supply chain network. It conducts supply chain planning, execution and cooperation on behalf of its owner. Each day these agents have to process a large volume of data from different sources with mixed signals not to be anticipated in advance. Thus, one challenge every agent has to face in this volatile environment is to quickly identify the impact of unexpected events, and take proper adjustments in both local procedures and related cross-boundary interactions. To facilitate the study of uncertainty in the complex system of MASCM, we model agent system behaviors by abstracting its significant operational aspects as observation, propagation and update of uncertainty ifnromation. The resulting theoretical model, called an extended Bayesian Belief Network (eBBN), may serve as the basis for developing an uncertainty management component for a large-scale electronic supply chain system. We also briefly describe ways this model can be used to solve different supply chain tasks and some simulation results that demonstrate the power of this model in improving the system performance.

1 Introduction

A Multi-agent System for Supply Chain Management (MASCM) comprises of a number of software agents (or agents for short in this paper) that sell and buy products (goods or services) on behalf of their owners. In a MASCM, the essential business activities of individual agents can be defined as an *Order Fulfillment Process* (OFP), which is the effort for an agent to satisfy the requests triggered by its customers' orders. At the system level, the supply chain management is the combination of all agents' activities ignited by one end order from the system's end customer. When an end order arrives, a Virtual Supply Chain (VSC), consisting of agents at different tiers in the chain, may emerge through multiple interconnected OFPs. The ultimate goal of the system management is to form VSCs that can successfully complete this end order, and the system's performance can be measured by the rate that all end orders are completed.

In the real life the formation of VSCs is affected by many unexpected factors within the system. They can be physical failures such as electricity outages, virus attacks, strikes, and so on. In addition, agents may change their trading partners following the owners' instructions, reflecting the change of the market. Uncertainty brought by these unexpected events may have negative impact on the system performance, e.g. prolong the time of VSC formation or breaking down an already formed VSC [1]. To protect their common interest of attracting more customers from such negative impacts, agents in a MASCM are often willing to cooperate with each other by sharing uncertainty information and analysis.

Bayesian Belief Network (BBN) has been established as a powerful and theoretically well-founded framework for representing and reasoning with ucnertainty. BBN initially arose from an attempt to incorporate the probability theory into expert systems, and has an origin and long history in decision analysis [2]. Nowadays, BBN model has been used in the fields such as diagnosis, reinforce learning, speech recognition, tracking, data compression, etc. One of the best-known examples of BBN applications is a decision-theoretic reformulation of the Quick Medical Reference (QMR) model [3] for internal medicine. Other practical applications include real time decision under uncertain situations [4], human-computer interaction analysis [5], deep-space exploration and knowledge acquisition [6], and the popular productive software Microsoft Office, to mention just a few.

In this paper, we present our research effort to develop a theoretical model, by extending the conventional BBN formulation, that formalizes agents' interactions in an uncertain environment. The model can be directly implemented as a separate component for MASCM system uncertainty management, and may also serve as the platform to analyze the relationship between uncertainty and various measures of system performance.

The rest of this paper is organized as follows. Section 2 gives a description of agent behaviors in OFPs and a general discussion on eBBN approach to modeling agent interactions; Section 3 introduces a simplified type of MASCM, called $MASCM_1$; Section 4 presents two eBBN models for the formation and evolution of VSCs in a $MASCM_1$. Finally, Section 5 concludes the paper with a brief discussion on how this model can be used to solve some important supply chain management tasks together with some simulation experiment results, and suggestions for further research. Due to the page limitation, proofs for theorems and lemmas are omitted.

2 Modeling agent behaviors

Suuply chain activities an agent is involved in can be abstracted as an order fulfillment process (OFP) [9], which can be logically divided into the following steps.

Order generation. Based on the commitment that is made to its customer's order or set by its human owner, the agent selects suppliers for the products needed to fulfill this commitment, generates orders and chooses negotiation strategies for each of the selected suppliers. The agent may generate more than one order in order to fulfill a given commitment.

Negotiation. The agent sends orders to the selected suppliers and negotiates with them. An agent can negotiate simultaneously with different suppliers. However, we assume in this paper that at any time, the agent only negotiates with one supplier. That is, the default negotiation protocol between two agents is bilateral. At the end of this stage, through negotiation, a mutual commitment between two agents may be reached.

