Novi Sad J. Math.
Vol. 30, No. 2, 2000, 29-42

Proceedings of the TARA 2000 Conference
Novi Sad, Yugoslavia, September 6-7, 2000

POSSIBILISTIC LOGIC FOR INTELLIGENT BUSINESS AGENTS

Raymond Lau[1], On Wong[2]

Abstract. With the rapid growth of electronic commerce on the Internet, it becomes increasingly important to have effective, secure, and low-cost methods of handling the monetary aspect of the on-line transactions. Recently, a number of electronic payment services have been introduced to the Web. An agent-based approach for electronic payment is appealing since agents can *proactively* monitor the latest information about settlement services on the Internet, and *autonomously* select the best settlement option on behalf of their customers. However, because of the intrinsic dynamics of the Internet, these agents are faced with the challenge of making good decisions under the constraint of uncertain and incomplete market information. Possibilistic logic provides an expressive formalism to capture these uncertainties, and a robust and powerful reasoning method to make sound decisions by considering the uncertainties related to the activities in payment processing. In addition, possibilistic deduction can be used to explain and justify an agent's decisions. Enhanced explanatory power promotes users' trust and satisfaction, and this is essential in agent-mediated electronic commerce. This paper proposes an agent-based electronic payment service. In particular, how possibilistic logic can be applied to develop intelligent business agents is discussed.

AMS Mathematics Subject Classification 1991): 03H10 Other applications of nonstandard models.

Key words and phrases: Possibilistic Logic, Business Agents, Electronic Commerce

1. Introduction

The exponential growth of the Internet has rapidly changed the way businesses are performed, and the way consumers do their shopping [12, 15, 16, 17]. Recently, a number of electronic payment services have emerged on the World Wide Web (Web) [18]. No doubt, electronic payment services will grow very rapidly and several large online organizations like Yahoo and AOL have already

[1]Cooperative Information Systems Research Centre, Faculty of Information Technology , Queensland University of Technology, GPO Box 2434, Qld 4001, Australia, e-mail: raymond@icis.qut.edu.au

[2]School of Computing Science, Faculty of Information Technology, Queensland University of Technology, GPO Box 2434, Qld 4001, Australia, e-mail: o.wong@qut.edu.au

joined in the race. There are several advantages for the consumers to make use of electronic payment services on the Web. Firstly, these payment services autonomously and accurately process the incoming bills on behalf of the consumers. Therefore, consumers do not need to worry about the tedious job of keeping track of their bills, and perhaps paying penalties for late payments. Secondly, there could be financial advantage of using electronic payment services. For example, the total transaction cost may be reduced by having a single bulk payment from the payment service rather than having several individual micro payments settled between a consumer and their biller. Security is also an important issue for electronic commerce. Payment service providers take care of all the security issues with other payment service providers, or the ultimate financial institutes where bill settlements take place. Therefore, the consumer's risk of conducting on-line shopping and payment is reduced to a minimum. In fact, similar advantages are also brought to the virtual stores or utility companies (e.g. electricity, gas, etc.). For instance, they do not need to spend a lot of money to set up their own payment services on the Web. Moreover, they are guaranteed by the payment company that outstanding bills will be settled once the services or goods are delivered to their clients.

The market of Internet-based electronic payment services is highly competitive, and there are new payment services brought to the Web everyday. In order to make profit and survive under such a keen competition, the payment service must be able to select the best settlement options (e.g. cheap, secured, and reliable settlement services) according to the latest market information such as the transaction costs and the service qualities of the external payment/settlement service providers. An agent-based electronic payment service is appealing because payment agents, a kind of business agents, can *proactively* monitor the latest market information on the Internet [19, 20]. Moreover, they can *autonomously* keep track of bill payments on behalf of each registered client and make sensible decisions regarding optimum settlement options available in a payment cycle. Some business agents can even learn the consumers' shopping requirements and recommend appropriate products for purchasing [14, 16]. Nevertheless, one difficulty that payment agents need to deal with is that market information (e.g. prices and service qualities of settlement services) available on the Internet is highly volatile. For instance, even though a settlement service was up and running few hours' ago, it might be out of service at the current payment processing cycle. Transaction cost pertaining to a settlement service may also vary quite frequently. This trend has already been revealed in nowadays telecommunication market. When a new payment/settlement service is first introduced to the Internet, it may even be difficult to have full knowledge about its service characteristic (e.g. reliability).

Therefore, payment agents are faced with the challenge of making good settlement decisions under the constraint of uncertain and incomplete information. Though sophisticated quantitative methods have been develop to model the decision making processes [6, 11], there are weaknesses of these methods. For example, those axioms underlying a particular decision theory may not be valid under all decision making situations [6]. Bayesian network has widely been used for uncertainty analysis. However, it is difficult to obtain all the conditional probabilities required in a large network model. Though assuming independencies among events may simplify the calculations, the resulting model may not reflect the realities of the underlying problem domain. In the context of agent-mediated electronic commerce, it is desirable for business agents to explain and justify their decisions so that consumer trust and satisfaction can be obtained [8, 9]. It is not easy to explain an agent's decisions purely based on a quantitative model where the relationships between various decision factors are buried by numerous conditional probabilities or weight vectors.

