Probabilistic Argumentation for Decision Making A Toolbox and Applications

Nguyen duy Hung

Abstract— **Argumentation frameworks developed in AI have greatly eased the developments of many kinds of intelligent systems. Recently, to deal with quantitative uncertainties, several authors integrate probabilities into such frameworks to propose probabilistic argumentation frameworks. However, the developments of intelligent systems using these new frameworks are still hindered by the lack of programming tools and environments. In a previous work, interested in the Probabilistic Assumption-based Argumentation framework (PABA), we have developed several inference procedures and a multi-semantics reasoning engine for it. In the current work, utilizing this engine, we propose a programming toolbox for developing argumentation-based decision systems capable of capturing different reasoning attitudes of decision makers in the presence of qualitative and quantitative uncertainties. We demonstrate the toolbox using examples of commonsense reasoning as well as reasoning by experts in smart electrical grid.**

Index Terms—**Probabilistic Argumentation, Decision Making, Reasoning Attitudes, Smart Grid**

I. Introduction

The developments of intelligent systems haven been greatly eased by argumentation frameworks developed in AI, notably Dung's Abstract Argumentation framework [5] (AA) which is now considered as the standard one. In this paper, we focus on argumentation-based decision making systems (or just decision systems for short) by which we mean intelligent systems capable of simulating practical reasoning of humans, which, as suggested by Dung himself [4], includes not only commonsense reasoning but also reasoning by experts and their integration. In fact many researchers in AI have viewed argumentation as an universal mechanism humans use in their practical reasoning, and hence they let argumentation play an important role in building their decision systems. Using a range of standard argumentation semantics, they can succinctly capture different *reasoning attitudes* of decision makers which they can hardly do with non-argumentation formalisms such as influence diagrams or Bayesian networks [13]. Let's illustrate this strength by an example. Suppose that you are planing a road trip with four friends: Anne, Bob, Chris, David [1], all of whom have expressed their desires to go to the beach, unfortunately your car seats at most three passengers. You think that both Chris and David are in love with Anne and hence if Chris and David join then Anne will not join. Suppose that you have two goals: "Bob joins" and "Anne joins", will you go to Pattaya - a coastal city - or look for another destination? Let's figure out who are three passengers in your car. It is clear that they can be any triple in {Anne, Bob, Chris, David} except {Anne, Chris, David}. In other words, they can be {Anne, Bob, Chris}, {Anne, Bob, Chris} or {Bob, Chris, David}. Thus, Bob surely will join while Anne may or may not join. Hence, if you have a *skeptical reasoning attitude*, you may count only the goal "Bob joins" and look for another destination. However, if you have a *credulous reasoning attitude*, then you will count both goals "Bob joins" and "Anne joins" and hence consider Pattaya as an acceptable destination.

To capture a credulous reasoning attitude, we often use the preferred (aka admissible) argumentation semantics [5]. To demonstrate, let's represent your beliefs about the trip planning by an Assumption-based Argumentation (ABA) framework $\mathcal{F} = (\mathcal{R}, \mathcal{A}, \overline{})$ consisting of a set of assumptions $\mathcal{A} = \{\lceil r_1 \rceil\} \cup \{arguably(x) \mid x \in \{aj, bj, cj, dj\}\}$ (with contraries $\neg r_1$ and $\neg x$ respectively) and a set inference rules $\mathcal{R}$ containing[2]:

$$
\begin{array}{ll}
r_1 : aj \leftarrow aw, \lceil r_1 \rceil, arguably(aj) & r_7 : aw \leftarrow beach \\
r_2 : bj \leftarrow bw, arguably(bj) & r_8 : bw \leftarrow beach \\
r_3 : cj \leftarrow cw, arguably(cj) & r_9 : cw \leftarrow beach \\
r_4 : dj \leftarrow dw, arguably(dj) & r_{10} : dw \leftarrow beach \\
r_5 : false \leftarrow aj, bj, cj, dj & r_{11} : beach \leftarrow \\
r_6 : \neg\lceil r_1 \rceil \leftarrow cj, dj &
\end{array}
$$

Here, rules $r_1, \ldots, r_4$ say that if your friends want to join (aw, bw, cw, dw stand for "Anne wants to join", ..., "David wants to join" respectively), then, if possible, they can always join (aj, bj, cj, dj stand for "Anne joins", ..., "David joins"). Rule r_5 is a shorthand for several transpositions such as $\neg aj \leftarrow bj, cj, dj$ to represent that your car seats at most three passengers. Rule r_6 says that r_1 is not applicable if cj, dj hold. Rule $r_7, \ldots, r_{10}$ say that all four friends want to go to the beach. Lastly r_{11} says that Pattaya is a coastal city.

The preferred ABA semantics identifies one or several subsets of $\mathcal{A}$ as preferred extensions and deems a proposition as accepted if it is supported by a preferred extension. Here there are three preferred extensions: $\{arguably(aj), arguably(bj), arguably(cj), \lceil r_1 \rceil\}$, $\{arguably(aj), arguably(bj), arguably(dj), \lceil r_1 \rceil\}$, $\{arguably(bj), arguably(cj), arguably(dj)\}$. So aj, bj are both accepted - coinciding with your conclusions if you are a credulous reasoner.

To capture a skeptical reasoning attitude, there are several argumentation semantics: the grounded semantics captures the "most" skeptical reasoning attitude; the ideal semantics

Nguyen duy Hung is with Sirindhorn International Institute of Technology, Thammasat University, Thailand. Email: hung.nd.siit@gmail.com

[1]The story line is borrowed from [24].

[2]ABA will be defined formally later.

captures the "ideal" skeptical reasoning attitude; while the skeptical preferred semantics captures the "right" skeptical reasoning attitude. For example, in the above ABA $\mathcal{F}$, bj is accepted under the skeptical preferred semantics, but not accepted under the grounded semantics and the ideal semantics, both of which has the empty set as an unique extension.

Now, to see the limitations of ABA-based decision making systems, let's extend your trip planing problem a bit. To encourage Anne to join, you look for another destination that Anne wants to go but Chris or David may not. You find out Chiang Mai - a mountainous city. In fact Anne does not want to go to the mountains but she wants to see the flower festival in Chiang Mai. Here clearly even though you are not certain whether Chris and David really do not want to go to the mountains, you can soundly conclude that the goal "Anne joins" is consolidated because provided that either Chris or David does not want, then Anne joins surely. Continue using ABA, we may use the following inference rules to represent the new information.

$aw \leftarrow flower \qquad flower \leftarrow$

$cw \leftarrow mountain, cwm \qquad mountain \leftarrow$

$dw \leftarrow mountain, dwm$

where cwm, dwm are assumptions representing uncertainties "Chris wants to go to the mountains" and "David wants to go to the mountains" respectively.

But these rules are not really right, for if you have some degrees of beliefs in "Chris wants to go to the mountains" and "David wants to go to the mountains", then you do not find your degrees of beliefs in these rules. In general, ABA represents uncertainties by assumptions and so these uncertainties have to be qualitative. Representations of quantitative uncertainties and/or degrees of beliefs necessarily involve numbers, which, traditionally, are probabilities. And in the presence of probabilities, ABA semantics can not capture the reasoning attitudes of decision makers. For example, in the above situation, you are interested in the lower/upper bound of probability that "Anne joins the trip", rather than merely whether Anne may join.

In fact, it has been well recognized that the standard Abstract Argumentation as well as its logic-based instances like ABA is inadequate in capturing argumentation involved quantitative uncertainties and/or probabilities. To remedy this inadequacy, several models of Probabilistic Argumentation (PA) have been proposed, notably [6], [9], [25], [12], [8], [24]. In a previous work [11], recognizing that many PA models can be easily be translated into Probabilistic Assumption-based Argumentation [6] (PABA), we focused on PABA, developing several inference procedures and a multi-semantics reasoning engine for it. In the current work, utilizing this engine, we propose a programming toolbox for the developments of argumentation-based decision systems that have to deal with both qualitative and quantitative uncertainties. Our toolbox consists of three components: 1) Decision framework allowing abstract specifications of decision situations with qualitative and quantitative uncertainties; 2) Translator converting such specifications into PABA frameworks; and 3) PABA reasoning engine computing the acceptability degrees of each decision under different reasoning attitudes.

To our best knowledge, so far the only application of PABA has been the simulation of jury-based dispute resolution by Dung and Thang [6] and the current work is the first proposal of decision making using Probabilistic Argumentation in general and PABA in particular. However, there is a long line of work done on decision making using AA as well as its logic-based instances among which closest to our work are those using ABA, notably [20], [18], [26], [7], [2]. In comparison with these, our work not only allows quantitative uncertainties but also has other advantages regarding the capturing of reasoning attitudes in the presence of quantitative uncertainties and the accrual of arguments for/against a decision, as will be elaborated in the paper.

The rest of this paper is structured as follows: section II reviews argumentation frameworks and a canonical decision framework with preferences and qualitative uncertainties; section III presents our toolbox; section IV uses the toolbox to develop a decision support system simulating the decision making of experts on electric distribution in smart grid[3]; finally section V concludes.