Commitment processing. The agent processes the outstanding commitment it made to its customer, handles the unexpected events, and exchanges information with its supplier and customers about the status of the commitment. At the end of this stage, an order an agent receives (e.g., the commitment its made to its customer) may or may not be eventually fulfilled. When one of the agent's suppliers aborts the commitment and there is no alternative supplier to provide the same product, it has to cancel the commitment to its customer. The consequence of commitment cancellation also causes the agent to cancel all orders to other direct suppliers involved in this particular transaction, provided these orders have not yet been eventually solved. The order cancellation may propagate both upstream and downstream. However, when all direct suppliers of an agent fulfill their commitments, that is, deliver all the products the agent needs, an OFP initialized by this agent is considered completed.

The OFP triggered by an end order will propagate through OFPs of its suppliers, and suppliers' suppliers, etc. and a virtual supply chain (VSC) consisting of all agents involved is dynamically formed. In OFPs, agents interact with each other in order to reach mutual agreement and when they indeed reach one, agents will keep contacting the other parties until their agreed commitments are fulfilled. In other words, the commitment plays a central role in agent interactions. Therefore, the probability that a commitment will be fulfilled successfully or unsuccessfully can be used to measure the uncertainty of an agent's behaviors in the process. Accordingly, the system performance in an uncertain environment can be described as the likelihood of commitments held by the end customer agents being successfully fulfilled.

Also note that in a particular OFP, as described above, the customer agent initiates the process, but the supplier agents determine the progress of the process. From this perspective, the supply-demand relationship between an agent and its direct suppliers can be viewed as a causal one where the failure of fulfilling commitments by one's suppliers may cause its commitment to its downstream customers to fail. Therefore, the failure probability of commitments held by a pair of supply and customer agents are causally linked. More specifically, in a VSC, commitments held by individual agents and the supply-demand relationships between them form a casual network. This observation allows us to use BBN as a framework to formalize agents' interaction in the uncertain environment as the following.

- Model commitment failure probabilities as agents' beliefs.
- Model direct supply-demand relationships between pairs of agents as directed causal links (from the direct supplier to the customer).
- Model information sharing between agents as belief propagation.

However, the conventional BBN framework is inadequate in modeling MASCM agent interactions for at least the following reasons. First, causal links in conventional BBNs are static (unless learning or adaptation is involved) while the supply-demand relationships among MASCM agents may change over time. Although each agent in the system has in its inventory a certain level of safety stock of products it needs, such safety stock can only smooth out the uncertain fluctuation of supplies to an extent. Significant change of current suppliers' commitments may cause an agent to terminate its current orders to one supplier and switch to another one for the same product. Therefore, the causal network of commitments is not static but dynamically created and updated with the evolution of a VSC. Secondly, conventional BBN can only represent observations but not actions [???]. However, agents' actions such as the decisions to cancel a commitment or to switch suppliers, as well as other strategic actions, are the important uncertain sources that impact the failure probabilities of commitments of other agents. These impacts can be propagated through agents in the whole VSC through interconnected OFPs and, thus, have to be modeled within the framework. In the following sections, we introduce extended Bayesian Belief Network (eBBN) models for a simply type of MASCM that can represent the dynamic casual structure and actions according to VSC evolution.

3 $MASCM_1$

In this section we define a simple type of MASCM, called $MASCM_1$. We first introduce the notations used, then state the assumptions that define $MASCM_1$.

3.1 Symbols

We use symbol A_i to denote an agent. Accordingly, the MASCM is defined as a set of agents $S = \{A_1, A_2, ... A_n\}$. The set of all products provided by all agents in a MASCM is denoted as $G = \{g_1, g_2, ... g_m\}$. The final product that sells to the end customers is denoted as g_F, and usually is the first element in G, i.e., $g_1 = g_F$. We use notation $G(A_i)$ to denote the products agent A_i provides to its direct customers. We use symbols A_i^s, A_i^c to denote the sets of A_i's direct suppliers and customers, respectively in a VSC; and $|A_i^s|$ and $|A_i^c|$ their cardinalities. Symbol $A_i \cdot A_j$ is used to denote that agent A_i and its direct supplier agent A_j are currently engaged in some business activities such as negotiation and exchange of commitment information.

3.2 Assumptions

Our work in this paper is based on a simplified MASCM system, $MASCM_1$, which is defined by the following assumptions.

- **Assumption 1.** There is only one end customer agent in the system, denoted as $A_1 \in$ S. In other words, $A_1^c = \phi$ since its customer is not an agent but an entity outside the MASCM.