This paper reports a preliminary study of applying possibilistic logic to business agents in general and payment agents in particular so that uncertain and incomplete market information can explicitly be represented and reasoned about during agents' decision making. Moreover, under such an integrated framework of quantitative and symbolic approaches, the explanatory power of these agents can also be enhanced. The reasons are that the relationship between an agent's decision and its justifications can be represented by more comprehensible causal rules, and the decision making process can be explained based on formal deduction. Enhanced explanatory capabilities of payment agents will subsequently lead to improved consumer trust, and the deployment of these agents to Internet-based electronic commerce. Section 2 gives an overview of agent-based electronic payment service. Preliminaries of possibilistic logic are provided in Section 3. The formulation of a payment agent's decision rules, and the representation of uncertain market information of settlement services are discussed in Section 4. Section 5 illustrates how possibilistic reasoning can be applied to the payment agent so that optimum settlement decisions are made. Finally, future work is proposed, and a conclusion summarising our findings is given.

2. An Overview of Agent-based Electronic Payment Service

An overview of the proposed Agent-based Electronic Payment Service (AEPS) is depicted in Figure 1. The Web site housing this system is certified digitally so that all the related parties can verify its identification. Moreover, encrypted transmissions are used to exchange information with external agents (e.g. customers, billers, banks, external payment services, etc.). A consumer must first register with AEPS by providing their personal information such as their digital certification and bank details. After acquiring utility services (e.g. electricity) or conducting on-line shopping (i.e. step 1 in Figure 1), registered customers or their agents will authorise AEPS to pay the related parties (i.e. step 2). The payment agent of AEPS can then handshakee with the retailers or their agents to obtain bills or settlement instructions (i.e. step 3). It is assumed that extensible markup language (XML) [7] is used to facilitate the exchange of such information. Finally, the payment agent settle the bills via appropriate financial institutes (e.g. banks) or external payment services (i.e. step 4). Communications with these agents can be conducted via dedicated lines, Internet connection with Secure Sockets Layer (SSL) or Secure Electronic Transaction

(SET). These external financial institutes or their agents may pass the payments through the settlement chain until the payments can finally reach the bankers of the retailers or the utility companies. For the discussion in this paper, these external financial institutes or payment services are collectedly referred to as ***settlement services*** or ***settlement agents***. The focus of this paper is on step 4 from which the payment agent selects the optimum settlement options according to the service characteristics of pertaining settlement services during a payment processing cycle. Because of the dynamic nature of the Internet, the characteristics of these settlement services are uncertain or incomplete. Therefore, a formalism that allows explicit representation of uncertainties and sound reasoning about these uncertainties is required for the development of the payment agents.

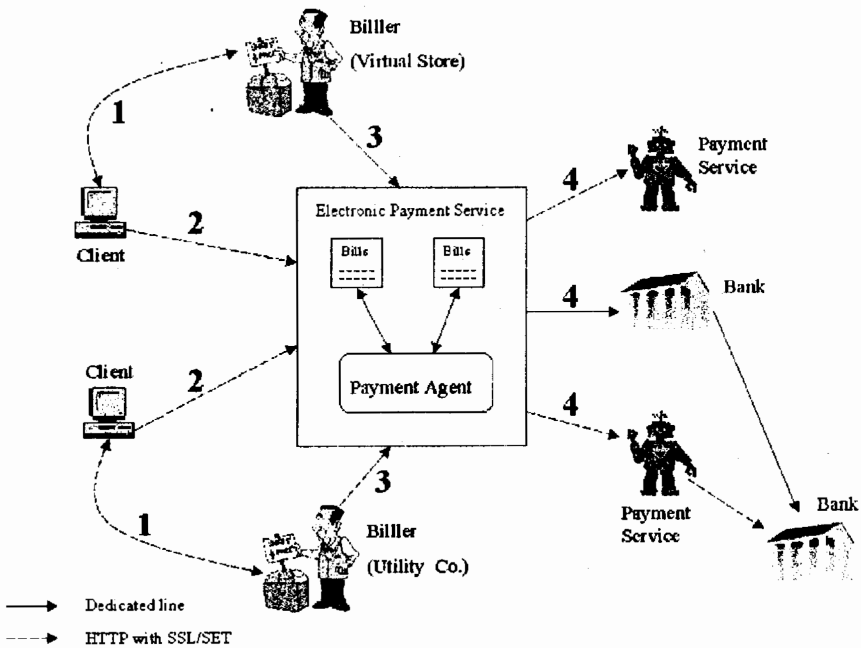

Figure 1: An Overview of Agent-based Electronic Payment Service

Since all the billing and payment records are stored in AEPS, a registered customer can review their billing and payment histories. Moreover, they can specify regular payment requirements (e.g. direct debits) and set maximum payment limit. In each payment processing cycle (e.g. every 2 hours, half day), the payment agent will scan through the billing database and extract billing items which are going to be due. Billing items are then grouped into bulk payments according to the settlement instructions pertaining to these bills.