II. Background

A. Abstract Argumentation

An AA framework [5] is a pair (AR, Att) where AR is a set of arguments, $Att \subseteq AR \times AR$ and $(A, B) \in Att$ means that A attacks B. $S \subseteq AR$ attacks $A \in AR$ iff $(B, A) \in Att$ for some $B \in S$. $A \in AR$ is acceptable wrt to S iff S attacks every argument attacking A. S is *conflict-free* iff S does not attack itself; *admissible* iff S is conflict-free and each argument in S is acceptable wrt S; *complete* iff S is admissible and contains every arguments acceptable wrt S; a *preferred* extension iff S is a maximal (wrt set inclusion) complete set; the *grounded* extension iff S is the least complete set. An argument A is accepted under semantics sem, denoted $AA\ \mathcal{F} \vdash_{sem} A$, iff A is in a sem extension. In this paper, we focus on $sem \in \{pr, gr\}$ - the **pr**eferred semantics and the **gr**ounded semantics. For any other semantics sem (see [5]), it holds that $AA\ \mathcal{F} \vdash_{gr} A \Rightarrow AA\ \mathcal{F} \vdash_{sem} A \Rightarrow AA\ \mathcal{F} \vdash_{pr} A$ and hence gr represents the *most skeptical* reasoning attitude while pr represents a *credulous* reasoning attitude.

B. Assumption-based Argumentation

As AA ignores the internal structure of argument, an instance of AA called Assumption-Based Argumentation (ABA [21], [19]) defines arguments by deductive proofs based on assumptions and inference rules. Assuming a language $\mathcal{L}$ consisting of countably many sentences, an ABA framework is a triple $\mathcal{F} = (\mathcal{R}, \mathcal{A}, \overline{})$ where $\mathcal{R}$ is a set of inference rules of the form $r : l_0 \leftarrow l_1, \ldots, l_n$ $(n \geq 0)$[4], $\mathcal{A} \subseteq \mathcal{L}$ is a set of assumptions, and $\overline{}$ is a (total) one-to-one mapping from $\mathcal{A}$ into $\mathcal{L}$, where $\overline{x}$ is referred to as the *contrary* of x. Assumptions do not appear in the heads of inference rules and contraries of assumptions are not assumptions.

[3]This section is a comprehensively revised and improved version of [17].

[4]For convenience, define $head(r) = l_0$ and $body(r) = \{l_1, \ldots l_n\}$.

A *(backward) deduction* of a conclusion π supported by a set of premises Q is a sequence of sets $S_1, S_2, \ldots, S_n$ where $S_i \subseteq \mathcal{L}$, $S_1 = \{\pi\}$, $S_n = Q$, and for every i, where σ is the selected proposition in S_i: $\sigma \notin Q$ and $S_{i+1} = S_i \setminus \{\sigma\} \cup body(r)$ for some inference rule $r \in \mathcal{R}$ with $head(r) = \sigma$.

An argument for $\pi \in \mathcal{L}$ supported by a set of assumptions Q is a deduction d from π to Q and denoted by (Q, d, π). An argument (Q, d, π) attacks an argument (Q', d', π') if π is the contrary of some assumption in Q'. For simplicity, we often refer to an argument (Q, d, π) by (Q, π) if there is no possibility for mistake.

A proposition π is said to be credulously/groundedly accepted in ABA $\mathcal{F}$, denoted ABA $\mathcal{F} \vdash_{pr} \pi$ (resp. ABA $\mathcal{F} \vdash_{gr} \pi$) if in the AA framework consisting of above defined arguments and attacks, there is an argument for π accepted under the preferred/grounded semantics.

C. Probabilistic Assumption-based Argumentation

AA as well as its logic-based instances including ABA can not model argumentation processes involving probabilities. To address this problem Dung and Thang in [6] first integrate probabilities into AA to propose a Probabilistic Abstract Argumentation framework (DT's PA) and then combine DT's PA with ABA to propose Probabilistic Assumption-based Argumentation (PABA) framework.

Definition 1: A probabilistic assumption-based argumentation [6] (PABA) framework $\mathcal{P}$ is a triple $(\mathcal{A}_p, \mathcal{R}_p, \mathcal{F})$ where

1) $\mathcal{F} = (\mathcal{R}, \mathcal{A}, \overline{})$ is an ABA framework.
2) $\mathcal{A}_p$ is a finite set of **positive probabilistic assumptions**. Elements of $\neg\mathcal{A}_p = \{\neg p \mid p \in \mathcal{A}_p\}$ are called **negative probabilistic assumptions**[5]**.**
3) $\mathcal{R}_p$ is a set of probabilistic rules of the form $[\alpha : x] \leftarrow \beta_1, \ldots, \beta_n \quad n \geq 0, x \in [0, 1], \alpha \in \mathcal{A}_p \cup \neg\mathcal{A}_p$, where $[\alpha : x]$, called a **probabilistic proposition**, represents that the probability of probabilistic assumption α is x.

Definition 2: (From [11], [6]) PABA $\mathcal{P} = (\mathcal{A}_p, \mathcal{R}_p, \mathcal{F})$ is **well-formed** if it satisfies four constraints below.

1) For each $\alpha \in \mathcal{A}_p \cup \neg\mathcal{A}_p$, α does not occur in $\mathcal{A}$ or in the head of a rule in $\mathcal{R}$, and $[\alpha : x]$ does not occur in the body of a rule in $\mathcal{R} \cup \mathcal{R}_p$.
2) If $\mathcal{R}_p$ contains $[\alpha : x] \leftarrow \beta_1, \ldots, \beta_n$, then it also contains a complementary rule $[\neg\alpha : 1-x] \leftarrow \beta_1, \ldots, \beta_n$.[6]
3) For each $\alpha \in \mathcal{A}_p \cup \neg\mathcal{A}_p$, there exists $Pa_\alpha \subseteq \mathcal{A}_p$ s.t. for each maximal consistent subset $\{\beta_1, \ldots, \beta_m\}$ of $Pa_\alpha \cup \neg Pa_\alpha$, $\mathcal{R}_p$ contains a rule $[\alpha : x] \leftarrow \beta_1, \ldots, \beta_m$.
4) If $\mathcal{R}_p$ contains two rules r_1, r_2 with heads $[\alpha : x]$ and $[\alpha : y]$, $x \neq y$, then either conditions below holds.
   a) $body(r_1) \subset body(r_2)$ or $body(r_2) \subset body(r_1)$.
   b) $\theta \in body(r_1)$ and $\neg\theta \in body(r_2)$ for some $\theta \in \mathcal{A}_p$.

Example 1: Continue the trip planning in the introduction, your beliefs about Chiang Mai can be represented by PABA $\mathcal{P} = (\mathcal{A}_p, \mathcal{R}_p, \mathcal{F})$ where

- ABA $\mathcal{F}$ consists of assumptions $\{\lceil r_1 \rceil\} \cup \{arguably(x) \mid x \in \{aj, bj, cj, dj\}\}$ and inference rules

$$\begin{array}{ll}
aj \leftarrow aw, \lceil r_1 \rceil, arguably(aj) & aw \leftarrow flower \\
bj \leftarrow bw, arguably(bj) & bw \leftarrow mountain, p_bwm \\
cj \leftarrow cw, arguably(cj) & cw \leftarrow mountain, p_cwm \\
dj \leftarrow dw, arguably(dj) & dw \leftarrow mountain, p_dwm \\
false \leftarrow aj, bj, cj, dj & mountain \leftarrow \\
\neg\lceil r_1 \rceil \leftarrow cj, dj & flower \leftarrow
\end{array}$$

- $\mathcal{A}_p = \{p\_bwm, p\_cwm, p\_dwm\}$ consisting of probabilistic assumptions representing your degrees of beliefs that Bob/Chris/David wants to go to the mountains.
- For the sake of example, let $\mathcal{R}_p$ consist of the following probabilistic inference rules
  $[p\_bwm : 0.5] \leftarrow \qquad [p\_cwm : 0.6] \leftarrow$
  $[p\_dwm : 0.9] \leftarrow p\_cwm \qquad [p\_dwm : 0.1] \leftarrow \neg p\_cwm$
  stating that Bob's and Christ's interests in going to the mountains are independent, being 50% and 60% respectively; but Davis's interest positively correlates with Chris's interest (probably because they are close friends).

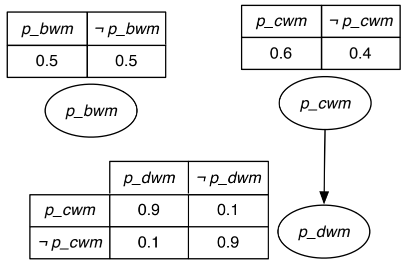

Fig. 1. Bayesian network representing $\mathcal{A}_p$ and $\mathcal{R}_p$.

In this paper, we restrict ourselves to so called *Bayesian PABA frameworks* for which in [11] we have developed inference procedures for different semantics and implemented them to obtain an PABA reasoning engine called PENGINE[7]. Intuitively, an PABA framework is Bayesian [11] just in case its $\mathcal{A}_p$ and $\mathcal{R}_p$ components can be represented by a Bayesian network [13] with a set of nodes $\mathcal{A}_p$ and conditional probabilities stated by $\mathcal{R}_p$. In defining a Bayesian PABA framework, instead of listing sets $\mathcal{A}_p$ and $\mathcal{R}_p$, we can just give a Bayesian network. For example, in defining the Bayesian PABA framework in Example 1, we could give the Bayesian network in Fig. 1.

To define the semantics of a (Bayesian) PABA $\mathcal{P} = (\mathcal{A}_p, \mathcal{R}_p, \mathcal{F})$, let's adopt some notations.