- **Assumption 2.** Each agent, except agent A_1, has exactly one customer in a VSC. That is, $\forall A_i \in$ S, if $i \neq 1$, then $|A_i^c| = 1$.
- **Assumption 3.** Each agent makes or holds no more than one commitment to its customer agent at a given time.
- **Assumption 4.** No agent will order the same product from two or more different suppliers at the same time. That is, at any given time, if $\exists \boldsymbol{A_i} \cdot \boldsymbol{A_j}$ and $\exists \boldsymbol{A_i} \cdot \boldsymbol{A_k}$, and $G(A_j) = G(A_k)$, then $j = k$.
- **Assumption 5.** $\forall A_i \in$ S, its commitment made to its customer has certain probability to fail when any of its demand for certain product to its suppliers is not satisfied. However, if all these demands are satisfied, the commitment will be fulfilled successfully, unless its owner decides to cancel it.
- **Assumption 6.** Different OFPs triggered by A_i are independent of each other.

Assumptions 1 and 2 simplify the system architecture, and Assumptions 3 and 4 simplify the agent interaction transactions. Assumption 5 says any failure from an agent A_i's direct supplier may cause its own commitment to fail. When all commitments (if there are any) by its direct suppliers have been fulfilled, the commitment that an agent made to its own customer agent is considered as successful accomplished. Assumption 6 regulates that OFPs between two agents, agent A_i and one of its direct supplier agent A_j, are not created or affected by other on-going or finished OFPs initiated of A_i's other suppliers. Assumptions 5 and 6 are similar to "Accountability" and "Exception Independence" assumptions made for Noisy-Or networks, a type of special BBN. A MASCM that follows above assumptions (Assumptions 1 - 6) is a system of $MASCM_1$.

4 eBBN Models for $MASCM_1$

In this section we show how to use and extend BBN framework to model $\boldsymbol{MASCM_1}$ agent interactions in an uncertain environment. Two models, $\boldsymbol{eBBN_0}$ and $\boldsymbol{eBBN_1}$, will be presented.

4.1 $\boldsymbol{eBBN_0}$: Modeling a Formed VSC

A formed VSC in a $MASCM_1$ consists of agents connected by OFPs, all the way to the upper most tiers of suppliers, triggered by one end order. If all commitments made by the agents in the VSC are successfully fulfilled, the order of the end customer will be accomplished. A formed VSC is thus represents an possible solution to an end order. The likelihood of the end order been accomplished is affected by the likelihood of commitments made by other agents to fail. Since a formed VSC is static, it can be modeled by a standard BBN without involving actions. This leads to our first model $\boldsymbol{eBBN}_0$ as follows.

Definition 1. Commitment Failure Variable (CFV) $\boldsymbol{x}_i$ is a binary random variable. Each CFV $\boldsymbol{x}_i$ is associated with an agent A_i in a formed VSC, representing the current belief of the status of the commitment made by agent A_i to its customer. $x_i = 1$ means the commitment fails; $x_i = 0$ means the commitment is successfully accomplished.

The CFVs are represented as nodes in the belief network, connected by direct causal links. Specifically, for any pair of agents $\boldsymbol{A}_j$ and $\boldsymbol{A}_i$ in a formed VSC and $\boldsymbol{A}_j \in \boldsymbol{A}_i^S$, there is a directed link $<\boldsymbol{x}_j, \boldsymbol{x}_i>$ from $\boldsymbol{x}_j$ to $\boldsymbol{x}_i$, as illustrated in the following figure, indicating that $\boldsymbol{x}_j$ (failure of commitment of $\boldsymbol{A}_j$ to $\boldsymbol{A}_i$) is a direct cause of $\boldsymbol{x}_i$ (failure of commitment of $\boldsymbol{A}_i$ to its customer).

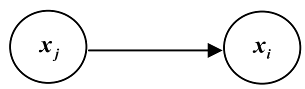

Figure 1. A direct link between two CFVs

Definition 2. For a given formed VCS, define $\boldsymbol{eBBN}_0 = (\boldsymbol{V}_0, \boldsymbol{E}_0)$, where $\boldsymbol{V}_0 = \{\boldsymbol{x}_i \mid \boldsymbol{x}_i \in \boldsymbol{VSC}\}$ and $\boldsymbol{E}_0 = \{<\boldsymbol{x}_j, \boldsymbol{x}_i> \mid \boldsymbol{A}_i \cdot \boldsymbol{A}_j \in \boldsymbol{VSC}\}$.

Model $\boldsymbol{eBBN}_0$ has two important properties.

Theorem 1. Model $eBBN_0$ is a tree.