Then, the payment agent needs to decide which settlement service is the best (e.g. being able to meet the payment deadline, cheap and secured) to settle each bulk payment. It is assumed that there could be more than one settlement options for each bulk payment processed in a payment processing cycle.

3. Preliminaries of Possibilistic Logic

This paper refers to necessity-valued possibilistic logic [1, 3]. Let $\mathcal{L}$ be a classical first-order language and Ω be the set of classical interpretations for $\mathcal{L}$. A possibilistic formula is of the form (α, m), where $\alpha \in \mathcal{L}$ is a closed formula and $m \in (0, 1]$ is a positive number. The intuitive meaning of the formula (α, m) is that the truth of α is certain at least to the degree m (i.e. $N(\alpha) \geq m$, where N is the necessity measure of α). The semantics of a set of classical formulae Δ is defined by a subset $\mathcal{M}(\Delta) \subset \Omega$ that satisfies all formulae in Δ. Each interpretation $\omega \in \mathcal{M}(\Delta)$ is called a model. For a set of possibilistic formulae $F = \{(\alpha_i, m_i), i = 1, \ldots, n\}$, a ***possibility distribution*** π over Ω that characterises the ***fuzzy set of models*** $\mathcal{M}(F)$ of F is introduced. In other words, F induces a preference ordering over Ω via π_F. The necessity measure N induced by π is then defined as [1]:

$$\forall \alpha \in \mathcal{L}, \; N(\alpha) = \inf\{1 - \pi(\omega), \omega \models \neg\alpha\}$$

In other words, the necessity measure (i.e. the lower bound certainty) of a formula α equals to the complement of the highest ***possibility*** attached to an interpretation ω where $\neg\alpha$ is classically satisfied. A possibility distribution π on Ω is said to satisfy the necessity-valued formula (α, m) (i.e. $\pi \models (\alpha, m)$), iff $N(\alpha) \geq m$. $\pi \models F$, iff $\forall i = 1, \ldots, n, \pi \models \alpha_i, m_i$. If $\forall \pi, \pi \models (\alpha, m)$, (α, m) is said to be valid and is denoted $\models (\alpha, m)$. A possibilistic formula Φ is a logical consequence of a set of possibilistic formulae F (i.e. $F \models \Phi$), iff $\forall \pi, (\pi \models F) \rightarrow (\pi \models \Phi)$. The consistency of F (i.e. $Cons(F)$) is a measure of to what degree that there is at least one completely possible interpretation for F and is defined by $Cons(F) = sup_{\omega \in \Omega} \pi_F(\omega)$. Then, the inconsistency degree of F is defined by: $Incons(F) = 1 - Cons(F) = 1 - sup_{\omega \in \Omega} \pi_F(\omega)$.

The deduction problem in possibilistic logic is taken as finding the best valuation m (i.e. $Val(\beta, F)$) such that F entails (β, m). Based on the classical resolution, a sound and complete proof method has been developed [1, 4] as follows:

1. A possibilistic knowledge base $F = \{(\alpha_i, m_i), i = 1, \ldots, n\}$ is converted to possibilistic clausal form (i.e. conjunctive normal form) $C = \bigwedge_{i,j}\{(c_{i,j}, m_i)\}$ where $c_{i,j}$ is a universally quantified classical first-order clause.

2. The negation of a first-order formula β, which is to be deduced from F, is also converted to clausal form $c_1, \ldots, c_n$.

3. Let $C' = C \cup \{(c_1, 1), \ldots, (c_n, 1)\}$.

4. Search for the empty clause $(\perp, \bar{m})$ by applying the ***possibilistic resolution rule*** (R):
   (1) $$(c_1, m_1), (c_2, m_2) \vdash (R(c_1, c_2), \min(m_1, m_2))$$
   from C' repeatedly until the maximal $\bar{m}$ is found. $R(c_1, c_2)$ is the classical resolvent of c_1 and c_2.

5. Let $Val(\beta, F) = \bar{m}$.

In addition, it has been shown that the inconsistency degree $Incons(F)$ of any possibilistic knowledge base F is the least certain formula $\min\{m_1, \ldots, m_n\}$ involved in the strongest contradiction (i.e. $(\perp, \bar{m})$). Based on these propositions, ***nontrivial possibilistic deduction*** ($\mid\!\sim$) is defined as [1]:

$$F \mid\!\sim (\beta, m) \text{ iff } F \models (\beta, m) \text{ and } m > Incons(F)$$

The intuition behind nontrivial possibilistic deduction is that the proof of a formula β is restricted to the subset F' of a partially inconsistent possibilistic knowledge base F where the information is more or less certain. For example, $\forall(\alpha_i, m_i) \in F' : m_i > Incons(F)$. In other words, the certainties attached to the formulae in F' must be strictly higher than the certainty of the formula in F that causes the inconsistency. Therefore, β is proved with the most reliable information (i.e. the most certain piece of knowledge) from the knowledge base F.