- A **possible world** is a maximal (wrt set inclusion) consistent subset of $\mathcal{A}_p \cup \neg\mathcal{A}_p$. $\mathcal{W}$ denotes the set of all possible worlds.
- For each possible world $\omega \in \mathcal{W}$, $ABA\,\mathcal{F}_\omega \triangleq (\mathcal{R}_\omega, \mathcal{A}, \overline{})$ where $\mathcal{R}_\omega \triangleq \mathcal{R} \cup \{p \leftarrow \mid p \in \omega\}$.

Definition 3: Wrt Bayesian $PABA\ \mathcal{P} = (\mathcal{A}_p, \mathcal{R}_p, \mathcal{F})$, the probability that a proposition π is acceptable wrt semantics sem is

$$Prob_{sem}(\pi) \triangleq \sum_{\omega \in \mathcal{W} : ABA\ \mathcal{F}_\omega \vdash_{sem} \pi} P(\omega)$$

where $P(\omega)$ is the probability of ω according to the Bayesian network representing $\mathcal{A}_p$ and $\mathcal{R}_p$.

[5] $\neg$ is the classical negation operator

[6] In examples, we will not list complementary rules to save space.

[7] http://pengine.herokuapp.com

From the following proposition, we can say that $Prob_{gr}(\pi)$ and $Prob_{pr}(\pi)$ are the lower/upper bound of the probability of the acceptability of π.

Lemma 1: $0 \leq Prob_{gr}(\pi) \leq Prob_{sem}(\pi) \leq Prob_{pr}(\pi) \leq \sum_{\omega \in \mathcal{W}} P(\omega) = 1$ for any semantics sem [11].

In other words, $Prob_{gr}$ represents the reasoning attitude of the most skeptical reasoners while $Prob_{pr}$ represents the reasoning attitude of credulous reasoners.

Example 2: (Continue Example 1) There are eight possible worlds:

	$\mathcal{W}$	$P(\omega)$
ω_0	$\{p_{bwm}, p_{cwm}, p_{dwm}\}$	0.27
ω_1	$\{p_{bwm}, p_{cwm}, \neg p_{dwm}\}$	0.03
ω_2	$\{p_{bwm}, \neg p_{cwm}, p_{dwm}\}$	0.02
ω_3	$\{p_{bwm}, \neg p_{cwm}, \neg p_{dwm}\}$	0.18
ω_4	$\{\neg p_{bwm}, p_{cwm}, p_{dwm}\}$	0.27
ω_5	$\{\neg p_{bwm}, p_{cwm}, \neg p_{dwm}\}$	0.03
ω_6	$\{\neg p_{bwm}, \neg p_{cwm}, p_{dwm}\}$	0.02
ω_7	$\{\neg p_{bwm}, \neg p_{cwm}, \neg p_{dwm}\}$	0.18
		$\sum = 1$

The acceptability of aj in each $ABA\ \mathcal{F}_\omega$ is as follows.

	ω_0	ω_1	ω_2	ω_3	ω_4	ω_5	ω_6	ω_7
$\mathcal{F}_\omega \vdash_{pr} aj$?	y	y	y	y	n	y	y	y
$\mathcal{F}_\omega \vdash_{gr} aj$?	n	y	y	y	n	y	y	y

Intuitively, Anne *surely* does not join if both Chris and David want to join but not Bob (i.e. $cw \wedge dw \wedge \neg bw$, which happens in possible world ω_4), because the rule $\neg\lceil r_5 \rceil \leftarrow cj, dj$ fires. However, if Bob, Chris and David all want to join (i.e. $bw \wedge cw \wedge dw$, which happens in possible world ω_0), then Anne may or may not join. When she joins, she will join with Bob, and with either Chris or David because the car can not seat four passengers (note that $\neg\lceil r_5 \rceil \leftarrow cj, dj$ does not fire in this situation). And when she does not join, then three passengers joining the trip are Bob, Chris and David.

Similarly, the acceptability of bj in each $ABA\ \mathcal{F}_\omega$ is as follows[8].

	ω_0	ω_1	ω_2	ω_3	ω_4	ω_5	ω_6	ω_7
$\mathcal{F}_\omega \vdash_{pr} bj$?	y	y	y	y	n	n	n	n
$\mathcal{F}_\omega \vdash_{gr} bj$?	n	y	y	y	n	n	n	n

So $Prob_{pr}(aj) = 1 - P(\omega_4) = 0.73; Prob_{gr}(aj) = Prob_{pr}(aj) - P(\omega_0) = 0.46$. Similarly, $Prob_{gr}(bj) = P(\omega_1) + P(\omega_2) + P(\omega_3) = 0.23; Prob_{pr}(bj) = Prob_{gr}(bj) + P(\omega_0) = 0.5$. In other words, if you have a credulous reasoning attitude, then your conclusions are: with 73% Anne will join; with 50% Bob will join. On the other hand, if you have the most skeptical attitude, then your conclusions are: with 46% Anne will join; with 23% Bob will join.

[8]Here we can see that in possible world ω_0, the grounded semantics is too skeptical. As mentioned in the introduction, the "right" skeptical semantics - the skeptical preferred semantics - accepts bj.

D. Decision Making with Preferences and Qualitative Uncertainties

Decision making can be viewed as a reasoning process in which the decision maker first evaluates alternative decisions, based on their attributes, to determine how they satisfy his goals, and secondly selects a decision taking into account the preferences between goals [20]. A decision framework should describe not only various forms of beliefs that the decision maker may have as input to this reasoning process, but also the criteria for selecting a decision given such beliefs. For example, a canonical decision framework which can deal with preferences and qualitative uncertainties is defined in [18], [26], [7], [2] as a tuple $\langle D, A, G, P, R_A, R_G \rangle$ where

- $D = \{d_1, d_2, \ldots\}$ is a finite set consisting of alternative decisions.
- $A = \{a_1, a_2, \ldots\}$ is a finite set consisting of attributes of decisions.
- $G = \{g_1, g_2, \ldots\}$ is a finite set consisting of goals which the decision maker wants to achieve.
- $P : G \rightarrow \{1, 2, \ldots\}$ ranks the goals so that the higher the number assigned to a goal, the more important the goal is for the decision maker.
- $R_A : D \times A \rightarrow \{1, -1, 0\}$ where $R_A(d, a) = 1$ (resp. -1) represents that the decision maker is *certain* that d has attribute a (resp. does not have a); and $R_A(d, a) = 0$ represents that the decision maker is *completely uncertain* about both propositions.
- $R_G : A \times G \rightarrow \{1, -1, 0\}$ where $R_A(d, a) = 1$ (resp. -1) represents that the decision maker is *certain* that g is satisfied by a (resp. not satisfied by a); and $R_A(d, a) = 0$ represents that the decision maker is *completely uncertain* about both propositions[9].

We shall assume that reasoning in making decision is purely by argumentation. So the decision maker concludes that a decision $d \in D$ satisfies $g \in G$, denoted $satBy(g, d)$, only if he has a reason for $satBy(g, d)$, which must be the existence of some $a \in A$ such that $R_A(d, a) = R_G(a, g) = 1$. Hence, for the decision maker, the value of d, denoted $valueOf(d)$, is the set $\{g \in G \mid satBy(g, d)\}$. Note that the actual value of d may be different from $valueOf(d)$ because the decision maker's beliefs may be incomplete or incorrect.

Hence we can say that (in the eyes of the decision maker) a decision d *dominates* [18] another decision d' iff $valueOf(d') \subseteq valueOf(d)$; d is a *weakly* (resp. *strongly*) *dominant* decision if d is not dominated by any decision (resp. d dominates every other decisions). As a general rule, the decision maker wants to select a strongly dominant decision. However in case no such decisions exist, he may have to select a weakly dominant decision.

Still, a problem with the notion of weakly dominant decisions is that there may exist more than one weakly dominant decision in a decision framework. For example, if $D = \{d, d'\}$ and $valueOf(d) \setminus valueOf(d') \neq \emptyset$ and $valueOf(d') \setminus valueOf(d) \neq \emptyset$, then neither decision is dominated by the other, and hence both d and d' are

[9]Our symbols 1, -1, 0 respectively correspond to symbols 1, 0, u in [7], [26], [2]

weakly dominant. It is clear that to select between d and d', the decision maker must compare the difference between $valueOf(d) \setminus valueOf(d')$ and $valueOf(d') \setminus valueOf(d)$, based on preferences associated with individual goals. Unfortunately, unless there is a way to accrue multiple goals, we have to equate G with $argmax\{P(g) \mid g \in G\}$. So, we may say that d is *max-preferred to* d' if $max\{P(g) \mid g \in valueOf(d) \setminus valueOf(d')\} > max\{P(g) \mid g \in valueOf(d') \setminus valueOf(d)\}$[10]. Then we can further say that d is *most preferred* if there is no $d' \in D \setminus \{d\}$ that is max-preferred to d.

Given a decision framework $\langle D, A, G, R_A, R_G, P \rangle$, computing weakly/strongly dominant decisions or most preferred decisions is a simple programming task. It can be programmed, for example, by ABA frameworks as presented in [18], [26], [7]. Note that the accrual of arguments is not addressed in ABA, and hence decision frameworks purposely engineered for ABA (e.g. those in [18], [26], [7]) often do not specify how to accrue multiple goals satisfied (or unsatisfied, reps.) by a decision in argumentation for (against, resp.) the decision. In a similar vein, ABA can not handle quantitative uncertainties, and hence such decision frameworks can not have quantitative uncertainties.