Theorem 1 comes directly from Assumptions 1 – 4 and Definition 2. To represent the underlying causal mechanism, as suggested in [7, 8], we use a random variable $\boldsymbol{c}_{ji}$ to denote the causal connection from $\boldsymbol{x}_j$ to $\boldsymbol{x}_i$. If $\boldsymbol{c}_{ji} = 1$, then $\boldsymbol{x}_j = 1$ indeed causes $\boldsymbol{x}_i = 1$. Otherwise, $\boldsymbol{x}_j = 1$ does not affect $\boldsymbol{x}_i = 1$. Then, we have the following Lemma, which comes directly from Assumptions 5 and 6..

Theorem 2. The model $\boldsymbol{eBBN}_0$ is a Noisy-Or network.

Theorems 1 and 2 show agent interaction in a formed VSC can be formalized as a Noisy-Or network. Therefore, agents can share and analyze uncertain information through the well-established rules for this type of belief networks. For example, at any given time, an agent can estimate the failure probability of the current commitment it holds based on the failure probabilities of its direct suppliers using the following equation [7,8],

$$\boldsymbol{P}(\boldsymbol{x}_i = 1) = 1 - \prod_{x_j \in \pi_i} (1 - \boldsymbol{e}_{ji} \boldsymbol{P}(\boldsymbol{x}_j = 1)) \tag{1}$$

where $\boldsymbol{e}_{ji}$ is the causal strength of link $<\boldsymbol{x}_j, \boldsymbol{x}_i>$, $\boldsymbol{\pi}_i$ is the set of parents of x_i (i.e., direct suppliers of A_i). Moreover, since $eBBN_0$ has a tree structure, belief propagation in $eBBN_0$ can be computed in time polynomial to the network size $|\boldsymbol{VSC}|$ [7].

$eBBN_0$ captures causal relations in a static VSC. However, in the uncertain environment, VSC hardly remain static. Cancellation of a commitment by an agent (either due to failures of its suppliers or other reasons) may cause the agent's customer to seek another, alternative supplier. In other words, the structure of a VSC in a $\boldsymbol{MASCM}_1$ may undergo changes over time, moving from one formed VSC to another, until a final solution VSC is realized or the end order fails eventually. To model the dynamic change of VSC in a $\boldsymbol{MASCM}_1$, we introduce the model of $\boldsymbol{eBBN}_1$ in the following subsection.

4.2 $\boldsymbol{eBBN}_1$: Modeling an Evolving VSC

After an end order arrives at the system until it is eventually resolved, a VSC keeps evolving as agents adjust their behaviors, e.g. canceling orders to one supplier and switching to another one, according to its accumulated uncertain information. To model the evolution of VSC, two types of nodes/variables are introduced and added into $\boldsymbol{eBBN}_0$. The resulting model is called $\boldsymbol{eBBN}_1$.

4.2.1 Definition of $\boldsymbol{eBBN}_1$

To model the dynamic change of the VSC, we need to represent the selection of a particular supplier for a given product an agent needs at a given time, as well as the change of the selection as the VSC evolves. We also need to ensure that, when all selections are made at a time, the model should works like $\boldsymbol{eBBN}_0$ because all selected agents form a VSC. This is achieved by the introducing into $\boldsymbol{eBBN}_0$ the following two types of new variables, $\boldsymbol{l}_{ji}$ and $\boldsymbol{y}_{ji}$.

Definition 3. $\boldsymbol{l}_{ji}$ is a binary random variable associated with an agent $\boldsymbol{A}_i$ and one of its supplier $\boldsymbol{A}_j$. If $\boldsymbol{l}_{ji} = 1$, then $\boldsymbol{A}_i \cdot \boldsymbol{A}_j$ is in $\boldsymbol{A}_i$'s OFP (i.e., $\boldsymbol{A}_j$ is selected as one of $\boldsymbol{A}_i$'s supplier), if $\boldsymbol{l}_{ji} = 0$, then agent $\boldsymbol{A}_j$ is not currently involved in agent $\boldsymbol{A}_i$'s OFP.

Variable $\boldsymbol{l}_{ji}$ represents an observable consequence of agent $\boldsymbol{A}_i$'s decisions for selecting or switching negotiation partners (suppliers). According to Assumption5, each agent in a $\boldsymbol{MASCM}_1$ can only chooses one direct supplier for certain product it needs at a time. This lead to the following lemma.