4. Knowledge Representation

It is believed that the first step towards decision making is to produce a quantitative description of the problem domain [10] (e.g. identifying decision variables and estimating uncertainties). This is also applied to a possibilistic-based framework of knowledge representation and reasoning. For easy of illustration, only the following decision variables are discussed in this paper: ***processing time***, ***availability***, ***risk***, and ***transaction cost***. Processing time and availability are considered as ***hard constraints***, whereas transaction cost and risk are treated as ***soft constraints*** [10]. For example, even though a particular settlement service is the most expensive one, the payment agent may still consider it because of its ability to meet the payment deadline and relatively low risk. Table 1 is a simplified example for four settlement services with corresponding service characteristics.

To transform the service characteristics depicted in Table 1 to possibilistic formulae, the certainty value associated with each characteristic (i.e. service value) pertaining to a settlement service is computed. For example, even though a settlement service announces that its processing time for a transaction is 2 hours on average, there is uncertainty related to this quoted figure because of the dynamics of the Internet (e.g. certain sites along the settlement chain are down). Similarly, even though the payment agent can be "handshakee" with a settlement service (e.g. by using the "ping" command), the service may go down when a transaction is finally routed there.

Table 1: Characteristics of Settlement Services

Services	Processing time	Availability	Risk	Cost
A	2 hours	Running	Low	60 cents/tran.
B	2 hours	Running	Medium	60 cents/tran.
C	1 hour	Running	Low	90 cents/tran.
D	1 hour	Likely Running	High	30 cents/tran.

Table 2 depicts the possibilistic formulation of the service characteristics for these settlement services. Under each service attribute (e.g. processing time), the left hand column is the predicate formulae of corresponding service values, and the right hand column is the associated certainty values. It is assumed that a history file is kept for each settlement service. If a settlement service is brand new, default values and associated certainties could be applied. Based on the history file, if a settlement agent A announces an average processing time of 2 hours, and nine out of ten times that a payment can be settled within 2 hours, the certainty attached to the predicate $Proctime(A, 2)$ will be 0.9. The predicate $Proctime(x, y)$ means that the average processing time of the settlement agent x is y hour. Availability of a settlement agent is modelled by the predicate $Down(x)$, which indicates if a service is down or not. If a settlement agent does not respond to the initial "handshake" command, the certainty of $Down(x)$ is 1.0. However, even though the remote agent responds, it is still possible that it will be out of service when a transaction arrives later on. The certainty m of $Down(x)$ is computed based on the history records (e.g. frequency of out of service given that it responds at the "handshake" stage). It is assumed that routing payments to external settlement agents is risky in nature. The certainty of the predicate $Risk(x)$ is derived subjectively according to certain basic features of a settlement service x. For example, it can be assessed based on whether it is a certified site, transaction history, kinds of secured transmission protocols supported (SSL/SET), etc.. If a settlement service A is housed at a certified site and it supports highly secured transmission protocol, it is not as risky as another service D which is not certified at all. The cost factor is modelled as a ***fuzzy predicate*** $Expensive(x)$ of a settlement service x. Expensive is a relative term for the evaluation of settlement services. There is not a definite value which will be considered as expensive. Among a group of settlement services, the one with the highest transaction cost will be considered as expensive with certainty 1.0, whereas the cheapest service will be assigned a certainty of 0.0. The rest of the settlement services can be evaluated according to a ***fuzzy membership function*** [22] μ. For the discussion in this paper, it is assumed that $\mu_{Expensive} = \frac{x - lowest}{highest - lowest}$, where *highest* and *lowest* represent the highest and the lowest transaction costs as quoted by the settlement agents, and x is the transaction cost of a particular settlement service.

The payment agent of AEPS will only select a settlement service x as a candidate $Cand(x)$ for payment processing if it is likely to satisfy the hard constraint