III. A Toolbox for developments of Decision Systems

In this section we present a programming toolbox for the developments of argumentation-based decision systems that have to deal with both qualitative and quantitative uncertainties. Our toolbox is intended for the development methodology illustrated in Fig. 2, in a similar way that UML diagram, UML diagram-Java converter and Java compiler forming a toolbox for the development of general Java applications in OOP methodology. Hence our toolbox consists of three components: 1) Decision framework allowing abstract specifications of decision situations with qualitative and quantitative uncertainties; 2) Translator converting such specifications into PABA frameworks; and 3) PABA reasoning engine computing the acceptability degrees of each decision under different reasoning attitudes.

A. Decision Framework with Qualitative and Quantitative Uncertainties

Let's start by extending the canonical Decision framework $\langle D, A, G, P, R_A, R_G \rangle$ presented in the previous section to deal with quantitative uncertainties and the accrual of multiple goals taking into account preferences over goals. Recall that there components R_A and R_G are functions from $D \times A$ and $A \times G$ to $\{1, -1, 0\}$, where symbol 1 (resp. -1) represents that the decision maker is *certain* that a particular decision has (resp. does not have) an attribute, or a particular goal is satisfied (resp. not satisfied) by some attribute. So these functions do not allow us to say that the decision maker has only some belief degrees in those propositions. To address

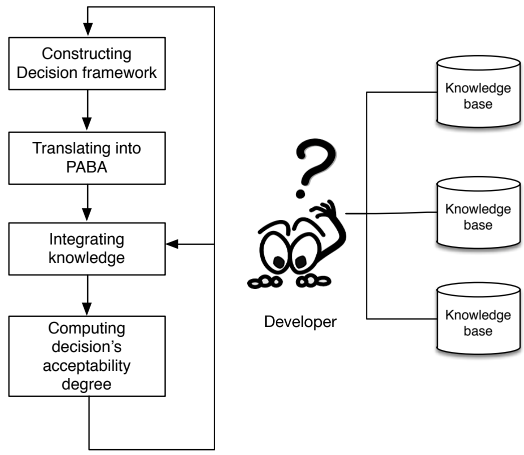

Fig. 2. Developing Decision systems

this problem, we change the domains of R_A and R_G to $[0, 1]$, where $R_A(d, a) \in [0, 1]$ (resp. $R_G(a, g) \in [0, 1]$) is interpreted as degree of belief or probability. For convenience, we shall use two sentential forms:

- $a \rightarrow^{\alpha} g$ representing that $R_G(g, a) = \alpha \in [0, 1]$
- $d \rightarrow^{\alpha} a$ representing that $R_A(d, a) = \alpha \in [0, 1]$

To allow goals to be satisfied by a conjunction of multiple attributes and/or to have subgoals, we extend the first form to the following form.

$$a_1, \ldots, a_m, sg_1, \ldots sg_n \rightarrow^{\alpha} g \quad \text{(f.G)}$$

where $m+n > 0$; $a_i \in A$ for $i = 1, \ldots, m$; $sg_j, g \in SG \cup G$ for $j \in 1, \ldots, n$ with SG being the set of sub-goals such that $SG \cap G = \emptyset$.

Note that form f.G could be viewed as generalizing many existing sentential forms for describing goals breakdown structure such as the form (ii) in [18] which is a special case of f.G with $\alpha = 1$.

Similarly, we extend the second form to the following:

$$d, f_1, \ldots f_k \rightarrow^{\alpha} a \quad \text{(f.A)}$$

where $d \in D$, $k \geq 0$, and $f_i \in F$ $(i = 1, \ldots, k)$ with F being the set of fluents - environment variables which often influence decision's attributes but not influenced by the decision itself.

To represent the decision maker's beliefs about fluents, we introduce a third sentencial form f.E

$$\rightarrow^{\alpha} f \quad \text{(f.E)}$$

representing that the decision maker has degree of belief α in the occurrence of fluent f [11].

To represent the decision maker's preferences over goals, we allow a forth sentential form f.P

$$\rightarrow^{\alpha} important(g) \quad \text{(f.P)}$$

Finally, to allow any dependencies between probabilities, we do not require α in the above sentential forms to be a

[10]Conventionally, $max\{\} = 0$. Note that this definition of "*max-preferred to*" is a slightly modified version of the definition of "*preferred to*" in [20].

[11]Note that we could have viewed fluents as a kinds of goals/subgoals and consider form f.E as a special case of form f.G with $m = n = 0$. However viewing fluents as goals/subgoals may create some confusion in reading form f.A.

probabilistic value in interval [0,1]. Instead, we allow α to be a binary random variable taken from a set of random variables associated with a joint probability distribution. Traditionally, such a distribution is represented by a Bayesian network.

Hence we define a Decision Framework with Qualitative and Quantitative Uncertainties (or just *Extended decision framework*, for short) by a tuple $\langle D, A, \mathcal{N}, B\rangle$ where

- $D = \{d_1, d_2, \dots\}$ is a finite set consisting of alternative decisions.
- $A = \{a_1, a_2, \dots\}$ is a finite set consisting of attributes.
- $\mathcal{N}$ is a Bayesian network defining a probability distribution $Pr_{\mathcal{N}}$ over a finite set of binary random variables $\mathcal{A}_p = \{\alpha_1, \alpha_2, \dots\}$.
- B is a finite set of beliefs in the following sentential forms

$$a_1, \dots, a_m, sg_1, \dots, sg_n \rightarrow^{[\alpha]} g \qquad \text{(f.G)}$$

$$d, f_1, \dots, f_k \rightarrow^{[\alpha]} a \qquad \text{(f.A)}$$

$$\rightarrow^{[\alpha]} f \qquad \text{(f.E)}$$

$$\rightarrow^{[\alpha]} important(g) \qquad \text{(f.P)}$$

where $d \in D$; $a_i, a \in A$; $\alpha \in \mathcal{A}_p$; $m + n > 0, k \geq 0$.

Note that notation $[\alpha]$ means that α is optional. The absence of α in a belief means that the belief is certain [12].

Example 3: Let's twist your trip planning problem in the introduction a bit: the flower festival in Chiang Mai is only during the first week of February. Further, your car can seat four passengers. Now your beliefs can be described by an Extended decision framework $\langle D, A, \mathcal{N}, B\rangle$ where $D = \{cmai, pat\}$, $A = \{beach, mountain, flower\}$, $\mathcal{N}$ has five nodes $p\_bwm, p\_cwm, p\_dwm, p\_im\_aj, p\_im\_bj$, and B consists of the following beliefs.

- Form f.G:
  $aw \rightarrow aj$ $\quad$ $flower \rightarrow aw$
  $bw \rightarrow bj$ $\quad$ $mountain \rightarrow^{p\_bwm} bw$
  $cw \rightarrow cj$ $\quad$ $mountain \rightarrow^{p\_cwm} cw$
  $dw \rightarrow dj$ $\quad$ $mountain \rightarrow^{p\_dwm} dw$
  $beach \rightarrow dw$
  $beach \rightarrow bw$
  $beach \rightarrow cw$
  $beach \rightarrow dw$
- Form f.A:
  $cmai \rightarrow mountain$ $\quad$ $pat \rightarrow beach$
  $cmai, firstWeekFeb \rightarrow flower$
- Form f.E:
  $\rightarrow firstWeekFeb$

[12] We do not need to explicitly include the set of fluents F, the set of goals G, the set of subgoals SG as components of the decision framework because these sets can be determined from other components. Namely, F contains an element f just in case f is the right-hand side of some belief of the form $f.E$ in B. G contains an element g just in case g occurs in the right-hand side of some belief of the form f.P; finally SG contains an element sg just in case sg occurs in a belief of the form $f.G$ and $sg \notin G \cup A$

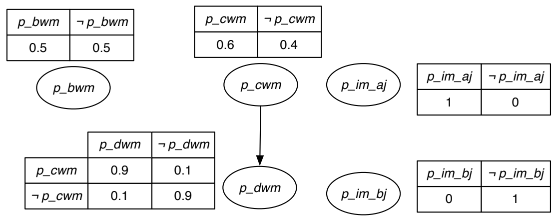

Fig. 3. Bayesian network $\mathcal{N}$.

- Form f.P
  $\rightarrow^{p\_im\_aj} important(aj)$ $\quad$ $\rightarrow^{p\_im\_bj} important(bj)$

For the sake of example, let $\mathcal{N}$ be given Fig. 3, which says that the goal "Anne joins" is extremely important while the goal "Bob joins" is not important at all.

To define the acceptability degree a decision, let's adopt some notions.

- A possible world is maximal consistent subset of $\mathcal{A}_p \cup \neg\mathcal{A}_p$.
  We say that in a possible world ω:
- Fluent f holds if B contains a belief for the form $\rightarrow^{[\alpha]} f$ where α is either absent or in ω.
- d has attribute a if B contains a belief for the form $d, f_1, \dots f_k \rightarrow^{[\alpha]} a$ where $f_1, \dots f_k$ hold and α is either absent or in ω.
- g is satisfied by d if B contains a belief for the form $a_1, \dots, a_m, sg_1, \dots sg_n \rightarrow^{[\alpha]} g$ where d has attributes $a_1, \dots, a_m$; $sg_1, \dots, sg_n$ are all satisfied by d; and α is either absent or in ω.