Lemma 1. At any given time, if l_{ji} =1 and l_{ki}=1, $A_j, A_k \in A_i^S, G(A_j) = G(A_k),$, then $j = k$.

The commitment failure variable x_j becomes a direct cause of x_i only when A_j is selected as a direct supplier of A_i (i.e., $l_{ji} = 1$). Otherwise, they are causally unrelated. This is captured by another type of node y_{ji}.

Definition 4. The binary random variable y_{ji} has two parents l_{ji}, and x_j; and one child x_i, with the following conditional probability distribution

$$P(y_{ji} = x_j \mid l_{ji} = 1, x_j) = P(y_{ji} = x_j \mid l_{ji} = 1) = 1;$$
$$P(y_{ji} = 0 \mid l_{ji} = 0, x_j) = P(y_{ji} = 0 \mid l_{ji} = 0) = 1.$$

The node y_{ji} serves as a "gate" between two CFV x_j and x_i, and is controlled by variable l_{ji}. When the gate is open (when $l_{ji} = 1$), node y_{ji} serves as the proxy node of x_j and passes its influence to x_i, causing x_i to update its belief. When the gate is closed (when $l_{ji} = 0$), y_{ji} becomes zero regardless the value of x_j, implying that x_j does not influence x_i (i.e., A_j is not part of the current VSC). With these variables and the links $< x_j, y_{ji} >$, $< y_{ji}, x_i >$, and $< l_{ji}, y_{ji} >$ among them, we can formally define $eBBN_1$.

Definition 5. For a given $MASCM_1$, define $eBBN_1 = (V_1, E_1)$, where

$V_1 = \{x_i, l_{ji}, y_{ji} \mid A_i, A_j \in S, A_j \in A_i^S\}$ and

$E_1 = \{< x_j, y_{ji} >, < y_{ji}, x_i >, < l_{ji}, y_{ji} > \mid A_i, A_j \in S, A_j \in A_i^S\}$.

The following figure shows a portion of an $eBBN_1$

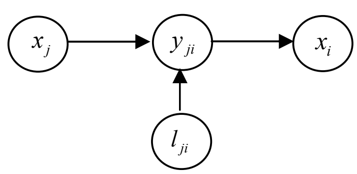

Figure 2. Nodes and links related in $eBBN_1$

4.2.2 Properties of $eBBN_1$

We have the following theorem about the structure of $eBBN_1$, based on Theorem 1 and Definition 5.

Theorem 3. Mode of $eBBN_1$ is a tree.

Similar to model of $\boldsymbol{eBBN}_0$, $\boldsymbol{eBBN}_1$ formalize agents' interactions in an evolving VSC as the probability distributions of individual CFV change. But unlike $\boldsymbol{eBBN}_0$, this model can represent dynamically changing causal structures with evolving VSC and extends the representation capability of conventional BBN. Accordingly, agents can use the following theorem to estimate the impact of outside uncertain factors on the commitment it holds.

Theorem 4. $\boldsymbol{P}(\boldsymbol{x}_i = 1) = \prod_{\substack{\boldsymbol{l}_{ji}=1 \\ \boldsymbol{x}_j \in \pi_i}} (1 - \boldsymbol{e}_{ji} \boldsymbol{P}(\boldsymbol{x}_j = 1)), \boldsymbol{A}_i, \boldsymbol{A}_j \in \boldsymbol{S}, \boldsymbol{A}_j \in \boldsymbol{A}_i^{\boldsymbol{S}}$.

Theorem 4 can be proved using Theorems 2 and 3, Lemma 1, Definitions 4 and 5, and Eq. (1) in Subsection 4.1. The apparent similarity of Theorem 4 and Eq. (1) is due to the fact that all agents in $\boldsymbol{MASCM}_1$ paired with $\boldsymbol{l}_{ji} = 1$ form a VSC which can be modeled by . Therefore, The belief updates in $\boldsymbol{eBBN}_1$ can be carried our in a way similar to $\boldsymbol{eBBN}_0$, provided the values of $\boldsymbol{l}_{ji}$ are properly determined.

5 Experiment

Limited computer simulations have been conducted to validate our theoretical models and to see if the system performance can be improved when some of these algorithms are used. In this section, we briefly discuss the simulation and experiment result.