Table 2: Possibilistic Formulation of Service Characteristics

Ser.	Processing Time		Availability		Risk		Cost	
A	$Proctime(A, 2)$	0.9	$Down(A)$	0.2	$Risky(A)$	0.3	$Expensive(A)$	0.5
B	$Proctime(B, 2)$	0.8	$Down(B)$	0.3	$Risky(B)$	0.4	$Expensive(B)$	0.5
C	$Proctime(C, 1)$	0.8	$Down(C)$	0.3	$Risky(C)$	0.3	$Expensive(C)$	1.0
D	$Proctime(D, 1)$	0.5	$Down(D)$	0.5	$Risky(D)$	0.7	$Expensive(D)$	0.0

such as processing time. The payment agent prefers settlement services which are cheap and less risky. The following formulae represent the payment agent's evaluation criteria of a good candidate service $Cand(x)$ and a bad candidate service $\neg Cand(x)$:

$$\begin{aligned}
&Proctime(x, y) \wedge Reqtime(z) \wedge lq(y, z) \rightarrow Cand(x), 1.0\\
&Down(x) \rightarrow \neg Cand(x), 1.0\\
&Risky(x) \rightarrow \neg Cand(x), 0.6\\
&Expensive(x) \rightarrow \neg Cand(x), 0.8\\
&Expensive(x) \rightarrow \neg Risky(x), 0.4\\
&Reqtime(2), 1.0
\end{aligned}$$

The first formula means that if a settlement service x's processing time is y hour and it is less than or equal to (i.e. predicate $lq(y, z)$) the required processing time z of the current processing cycle, it is a candidate service (i.e. $Cand(x)$) with certainty 1.0; If a service x is unavailable (i.e. $down(x)$), it is not a candidate service (i.e. $\neg Cand(x)$) with certainty 1.0; A risky service is not a candidate service with certainty 0.6; An expensive settlement service is not a candidate service with certainty 0.8; An expensive service may imply that it is not risky with certainty 0.4, a low confidence level. It is assumed that the deadline of processing the bulk payments in the current processing cycle is within 2 hours, and so $Reqtime(2), 1.0$ is added to the payment agent's knowledge base K.

5. Possibilistic Reasoning for Smart Payment Processing

The payment agent in AEPS employs possibilistic deduction to infer if a settlement service is a feasible solution (i.e. candidate) according to its preference (e.g. cheap, less risky, meeting deadline, etc.). When a settlement service is evaluated, its characteristics are encoded as possibilistic formulae and added to the payment agent's knowledge base as ***assumptions***. If the payment agent's knowledge base K entails a settlement service x as a candidate service (i.e. $Cand(x)$), x will be added to the set S of feasible solutions. This scenario is similar to the symbolic approach of finding a feasible plan or schedule through ***assumption based reasoning*** [13]. In MXFRMS [13], each possible plan is added to the agent's knowledge base as assumption. If the plan is consistent with the knowledge base where the constraints about the planning process is stored, the plan is considered feasible. However, for the payment agent, some of the characteristics of a service x may lead to its consideration as a candidate service, whereas other service qualities may remind the agent to exclude it from consideration. This is a general problem in multiple criteria decision making [23]. In logical term, inconsistency ($\perp$) may exist in the resulting possibilistic knowledge base K. Therefore, the nontrivial possibilistic deduction $\mid\!\sim$ is used so that the payment agent can draw sensible conclusions based on the most certain part of K even though some of its elements are contradictory to each other. To choose the optimal settlement option(s) from S, the valuation $Val(Cand(x), K)$ will be compared for each $x \in S$. A candidate settlement service that receives the highest valuation will be chosen as the settlement service since the payment agent is most certain that it should be a candidate service.

With reference to our example, the formulae representing the characteristics of each settlement service will be added to the payment agent's knowledge base K as assumptions. This process creates K_A, K_B, K_C, and K_D respectively. By possibilistic resolution, the inconsistency degree of each revised knowledge base can be computed (e.g. $Incons(K_A)$). The third step is to compute the valuation $Val(Cand(x), K_x)$. According to the definition of nontrivial possibilistic deduction $\mid\!\sim$ described in Section 3, if $Val(Cand(x), K_x) > Incons(K_x)$ is true, $K_x \mid\!\sim Cand(x)$ can be established. To conduct possibilistic resolution, all the formulae must be converted to their clausal form first. The following is a snapshot of K_A after the characteristics of settlement service A is added to K:

$$\neg Proctime(x, y) \vee \neg Reqtime(z) \vee \neg lq(y, z) \vee Cand(x), 1.0$$
$$\neg Down(x) \vee \neg Cand(x), 1.0$$
$$\neg Risky(x) \vee \neg Cand(x), 0.6$$
$$\neg Expensive(x) \vee \neg Cand(x), 0.8$$
$$\neg Expensive(x) \vee \neg Risky(x), 0.4$$
$$Reqtime(2), 1.0$$

$$Proctime(A, 2), 0.9$$
$$Down(A), 0.2$$
$$Risky(A), 0.3$$
$$Expensive(A), 0.5$$

It can easily be observed that K_A is partially inconsistent (e.g. $Cand(A) \in K_A$, $\neg Cand(A) \in K_A$). Therefore, $Incons(K_A) > 0$ is derived. In addition, there are several valuations of $Val(\perp, K_A)$. The maximal valuation $\bar{m} = 0.5$ is derived from the resolution path depicted in Figure 2. It is assumed that standard unification procedure in Prolog and the possibilistic resolution procedure described in Section 3 are used to derive the refutation. As can be seen, $Incons(K_A) = 0.5$ is derived. To find an optimal refutation without traversing a large number of nodes along the resolution paths, efficient resolution strategies have been proposed [2]. To see how strong the payment agent's knowledge base K_A entails $Cand(A)$ (i.e. how strong the payment agent believes that service