Definition 4: Wrt a possible world ω in an Extended decision framework $\langle D, A, \mathcal{N}, B\rangle$, a decision $d \in D$ is acceptable if for each statement $\rightarrow^{\alpha} important(g)$ in B, either g is satisfied by d or $\alpha \notin \omega$.

Example 4: (Continue Example 3) Wrt possible world $\{\neg p\_bwm, p\_cwm, p\_dwm, p\_im\_aj, \neg p\_im\_bj\}$, $cmai$ is acceptable. Intuitively, this says that even though "Bob does not want to go to the mountains" and hence the goal "Bob joins" is not achieved, but as long as the goal is not important for you, Chiang mai is still an acceptable destination.

Definition 5: The degree of the acceptability of a decision d, denoted $AccDegree(d)$, is defined by the sum of $Pr_{\mathcal{N}}(\omega)$ over the set of possible worlds in which d is acceptable.

B. Translation into PABA

Extended decision frameworks can be translated into PABA as follows.

Definition 6: An PABA framework $(\mathcal{A}_p, \mathcal{R}_p, \mathcal{F})$ for a decision $d \in D$ in an Extended decision framework $\langle D, A, \mathcal{N}, B\rangle$ is such that

- $\mathcal{A} = \{d\} \cup \{\neg g \mid g \in G\}$ where $\overline{d} = \neg d$ and $\overline{\neg g} = g$
- $\mathcal{R}$ consists of the following rules
  - $g \leftarrow a_1, \dots, a_m, sg_1, \dots sg_n, [\alpha]$
    if B contains a belief of the form $a_1, \dots, a_m, sg_1, \dots sg_n \rightarrow^{[\alpha]} g$.
  - $a \leftarrow f_1, \dots f_k, [\alpha]$

if B contains a belief of the form $d, f_1, \dots f_k \rightarrow^{[\alpha]} a$.

- $f \leftarrow [\alpha]$
  if B contains a belief of the form $\rightarrow^{[\alpha]} f$.
- $\neg d \leftarrow \neg g, [\alpha]$
  if B contains a belief of the form $\rightarrow^{\alpha} important(g)$.

- $\mathcal{R}_p$ and $\mathcal{A}_p$ represents $\mathcal{N}$.

Example 5: (Continue Example 3) The PABA framework $(\mathcal{A}_p, \mathcal{R}_p, \mathcal{F})$ for decision $cmai$ is as follows.

- $\mathcal{A} = \{d, \neg aj, \neg bj\}$ where $\overline{d} = \neg d$, $\overline{\neg aj} = aj$ and $\overline{\neg bj} = bj$
- $\mathcal{R}$ consists of
  - Form f.G
    $aj \leftarrow aw$ $\quad aw \leftarrow flower$
    $bj \leftarrow bw$ $\quad bw \leftarrow mountain, p\_bwm$
    $cj \leftarrow cw$ $\quad cw \leftarrow mountain, p\_cwm$
    $dj \leftarrow dw$ $\quad dw \leftarrow mountain, p\_dwm$
    $aw \leftarrow beach$
    $bw \leftarrow beach$
    $cw \leftarrow beach$
    $dw \leftarrow beach$
  - Form f.A
    $mountain \leftarrow$
    $flower \leftarrow firstWeekFeb$
  - Form f.E
    $firstWeekFeb \leftarrow$
  - Form f.P
    $\neg d \leftarrow \neg aj, p\_im\_aj$ $\quad \neg d \leftarrow \neg bj, p\_im\_bj$
- $\mathcal{R}_p$ and $\mathcal{A}_p$ represents the Bayesian network in Fig. 3.

The correctness of the translation is stated by the following lemma.

Lemma 2: Let $(\mathcal{A}_p, \mathcal{R}_p, \mathcal{F})$ be an PABA framework for a decision $d \in D$ in an Extended decision framework $\langle D, A, \mathcal{N}, B\rangle$. Then $AccDegree(d) = Prob_{sem}(d)$ for any semantics sem.

C. Structured PABA framework for Decision Making

As illustrated by Fig. 2, our toolbox is intended for the development methodology of decision systems where the developer starts by constructing a decision framework describing (not necessarily fully) the situation at hand. He then translates this decision framework into an PABA framework and may integrate into this PABA framework further knowledge. At any time, he can produce an executable decision system by just stacking the current PABA framework on the provided PABA engine, or come back to any of the above steps to redo it. We intend that what a decision framework is to a final PABA framework for decision making is analogous to what an UML diagram is to a final Java program that solves the problem described initially by the UML diagram. And like the fact that the final Java program often retains some structure from the UML diagram (e.g. inheritance relations, method signatures), the final PABA framework often retains some structure from the decision framework. Hence we define structured PABA frameworks for decision making as follows.

Definition 7: Wrt a set of goals G, a set of subgoals SG, a set of attributes A and a set of fluents F, a structured PABA framework $(\mathcal{A}_p, \mathcal{R}_p, (\mathcal{R}, \mathcal{A}, \overline{}))$ for a decision d is such that

- $\mathcal{A}$ contains d and $\neg g$ for each $g \in G$ where $\overline{d} = \neg d$ and $\overline{\neg g} = g$.
- $\mathcal{R}$ contains subsets $\mathcal{R}_G$, $\mathcal{R}_A$, $\mathcal{R}_E$ and $\mathcal{R}_P$ where
  - $\mathcal{R}_G$ describes goal breakdown structure, containing inference rules of the form
    $$g \leftarrow a_1, \dots, a_m, sg_1, \dots sg_n, \dots$$
    where $a_1, \dots a_m \in A \cup \neg A$; $g \in (G \cup SG)$; $sg_1, \dots, sg_n \in (G \cup SG) \cup \neg(G \cup SG)$; and $m+n > 0$[13].
  - $\mathcal{R}_A$ describes attributes of decision d, containing inference rules of the form
    $$a \leftarrow f_1, \dots f_k, \dots$$
    where $a \in A \cup \neg A$; $f_1, \dots f_k \in F \cup \neg F$ and $k \geq 0$.
  - $\mathcal{R}_F$ represents information about the environment and/or background knowledge, containing inference of the form
    $$f \leftarrow \dots$$
    where $f \in F \cup \neg F$.
  - $\mathcal{R}_P$ represents the decision maker's preferences over goals, containing inference rules of the form
    $$\neg d \leftarrow \neg g, \dots$$
    where $g \in G$.

Example 6: (Continue Example 5) To represent the situation in the introduction, we need to integrate more knowledge, e.g. that your car can not seat more than three passengers. The final structured PABA framework $(\mathcal{A}_p, \mathcal{R}_p, (\mathcal{R}, \mathcal{A}, \overline{}))$ can be as follow.

- $\mathcal{A} = \{d, \neg aj, \neg bj\} \cup \mathcal{A}_C$ where $\mathcal{A}_C = \{\lceil r_1 \rceil\} \cup \{arguably(x) \mid x \in \{aj, bj, cj, dj\}\}$.
- $\mathcal{R} = \mathcal{R}_G \cup \mathcal{R}_A \cup \mathcal{R}_E \cup \mathcal{R}_P$ where
  - $\mathcal{R}_G$ consists of
    $aj \leftarrow aw, \lceil r_1 \rceil, arguably(aj)$ $\quad aw \leftarrow flower$
    $bj \leftarrow bw, arguably(bj)$ $\quad bw \leftarrow mountain, p\_bwm$
    $cj \leftarrow cw, arguably(cj)$ $\quad cw \leftarrow mountain, p\_cwm$
    $dj \leftarrow dw, arguably(dj)$ $\quad dw \leftarrow mountain, p\_dwm$
    $false \leftarrow aj, bj, cj, dj$ $\quad aw \leftarrow beach$
    $\neg\lceil r_1 \rceil \leftarrow cj, dj$ $\quad bw \leftarrow beach$
    $cw \leftarrow beach$
    $dw \leftarrow beach$
  - $\mathcal{R}_A$ consists of
    $mountain \leftarrow$
    $flower \leftarrow firstWeekFeb$
  - $\mathcal{R}_E$ consists of
    $firstWeekFeb \leftarrow$
  - $\mathcal{R}_P$ consists of
    $\neg d \leftarrow \neg aj, p\_im\_aj$ $\quad \neg d \leftarrow \neg bj, p\_im\_bj$
- $\mathcal{A}_p$ and $\mathcal{R}_p$ are given in Fig. 3.

Definition 8: Given a structured PABA framework for a decision d, the lower/upper acceptability degree of d is defined as $Prob_{gr}(d)$ and $Prob_{pr}(d)$ respectively.

Example 7: (Continue Example 6) From the importance of aj vs that of bj, it is easy to see that $Prob_{gr}(d) = Prob_{gr}(aj) = 0.46$ and $Prob_{pr}(d) = Prob_{pr}(aj) = 0.73$.

[13]Note that for a set X, $\neg X$ denotes $\{\neg x \mid x \in X\}$

	Preferences		Acceptability degrees	
	$P(p\_im\_aj)$	$P(p\_im\_bj)$	$Prob_{pr}(d)$	$Prob_{gr}(d)$
1	1	0	0.73	0.46
2	0	1	0.5	0.23
3	1	1	0.5	0.23
4	0.5	0.5	0.6825	0.48
5	0	0	1.0	1.0

TABLE I
THE ACCEPTABILITY DEGREES OF "CHIANG MAI" UNDER DIFFERENT PREFERENCE PROFILES.