The implemented MASCM consists of eight different agents. They sit at three different tiers. At Tier 0, there is only one end customer agent. At Tier 1, there are three agents. They are suppliers of the end customer agents. At Tier 2, there are four agents. Agents have known their direct customer and suppliers at system design time. When there is an end order arrives, the inter-connected OFPs will be triggered and an evolving VSC emerges. Each agent has similar architectures to complete an OFP with three processes inside, a supplier selection procedure, a customer relationship management process, and a local order fulfillment decision process. The system satisfied all of the assumptions we listed in Section 4, thus it can be modeled by an $eBBN_1$.

We intend to compare different information cooperation schemas in an uncertain environment based on the model of $eBBN_1$. The uncertain environment here is measured by the rate of unexpected events that occurring in the agents at Tier 2 during the time period between an end order's arrival and its disappearance. The unexpected events represent the uncontrollable factors from inside or outside of MASCM that are observed by agents. These events change the possibility of the on-going OFP that the agent is currently processing. Use the term of $eBBN_1$, these changes update the failure probability distribution of variable of x_i

Two cooperation schemas in the experiment represent the most likely long-term cooperation strategies in terms of supply chain management. The first one is that agent will notify others whenever there are some observed changes that might cause the OFP not to be finished according to the original negotiated contracts; in the second schema, an agent notifies the others when an OFP has been finalized, that is, either is successfully accomplished or aborted in the half way. We called these two schemas as S1 and S2 respectively.

In the experiment we compare two schemas by counting the ratio of the number of successful accomplished orders to total incoming orders given certain amounts of unexpected events occurs during one end order life cycle. The ratio is defined as the system performance. The experiment shows without considering other factors, the overall system performance, which is measured by the rate or the percentage of all end orders that can be successfully fulfilled by the formed VSCs, is heavily affected by the number of unexpected events occurring in the system. The higher frequency of unexpected event occurs, the lower system performance is. However, our result also shows if agents interactions follow S1, and when algorithms discussed above are used in agent decision procedures, system performance can keep at a relatively stable level even when the number of total uncertain events increases. The following figure shows the comparison of system performance when agent interactions follow S1 and S2 as the number of unexpected events in the system increases with 1000 end orders. Additional experiments show that this trend continues when the number of end orders increased to 3000.

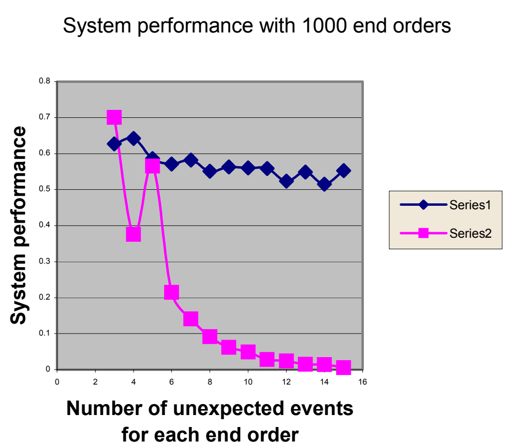

Fig. 4. System performance comparison in computer simulation

6 Conclusions

In the previous sections, we have discussed how to formalize agent interactions in a formed and evolving VSC in a $MASCM_1$ using conventional and extended BBN frameworks, $eBBN_0$ and $eBBN_1$, respectively. Model $eBBN_0$ establishes the theoretical basis to study agent interactions in an OFP. Model $eBBN_1$ further extends the representation capabilities of conventional BBN to describe the dynamically updating supply-demand relationship when interactions are exposed in an uncertain environment. These models can be used to help solving various supply chain management tasks, and several algorithms have been developed. They include algorithms for individual agents to compute beliefs of their commitments based on beliefs of commitments from their direct suppliers, to select prospective suppliers (either initially or when a previously selected supplier fails) during VSC evolution, to cancel an existing commitment based on the expected utility function, and algorithms to identify the most critical link (the agent in a VSC whose commitment has the highest failure probability) and the most fragile link (the agent in a VSC who is most responsible when the end order fails).

Work reported in this paper represents the first step of our effort toward a comprehensive solution to the uncertain management in supply chain. One obvious limitation of this work is with the assumptions made $MASCM_1$ and $eBBN_1$. Future work is needed to relax these restrictions so that more realistic situations can be modeled. This include allowing each agent to received multiple orders from more than one direct customers at the same time, and each type of product to supplied by more than one suppliers in a VSC. These may be achieved by extending our models from Noisy-Or like networks to more general ones with more complex conditional probability distributions. Also, one of the important uncertainty source, agents' strategic actions based on its internal decision process, are not included in the representation. How to incorporate these actions into our uncertainty models, and what information sharing rules and algorithms are needed for that purpose is another direction of further investigation.

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