A is a candidate for processing payments), the valuation $Val(Cand(A), K_A)$ is computed. According to the resolution procedure described in Section 3, $(\neg Cand(A), 1)$ is added to K_A, several refutations can be found again. Figure 3 depicts the resolution path with the strongest refutation. Therefore, $Val(Cand(A), K_A) = 0.9$ and $K_A \models (Cand(A), 0.9)$ are established. According to the definition of nontrivial possibilistic deduction $\mid\!\sim$ described in Section 3, $K_A \mid\!\sim Cand(A)$ since $Val(Cand(A), K_A) = 0.9 > Incons(K_A) = 0.5$. In other words, settlement service A is a feasible solution.

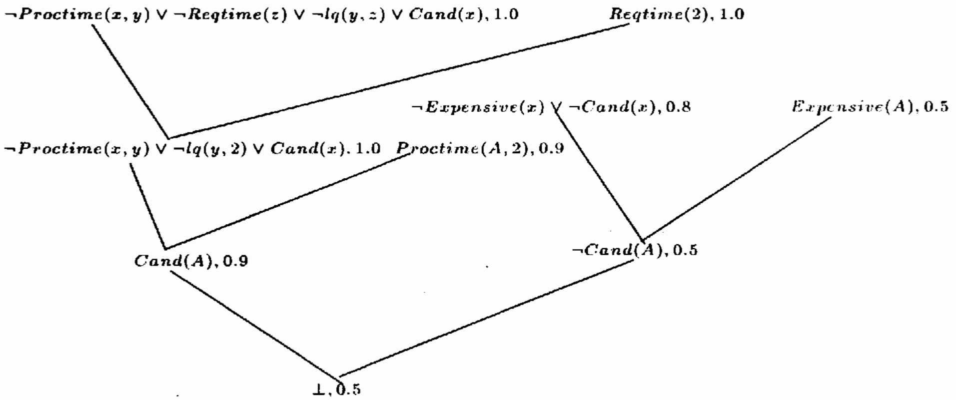

Figure 2: Resolution Path for the maximal $Val(\perp, K_A)$

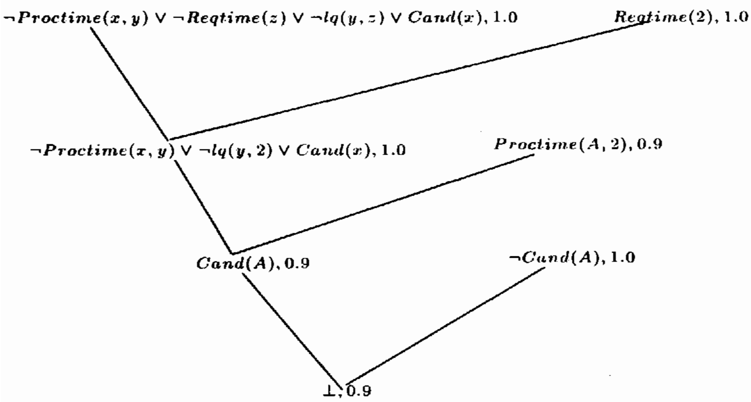

Figure 3: Resolution Path for the maximal $Val(Cand(A), K_A)$

Similarly, $(Proctime(B,2), 0.8)$, $(Down(B), 0.3)$, $(Risky(B), 0.4)$, and $(Expensive(B), 0.5)$ are added to the possibilistic knowledge base K as assumptions. By means of possibilistic resolution, $Incons(K_B) = 0.5$ and $Val(Cand(B), K_B) = 0.8$ are derived. Therefore, the payment agent can also deduce that $K_B \mid\!\sim Cand(B)$. Consequently, settlement service B is also a potential solution. According to the characteristics of the settlement services described in Table 2,

$(Proctime(C, 1), 0.8)$, $(Down(C), 0.3)$, $(Risky(C), 0.3)$, and $(Expensive(C), 1.0)$ are also added to K as assumptions. By means of possibilistic resolution, $Incons(K_C) = 0.8$ and $Val(Cand(C), K_C) = 0.8$ are derived. The payment agent deduces that $K_C \not\mid\!\sim Cand(C)$ based on the definition of nontrivial possibilistic deduction. Therefore, settlement agent C will not be considered for payment processing because the payment agent is not certain that C should be a candidate service (e.g. it is an expensive service). To evaluate the settlement service D, the assumptions of $(Proctime(D, 1), 0.5)$, $(Down(D), 0.5)$, $(Risky(D), 0.7)$, and $(Expensive(D), 0.0)$ are used to derive K_D. Accordingly, $Incons(K_D) = 0.5$ and $Val(Cand(D), K_D) = 0.5$ are computed. Therefore, $K_D \not\mid\!\sim Cand(D)$ is also established. In other words, it is uncertain that settlement service D can fulfill the requirements of being a candidate service because of its frequent down time and relatively high risk. In summary, the payment agent draws the following conclusions based on nontrivial possibilistic deduction:

$$
\begin{aligned}
K_A &\mid\!\sim Cand(A) \\
K_B &\mid\!\sim Cand(B) \\
K_C &\not\mid\!\sim Cand(C) \\
K_D &\not\mid\!\sim Cand(D)
\end{aligned}
$$