So if you are a credulous reasoner, then you consider that with 73%, Chiang mai is an acceptable destination; while if you are a skeptical reasoner, then you consider that with 46% Chiang mai is acceptable.

Table I shows the lower/upper acceptability degrees of the decision "Chiang mai" under different preference profiles. It is not difficult but laborious to arrive at these results manually so in the next section we show how to obtain them from our PABA reasoning engine. Here let's see how these results are understandable: in profile 2 where we consider that "Bob joins" is extremely important and "Anne joins" is not important at all, $Prob_{pr}(d) = Prob_{pr}(bj)$ and $Prob_{gr}(d) = Prob_{gr}(bj)$. In profiles from 3 to 5, we consider "Bob joins" and "Anne joins" equally important, $Prob_{pr}(d)$ and $Prob_{gr}(d)$ increase as the importance of the goals decrease. When the goals are both not important at all, $Prob_{pr}(d) = Prob_{gr}(d) = 1$.

D. PABA engine

Our toolbox uses PENGINE - an PABA engine developed in [11]. As illustrated by code Listings 1 and 2 which specify the PABA framework in Example 6, the concrete syntax of PENGINE for receiving a (Bayesian) $PABA\ \mathcal{P} = (\mathcal{A}_p, \mathcal{R}_p, (\mathcal{R}, \mathcal{A}, \overline{}))$ consists of several predicates and functors: `iNas([...])` lists assumptions in $\mathcal{A}$; `contr(...)` refers to the contrary of a given assumption; `iRule(..., [...])` declares an inference rule of $\mathcal{F}$; `iPas([...])` lists probabilistic assumptions in $\mathcal{A}_p$; and `iBN(...)` specifies a file containing a Bayesian network (in JSON format in accordance with libpgm[14]) to represent $\mathcal{R}_p$.

Listing 1. Specifying the PABA framework in Example 6.

```
%% Assumptions
iNas([d, not_aj, not_bj, r1, arguably(aj),
   arguably(bj), arguably(cj), arguably(dj)]).
%% Contraries
iRule(contr(not_aj),[aj]).
iRule(contr(not_bj),[bj]).

%% R_G (goal breakdown structure)
iRule(aj,[aw, r1, arguably(aj)]).
iRule(bj,[bw, arguably(bj)]).
iRule(cj,[cw, arguably(cj)]).
iRule(dj,[dw, arguably(dj)]).
iRule(contr(arguably(aj)),[bj, cj, dj]).
iRule(contr(arguably(bj)),[aj, cj, dj]).
iRule(contr(arguably(cj)),[aj, bj, dj]).
iRule(contr(arguably(dj)),[aj, bj, cj]).
iRule(contr(r1),[cj, dj]).
iRule(aw,[flower]).
iRule(bw,[mountain, p_bwm]).
iRule(cw,[mountain, p_cwm]).
iRule(dw,[mountain, p_dwm]).

%% R_A (attributes)
iRule(mountain,[]).
iRule(flower,[firstWeekFeb]).

%% R_E (environment)
iRule(firstWeekFeb,[]).

%% R_P (preferences)
iRule(contr(d),[not_aj, p_im_aj]).
iRule(contr(d),[not_bj, p_im_bj]).

%% BN network
iBN("./tests/paba-for-dm.json").
iPas([p_bwm,p_cwm,p_dwm,p_im_aj, p_im_bj]).
```

[14]See http://pythonhosted.org/libpgm.

Listing 2. Textual content of paba-for-dm.json


```
{
    "V": ["p_bwm","p_cwm","p_dwm","p_im_aj","p_im_bj"],
        "E": [["p_cwm","p_dwm"]],
        "Vdata": {
                "p_bwm": {
                        "ord": 0,
                        "numoutcomes": 2,
                        "vals": ["true","false"],
                        "parents": null,
                        "children": null,
                        "cprob": [0.5,0.5]
                },
                "p_cwm": {
                        "ord": 1,
                        "numoutcomes": 2,
                        "vals": ["true","false"],
                        "parents": null,
                        "children": ["p_dwm"],
                        "cprob": [0.6,0.4]
                },
                "p_dwm": {
                        "ord": 2,
                        "numoutcomes": 2,
                        "vals": ["true","false"],
                        "parents": ["p_cwm"],
                        "children": null,
                        "cprob": {"['true']": [0.9,0.1],
                                "['false']": [0.1,0.9]}
                },
                "p_im_aj": {
                        "ord": 3,
                        "numoutcomes": 2,
                        "vals": ["true","false"],
                        "parents": null,
                        "children": null,
                        "cprob": [1,0]
                },
                "p_im_bj": {
                        "ord": 4,
                        "numoutcomes": 2,
                        "vals": ["true","false"],
                        "parents": null,
                        "children": null,
                        "cprob": [0,1]
                }
        }
}
```


Once we have an PABA framework in the above syntax, we can load it into PENGINE and query $Prob_{sem}(.) =?$, as illustrated by Fig. 4. For example, if you load the PABA in Listings 1 and 2 and then query $Prob_{pr}(d) =?$ and $Prob_{gr}(d) =?$, we will receive answers 0.73 and 0.46 respectively (see the demonstration at http://pengine.heroku.com).

IV. SIMULATING EXPERT'S DECISION MAKING

In this section, we use the toolbox presented in the previous section to develop a decision system simulating the decision making of experts on electric distribution systems.

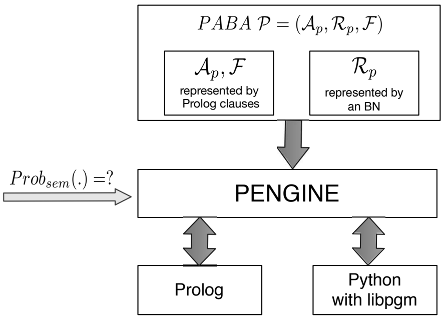

Fig. 4. PENGINE

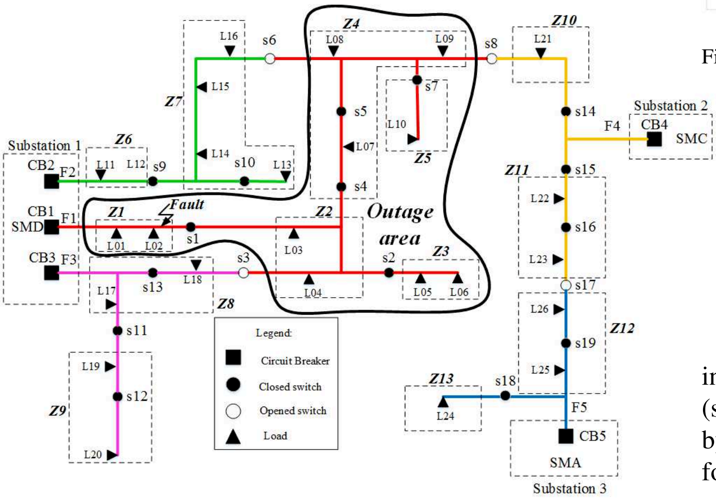

Fig. 5. A power distribution network of Provincial Electricity Authority, Thailand.

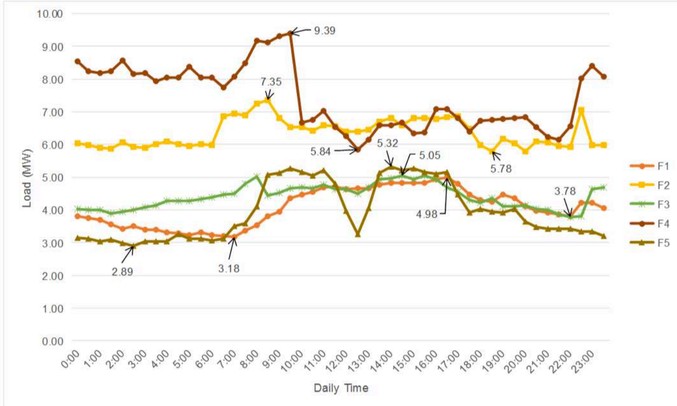

Fig. 6. SCADA's observations for the loads within 24 hours

Plans	Switching operations	Applied heuristics
# 1	Close S8	H1
# 2	Close S3	H1
# 3	Open S4, Close S6, Close S3	H2, H1, H1
....	....	....

TABLE II
CONSTRUCTION OF POSSIBLE PLANS BY APPLYING HEURISTICS

A. Service Restoration in Electric Distribution Systems

Fault in electric distribution systems is unpredictable, and often results in a power outage. *Service restoration* aims at finding a *restoration plan* - series of switching operations - to restore power for the outage area, considering multiple objectives and constraints. To get a handle on current practices in service restoration, we did a case study at a power company[15]. Fig. 5 shows a power distribution system under its management which consists 3 substations, 5 feeders, 26 loads, and 19 switches. Power from substations flow through feeders to be consumed at loads. A zone consists of adjacent loads and connects with another zone via switches. Often the spare capacities of feeders and the total loads of zones are observed frequently by SCADA systems. Loads often vary during time of day. Fig. 6 shows SCADA's observations for the loads within 24 hours. We can see the trend that loads are at peak during working time and reduce during night time or lunch time.