Since $Val(Cand(A), K_A)$ is higher than $Val(Cand(B), K_B)$, the payment agent is more certain that settlement service A is a candidate service for payment processing. The intrinsic nature of the Internet is very dynamic, and so the Web-based electronic commerce. A full set of service attributes pertaining to a particular settlement service may not be available for decision making. Therefore, it is desirable for the payment agent to draw sensible conclusions with incomplete information. Possibilistic reasoning is also useful under such a circumstance. For instance, if the only information available for service A is processing time and availability, $K_A \mid\!\sim Cand(A)$ is still maintained according to the given evidence. So, A is still considered as a feasible solution because of its likelihood to meet the payment deadline. However, further investigation is required to study the expected rational behavior of payment agents when they are faced with uncertain or missing market information. According to the above example, it also sheds light on the explanation ability of payment agents. For example, the reason why settlement service A is considered as a candidate $Cand(A)$ is that there is high certainty (0.9) of it being able to meet the processing deadline. Comparatively speaking, it is unlikely (0.5) that A should not be a candidate service $\neg Cand(A)$. The reason is that there are low certainties for out of service (i.e.$Down(A), 0.2$) and risk (i.e. $Risky(A), 0.3$), and medium certainty for high cost (i.e. $Expensive(A), 0.5$). Possibilistic logic provides an explicit representation of these causal relationships and a gradated assessment of the likelihood of these relationships given the available evidence.

6. Conclusions and Future Work

This paper proposes a theoretical framework for an agent-based electronic payment system. However, it is important to implement and evaluate such a framework. Particularly, effectiveness and computational efficiency of the payment agent, which is underpinned by possibilistic logic, need to be examined further. One of the possible ways to conduct a quantitative evaluation of the payment agent is to compare its performance (i.e. accuracy of decision, latency of making a decision) with the traditional quantitative approach of multiple criteria decision making [11]. Initially, simulation of the agent-based electronic payment service will be conducted in an Intranet environment. For example, several artificial sites can be set up as settlement services. Each service will be equipped with various service characteristics. By comparing the decisions which are made based on possibilistic reasoning with that based on traditional quantitative approach, some ideas about the effectiveness of the possibilistic payment agents can be obtained.

The possibilistic resolution method illustrated in this paper is for non-fuzzy predicates. Since payment agents also deal with fuzzy predicates (e.g. *Expen–sive*(x)), further work may include applying the fuzzy possibilistic resolution method [5] to the payment agents. Apart from intelligently choosing the optimum settlement service, a step further for the development of the agent-based payment service is to support negotiation between the payment agent and external settlement agents for better deals (e.g. cheaper cost per transaction for larger amounts of payments). Whether it is feasible to integrate existing negotiation protocols [21] with possibilistic reasoning in a payment agent, and "how to implement it" is another interesting research question.

The proposed agent-based electronic payment system sheds light on a formal approach towards electronic payment on the Internet. Because of the intrinsic dynamics of the Internet-based electronic commerce, payment agents are faced with the challenge of making good decisions under the constraint of uncertain and incomplete market information. Possibilistic logic provides an expressive language to formalise uncertainties that are often associated with activities in electronic commerce. Moreover, nontrivial possibilistic deduction allows a payment agent to make sound decisions based on the most certain and reliable information held in its knowledge base. The explicit modelling of the causal relationships between a decision and its justifications also facilitates the explanation of the agent's decision making process. From our initial study, it is technically feasible to apply possibilistic knowledge representation and reasoning to intelligent payment agents in electronic commerce. Nevertheless, to obtain more insights about the effectiveness and the efficiency of these agents, a quantitative evaluation of these agents is required.

References

[1] Dubois, D., Lang, J., Parade, H., Possibilistic Logic, In D. M. Gabbay, C. J. Hogger, J. A. Robinson, and D. Nute, editors, Handbook of Logic in Artificial Intelligence and Logic Programming, volume 3, pages 439–513. Oxford University Press, Oxford, UK, 1993.

[2] Dubois, D., Lang, J., Prade, H., Theorem proving under uncertainty - a possibility theory based approach, In John McDermott, editor, Proceedings of the

Tenth International Joint Conference on Artificial Intelligence, pages 984–986, San Francisco, CA, August 1987. Morgan Kaufmann Publishers Inc.

[3] Dubois, D., Lang, J., Prade, H., A brief overview of possibilistic logic. In Rudolf Krause and Pierre Siegel, editors, Proceedings of Symbolic and Quantitative Approaches to Uncertainty (ECSQAU '91), volume 548 of *LNCS*, pages 53–57, Berlin, Germany, October 1991. Springer.

[4] Dubois, D., Lang, J., Prade, H., Automated Reasoning using Possibilistic Logic: Semantics, Belief Revision, and Variable Certainty Weights, IEEE Transactions on Knowledge and Data Engineering, 6(1):64–71, February 1994.

[5] Dubois, D., Prade, H., Resolution principles in possibilistic logic, International Journal of Approximate Reasoning, 4(1):1–21, 1990.

[6] Edwards, W., Utility Theories: Measurements and Applications, Kluwer Academic Publishers, Norwell, Massachusetts, 1992.

[7] Glushko, R., Tenenbaum, J., Meltzer, B., An XML Framework for Agent-Based E-commerce, Communications of the ACM, 42(3):106–114, March 1999.

[8] Guttman, R., Maes, P., Cooperative vs. Competitive Multi-Agent Negotiations in Retail Electronic Commerce. In Proceedings of the Second International Workshop on Cooperative Information Agents (CIA'98), volume 1435 of Lecture Notes in Artificial Intelligence, pages 135–147, Berlin, 1998. Springer.

[9] Hoffman, D., Novak, T., Peralta, M., Building consumer trust online, Communications of the ACM, 42(4):80–85, April 1999.

[10] Holtzman, S., Intelligent Decision Systems, Addison-Wesley Publishing Co., Reading, Massachusetts, 1989.

[11] Keeney, R., Raiffa, H., Decisions with Multiple Objectives: Preferences and Value Tradeoffs, Cambridge University Press, Cambridge, UK, 1993.

[12] Ketchpel, S., Garcia-Molina, H., Paepcke, A., Shopping models: a flexible architecture for information commerce. In Robert B. Allen and Edie Rasmussen, editors, Proceedings of the 2nd ACM International Conference on Digital Libraries, pages 65–74, New York, July 23–26 1997. ACM Press.

[13] Kraetzschmar, G., Distributed reason maintenance for multiagent systems, In PhD Thesis, School of Engineering, University of Erlangen-Nürnberg, Erlangen, Germany, volume 1229 of Lecture Notes in Artificial Intelligence, pages 1–261, Berlin, Germany, 1997. Springer.

[14] Lau, R., Hofstede, A.H.M., Bruza, P.D., Adaptive Profiling Agents for Electronic Commerce, In Proceedings of the 4th CollECTeR Conference on Electronic Commerce, Breckenridge, Colorado, April 2000.

[15] Lohse, G., Spiller, P., Electronic shopping. Communications of the ACM, 41(7):81–87, July 1998.

[16] Maes, P., Guttman, R., Moukas, A., Agents that buy and sell, Communications of the ACM, 42(3):81–91, March 1999.

[17] Müller, J., Pischel, M. Doing business in the information marketplace: A case study. In Oren Etzioni, Jörg P. Müller, and Jeffrey M. Bradshaw, editors, Proceedings of the Third Annual Conference on Autonomous Agents (AGENTS-99), pages 139–146, New York, May 1–5 1999. ACM Press.

[18] Panurach, P., Money in electronic commerce: Digital cash, electronic fund transfer, and ecash. Communications of the ACM, 39(6):45–50, June 1996.

[19] Saeyor, S., Ishizuka, M., Formation of cooperative behavior among information agents in web repository change monitoring service. In Matthias Klusch, Onn M. Shehory, and Gerhard Weiss, editors, Proceedings of the 3rd International Workshop on Cooperative Information Agents III (CIA-99), volume 1652 of Lecture Notes in Artificial Intelligence, pages 101–112, Berlin, July 31–August 2 1999. Springer, Germany

[20] Takahashi, K., Nishibe, Y., Morihara, I., Hattori, F., Collecting shop and service information with software agents, Applied Artificial Intelligence, 11(6):489–500, 1997.

[21] Wang, X.F., Yi, X., Lam, K.Y., Zhang, C.Q., Okamoto, E., Secure agent-mediated auctionlike negotiation protocol for internet retail commerce. In Matthias Klusch, Onn M. Shehory, and Gerhard Weiss, editors, Proceedings of the 3rd International Workshop on Cooperative Information Agents III (CIA-99), volume 1652 of Lecture Notes in Artificial Intelligence, pages 291–302, Berlin, July 31–August 2 1999. Springer,Germany.

[22] Zadeh, L.A., Fuzzy sets as a basis for a theory of possibility. Fuzzy sets and systems, 1:3–28, 1978.

[23] Zeleny, M., Multiple Criteria Decision Making, McGraw-Hill, New York, New York, 1982.