Now suppose that a fault occurs at $Z1$ in feeder $F1$. The circuit breaker $CB1$ will trip automatically to isolate the fault, causing a power outage in all zones from $Z1$ to $Z5$. Assume that the operator has opened switch $S1$ to isolate the fault. Now he needs to find a plan to restore power for all loads in the outage area, which consists of zones from $Z2$ to $Z5$ (see Fig. 5). The first step is to construct possible plans. Here by experience the operator often applies several heuristics, for example: H1 (*Group restoration*): If support feeders have enough spare capacity for the entire outage area, then close a normally opened switch between these feeders and the outage area; H2 (*Zone restoration*): If support feeders do not have enough spare capacity, then close a normally opened switch to transfer some load of the outage area to a lateral feeder; H3 (*Load transfer*): The capacity of a supporting feeder can be increased by transferring some part of its load to other feeders. One application of a heuristic gives rise to one switching operation, hence to construct a plan, the operator may need to apply different heuristics multiple times, as illustrated by Table II.

Once the operator has constructed possible plans, he needs to evaluate how each plan satisfies his goals. Table III below lists some common goals. Parameters related to goals could be classified into: 1) *system parameters* are those intrinsic to the power distribution system and often they can be computed from a physical description of the system, and 2) *environment parameters* are those extrinsic to the power distribution system and often they come from the environment. For example, for the goal "the current on j^{th} feeder is in range", the feeder current I_j is a system parameter, while the maximal allowed current I_{j_max} is an environment parameter specified by the power company. This classification is not meant to be clear-cut, but often it makes sense, and more importantly it suggests that we can obtain approximations of system parameters by physically simulating a plan. Fig. 7 shows the simulation of restoration plan#1 (see Table II) using DIgSILENT PowerFactory[1] - an industrial-strength power system simulation software. So, the simulation says that the current on feeder $F1$ is 0 Ampere (due to the fault). The

[15]Provincial Electricity Authority of Thailand

Goals	Related parameters	Information sources
Maintain the radial network	Network topology	DIgSILENT
Bus voltages in range: $V_{min} \leq V_j \leq V_{max}$	V_j: voltage on j^{th} bus V_{min}: allowed min voltage V_{max}: allowed max voltage	DIgSILENT Company's policy
Feeder currents in range: $I_j \leq I_{j\_max}$	I_j: current on j^{th} feeder I_{j_max}: allowed max current	DIgSILENT Company's policy

TABLE III
COMMON GOALS

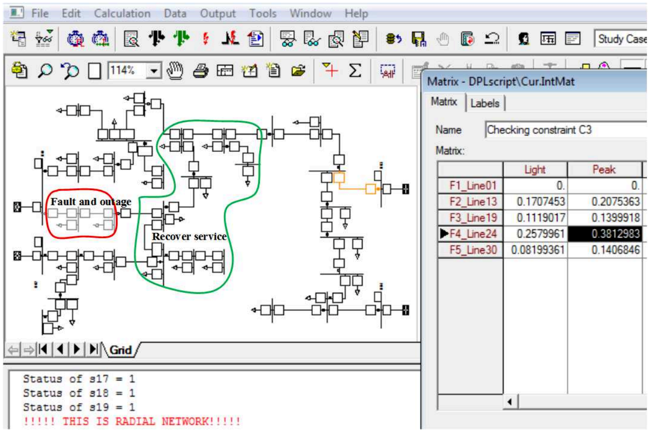

Fig. 7. Using DIgSILENT to simulate restoration plan#1

currents on other feeders ($F2$ to $F5$) depending on the actual loads. Focusing on $F4$, for example, in a light load period, the current on feeder $F4$ is around 0.258 (kA) while in a peak load period, the current is around 0.381 (kA) (see Table IV for detailed results related to $F4$). By the policy of the power company, if the nominal cross-section area of a feeder is 150 mm^2, then its maximal allowed current is 0.36 (kA). So, if feeder $F4$ has this the nominal cross-section area, then we can conclude that plan#1 satisfies the goal "the current on feeder $F4$ is in range" during the light load period, but not during the peak load period.

B. Service Restoration Decision System

Following the methodology shown in Fig. 8, we arrive at a more detailed structure of PABA framework $(\mathcal{A}_p, \mathcal{R}_p, (\mathcal{R}, \mathcal{A}, \overline{}))$ for a restoration plan d as follows.

- $\mathcal{A} \supseteq \{d\} \cup \{\neg g \mid g \in G\}$ where G contains the following goals (see Table III):
  - $radialNetwork$ (radial network topology)
  - $cFeeder_iInRange$ (current on feeder i^{th} in range)
  - $vBus_iInRange$ (voltage on bus i^{th} is in range)
  - $zone_iPowered$ (zone i^{th} is powered)

Feeder	Current (kA)	Powered zones	Buses	Bus voltage (kV)
$F4$	0.258/0.381	$Z10$	$B402$	22.46/22.39
		$Z11$	$B404$	22.60/22.59
			$B405$	22.55/22.51

TABLE IV
SIMULATION RESULTS RELATED TO $F4$ ASSUMING LIGHT/PEAK LOADS.

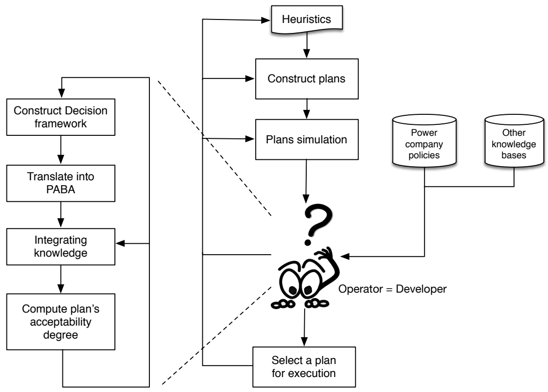

Fig. 8. Service Restoration work flow.

- $\mathcal{R} = \mathcal{R}_G \cup \mathcal{R}_A \cup \mathcal{R}_E \cup \mathcal{R}_P$ where
  - $\mathcal{R}_G$ contains inference rules of the following forms:
    - $radialNetwork \leftarrow networkTopo(radial)$.
      where predicate $networkTopo/1$ describes the network topology (e.g. radial, cyclic)
    - $cFeeder_iInRange \leftarrow cFeeder_i(C), maxCFeeder_i(M), M > C.$
      representing that the current in feeder i^{th} is in range if it is less than the maximally allowed current on that feeder.
    - $vBus_iInRange \leftarrow vBus_i(V), maxVoltage(Vmax), Vmax > V, minVoltage(Vmin), V > Vmin.$
      representing that the voltage on bus i^{th} is in range if is within the maximally and minimally allowed voltages on that bus.
    - $zone_iPowered \leftarrow fedBy(zone_i, feeder_j), cFeeder_j(C), C > 0$
      representing that a zone i^{th} is powered if it is fed by a feeder with a non-zero current.
  - $\mathcal{R}_A$ contains inference rules of the following form
    - $networkTopo(\_) \leftarrow \ldots$
    - $cFeeder_i(\_) \leftarrow \ldots$
    - $vBus_i(\_) \leftarrow \ldots$
    - $fedBy(\_, \_) \leftarrow \ldots$

    representing the results of simulation.
  - $\mathcal{R}_F$ contains inference of the following form
    - $maxCFeeder_i(\_) \leftarrow \ldots$
    - $minVoltage(\_) \leftarrow \ldots$
    - $maxVoltage(\_) \leftarrow \ldots$

    representing the power company's policies
  - $\mathcal{R}_P$ contains inference rules of the following form
    - $\neg d \leftarrow \neg radialNetwork, \ldots$
    - $\neg d \leftarrow \neg cFeeder_iInRange, \ldots$
    - $\neg d \leftarrow \neg vBus_iInRange, \ldots$
    - $\neg d \leftarrow \neg zone_iRestored, \ldots$

    representing the power company 's preferences over goals.

For example, focusing on feeder $F4$ of the distribution network in Fig. 5, the PABA framework $(\mathcal{A}_p, \mathcal{R}_p, (\mathcal{R}, \mathcal{A}, \overline{}))$ for a restoration plan#1 (Table II) might be such that:

- $\mathcal{A} \supseteq \{d\} \cup \{\neg g \mid g \in G\}$ where G contains
  - $radialNetwork$
  - $cFeeder_4InRange$
  - $vBus_{402}InRange, vBus_{404}InRange,$ $vBus_{405}InRange.$
  - $zone_{10}Powered, zone_{11}Powered$
- $\mathcal{A}_p$ contains $lightLoad, peakLoad, workingHours,$ $simReliable$ (simulation is reliable), etc.
- $\mathcal{R} = \mathcal{R}_G \cup \mathcal{R}_A \cup \mathcal{R}_E \cup \mathcal{R}_P$ where
  - $\mathcal{R}_A$ contains (see Table IV)
    * $networkTopo(radial) \leftarrow$
    * $cFeeder_4(258A) \leftarrow lightLoad, simReliable$
    * $cFeeder_4(381A) \leftarrow peakLoad, simReliable$
    * $vBus_{402}(22.46kV) \leftarrow lightLoad, simReliable$
    * $vBus_{402}(22.39kV) \leftarrow peakLoad, simReliable$
    * $vBus_{404}(22.60kV) \leftarrow lightLoad, simReliable$
    * $vBus_{404}(22.59kV) \leftarrow peakLoad, simReliable$
    * $vBus_{405}(22.55kV) \leftarrow lightLoad, simReliable$
    * $vBus_{405}(22.51kV) \leftarrow peakLoad, simReliable$
    * $fedBy(zone_{10}, feeder_4) \leftarrow$
    * $fedBy(zone_{11}, feeder_4) \leftarrow$
  - $\mathcal{R}_F$ contains
    * $maxCFeeder_4(410A) \leftarrow$
    * $minVoltage(19.8kV) \leftarrow$
    * $maxVoltage(24.2kV) \leftarrow$
  - $\mathcal{R}_P$ contains
    * $\neg d \leftarrow \neg radialNetwork$
    * $\neg d \leftarrow \neg cFeeder_4InRange$
    * $\neg d \leftarrow \neg vBus_{402}InRange$
    * $\neg d \leftarrow \neg vBus_{404}InRange$
    * $\neg d \leftarrow \neg vBus_{405}InRange$
    * $\neg d \leftarrow \neg zone_{10}Powered$
    * $\neg d \leftarrow \neg zone_{11}Powered$

V. Conclusions and discussion

The developments of intelligent systems haven been greatly eased by argumentation frameworks developed in AI, notably Dung's Abstract Argumentation framework [5] (AA). However AA as well as its logic-based instances like ABA is inadequate in capturing argumentation involved quantitative uncertainties and/or probabilities. To remedy this inadequacy, several models of Probabilistic Argumentation (PA) have been proposed. Notably, on the abstract level there are Dung and Thang's model [6] (DT's PA), Li et al's model [9] (Li's PA) among others [25], [12], [8]. And on the instantiated level, there are Dung and Thang's PABA [6] which instantiates DT's PA by using ABA to structure arguments; p-ASPIC [24] which also instantiates DT's PA but using (a simplified version of) ASPIC [22]. However, developments of practical systems using these new frameworks are still hindered by the lack of programming tools and environments. In a previous work [11], recognizing that many PA models can be easily be translated into PABA, we focused on PABA, developing several inference procedures and a multi-semantics reasoning engine for it. In the current work, utilizing this engine, we propose a programming toolbox for the developments of argumentation-based decision systems that have to deal with both qualitative and quantitative uncertainties. To our best knowledge, the current work is the first proposal of decision making using PABA. So far the only application of PABA has been the simulation of jury-based dispute resolution by Dung and Thang [6]. However, there is a long line of work done on decision making using AA or its logic-based instances among which closest to our work are those using ABA, notably [20], [18], [26], [7], [2]. In comparison with these, our work differs distinctively on the ways we handle uncertainties, reasoning attitudes of decision makers and the accrual of goals to argue for/against a decision.

We have demonstrated the toolbox using sophisticated examples especially a case study of reasoning by experts on electrical service restoration. So far many methods have been proposed to solve the service restoration problem, from different perspectives or interests, focusing on only one or several steps of the problem [28], [15]: plan construction, attributes determination, or plan comparison/selection. For example, in [27] heuristics representing the expertise of experienced operators are hard-coded in the proposed algorithm to construct alternative plans. In [10] Huang C.M. proposes to use Fuzzy cause-effect networks to deal with imprecise linguistic terms occurring in such heuristics. In [3] the authors highlighted the concept of relative performance index in evaluating and ranking alternative plans. Optimization techniques like Ant-Colony Optimization are applied when there is a large number of plans to consider [23], [14], [16]. However, in practice power restoration is still a manual process responsible by experienced human operators. An important reason that makes it hard to put proposed systems into practice is that the human operators (users) and the system developers are different persons, and so the operators constantly find a lot of information important and relevant for a restoration task at hand, but either oversimplified or totally ignored by the system developers. As a result, the systems do not truly simulate the decision making of the operators, let alone the operators' reasoning attitudes. To address this problem, we believe that programming tools like the one we are proposing play an essential role, for they can help operators to develop decision systems themselves.

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References

[1] Digsilent powerfactory.

[2] Francesca Toni Andrei Mocanu, Xiuyi Fan and Matthew Williams and. Recomedic: recommending medical literature through argumentation. *4th International Workshop on Combinations of Intelligent Methods and Applications (CIMA 2014)*, 2014.

[3] Wen-Hui Chen. Quantitative decision-making model for distribution system restoration. *IEEE Transactions on Power Systems*, 25(1):313–321, 2010.

[4] P. M. Dung. Argumentation for practical reasoning. *Proceedings of the Fifth International Conference on Knowledge and Systems Engineering*, page 5, 2013.

[5] Phan Minh Dung. On the acceptability of arguments and its fundamental role in nonmonotonic reasoning, logic programming and n-person games. *Artificial Intelligence*, 77(2):321–357, 1995.
[6] Phan Minh Dung and Phan Minh Thang. Towards (probabilistic) argumentation for jury-based dispute resolution. *COMMA 2010*, pages 171–182, 2010.
[7] Xiuyi Fan and Francesca Toni. Springer berlin heidelberg. *Decision Making with Assumption-Based Argumentation*, pages 127–142, 2014.
[8] Dov M. Gabbay and Odinaldo Rodrigues. Probabilistic argumentation. an equational approach. *CoRR, abs/1503.05501*, 2015.
[9] Nir Oren Hengfei Li and TimothyJ. Norman. Probabilistic argumentation frameworks. *Theorie and Applications of Formal Argumentation, Lecture Notes in Computer Science*, 7132:1–16, 2012.
[10] Chao-Ming. Huang. Multiobjective service restoration of distribution systems using fuzzy cause-effect networks. *IEEE Transactions on Power Systems*, 18.2:867–874, 2003.
[11] Nguyen Duy Hung. Computing probabilistic assumption-based argumentation. *Trends in Artificial Intelligence 14th Pacific Rim International Conference on Artificial Intelligence*, 2016.
[12] Anthony Hunter. A probabilistic approach to modelling uncertain logical arguments. *International Journal of Approximate Reasoning*, 54(1):47–81, 2013.
[13] Daphne Koller and Nir Friedman. Probabilistic graphical models: Principles and techniques - adaptive computation and machine learning. *The MIT Press*, 2009.
[14] Biswarup Das Kumar, Yogendra and Jaydev Sharma. Service restoration in distribution system using non-dominated sorting genetic algorithm. *Electric Power Systems Research*, 76.9:768–777, 2006.
[15] Das B. Sharma Kumar, Y. and Jaydev. Multiobjective, multiconstraint service restoration of electric power distribution system with priority customers. *IEEE Transactions on Power Delivery*, 23(1):261–270, 2008.
[16] Ehsan Moazami and et al. Optimal penalty method in distribution service restoration using genetic algorithm. *Power Engineering and Optimization Conference (PEOCO)*, 2013.
[17] Santi Kaisaard Nguyen Duy Hung and Saung Hnin Pwint Oo. Probabilistic argumentation for service restoration in power distribution networks. *Proceedings of the 10th International Conference on Knowledge Information and Creativity Support Systems (KICSS 2015)*, pages 70–82, 2015.
[18] Francesca Toni Paul-Amaury Matt and Juan R. Vaccari. Dominant decisions by argumentation agents. *Springer Berlin Heidelberg*, pages 42–59, 2010.
[19] Paolo Mancarella Phan Minh Dung and Francesca Toni. Computing ideal skeptical argumentation. *Artificial Intelligence*, 171(10-15):642–674, 2007.
[20] Phan Minh Thang Phan Minh Dung and Francesca Toni. Towards argumentation-based contract negotiation. *Proceedings of the Conference on Computational Models of Argument*, pages 134–146, 2008.
[21] Robert A. Kowalski Phan Minh Dung and Francesca Toni. Dialectic proof procedures for assumption-based, admissible argumentation. *Artificial Intelligence*, 170(2):114–159, 2006.
[22] Henry Prakken. An abstract framework for argumentation with structured arguments. *Argument & Computation*, 1(2):93–124, 2010.
[23] Yogendra Kumar Rajneesh Karn and Gayatri Agnihotri. ACO based method for service restoration in distribution system using fuzzy M.O.M.C approach. *International Joural of Soft Computing and Engineering*, 1(4), 2011.
[24] Tjitze Rienstra. Towards a probabilistic dung-style argumentation system. *Proceedings of the First International Conference on Agreement Technologies*, pages 138–152, 2012.
[25] Matthias Thimm. A probabilistic semantics for abstract argumentation. *ECAI*, 242:750–755, 2012.
[26] Ramsay Singer-Francesca Toni Xiuyi Fan, Robert Craven and Matthew Williams. Assumption-based argumentation for decision-making with preferences: A medical case study. *Springer Berlin Heidelberg*, pages 374–390, 2013.
[27] H.-C. Kuo S.K. Peng C.W. Chang K.J. Chang H.S. Yu C.E. Chow Yuan-Yih Hsu, M.M. Huang and R.T. Kuo. Distribution system service restoration using a heuristic search approach. *Proceedings of the Transmission and Distribution Conference*, pages 639–645, 1991.
[28] A. Zidan and E.F. El-Saadany. A cooperative multiagent framework for self-healing mechanisms in distribution systems. *Smart Grid, IEEE Transactions on*, 3(3):1525–1539, 2012.

Nguyen duy Hung has been a lecturer of Sirindhorn International Institute of Technology, Thammasat University since 2013. Hung holds an M.Eng. and Ph.D. from Asian Institute of Technology (AIT), Thailand in 2002 and 2012. His Ph.D. thesis title is: Dialectical Proof Procedures and Applications in Contract Dispute Resolution. His current interests include argumentation systems, proof procedures and their applications in decision making, negotiation, legal reasoning, dispute resolution, dialogues, multi-agents and sensor networks.