Stable Models of Fuzzy Propositional Formulas

Joohyung Lee and Yi Wang

School of Computing, Informatics, and Decision Systems Engineering
Arizona State University, Tempe, USA
{joolee,ywang485}@asu.edu

Abstract. We introduce the stable model semantics for fuzzy propositional formulas, which generalizes both fuzzy propositional logic and the stable model semantics of classical propositional formulas. Combining the advantages of both formalisms, the introduced language allows highly configurable default reasoning involving fuzzy truth values. We show that several properties of Boolean stable models are naturally extended to this formalism, and discuss how it is related to other approaches to combining fuzzy logic and the stable model semantics.

1 Introduction

Answer set programming (ASP) [1] is a widely applied declarative programming paradigm for the design and implementation of knowledge intensive applications. One of the attractive features of ASP is its capability to model the nonmonotonic aspect of knowledge. However, as its mathematical basis, the stable model semantics, is restricted to Boolean values, it is too rigid to represent imprecise and vague information. Fuzzy logic [2], as a form of many-valued logic, can handle vague information by interpreting propositions with a truth degree in the interval of real numbers [0,1]. The availability of various fuzzy operators gives the user great flexibility in combining truth degrees. However, the semantics of fuzzy logic is monotonic, and is not flexible enough to handle default reasoning allowed in answer set programming.

Both the stable model semantics and fuzzy logic are generalizations of classical propositional logic in different ways. While they do not subsume each other, it is clear that many real-world problems require both their strengths. This led to the body of work on combining fuzzy logic and the stable model semantics, known as fuzzy answer set programming (e.g., [3,4]). However, their syntax is restricted to rules, and does not allow connectives nested arbitrarily as in fuzzy logic.

Unlike existing work on fuzzy answer set semantics, in this paper, we extend the general stable model semantics from [5] to many-valued propositional formulas. The syntax of this language is the same as the syntax of fuzzy propositional logic. The semantics, on the other hand, defines stable models instead of models. The language is a proper generalization of both fuzzy propositional logic and the stable model semantics for Boolean propositional formulas. This generalization is not simply a pure theoretical pursuit, but has practical use in conveniently modeling defaults involving fuzzy truth values in dynamic domains. For example, consider modeling dynamics of trust in social network. People trust each other in different degrees under some normal assumptions. If person A trusts another person B, then A tends to trust person C whom B trusts

to a degree which is positively correlated to the degree to which A trusts B and the degree to which B trusts C. If nothing happens, the trust degrees would not change. But there may be less trust between two people when a conflict arises between them. Modeling such a domain requires expressing defaults involving fuzzy truth values. We demonstrate that such examples can be conveniently modelled in our proposed language by taking advantage of its generality over the existing approaches to fuzzy ASP.

The paper is organized as follows. Section 2 reviews the syntax and the semantics of fuzzy propositional logic we discuss in the paper, as well as the stable model semantics of classical propositional formulas. Section 3 presents the stable model semantics of fuzzy propositional formulas along with examples, followed by Section 4 that formalizes the trust example above in the proposed language. Section 5 shows how the fuzzy stable model semantics is related to the Boolean stable model semantics, and Section 6 shows how our fuzzy stable model semantics is related to other approaches to fuzzy ASP. Section 7 shows that several well-known properties of the Boolean stable model semantics can be easily extended to our fuzzy stable model semantics.

2 Preliminaries

2.1 Review: Stable Models of Classical Propositional Formulas

We review the definition of a stable model from [5] by limiting attention to the syntax of propositional formulas. Instead of defining stable models in terms of second-order logic as in [5], we express the same concept using auxiliary atoms that do not belong to the original signature. This slight reformulation will simplify our efforts in extending the stable model semantics to fuzzy propositional formulas without resorting to "second-order fuzzy logic."

Let σ be a classical propositional signature, $\mathbf{p}=(p_1,\ldots,p_n)$ be a list of distinct atoms belonging to σ , and let $\mathbf{q}=(q_1,\ldots,q_n)$ be a list of new propositional atoms not in σ .

For two interpretations I and J of σ , $I \cup J_{\mathbf{q}}^{\mathbf{p}}$ denotes the interpretation of $\sigma \cup \mathbf{q}$ that agrees with I and J on all atoms not in $\mathbf{p} \cup \mathbf{q}$, and

```
- for each p \in \mathbf{p}, (I \cup J_{\mathbf{q}}^{\mathbf{p}})(p) = I(p);

- for each q \in \mathbf{q}, (I \cup J_{\mathbf{q}}^{\mathbf{p}})(q) = J(p).
```

For any classical propositional formula F of signature σ , $F^*(\mathbf{q})$ is a classical propositional formula of signature $\sigma \cup \mathbf{q}$ that is defined recursively as follows:

```
\begin{aligned} &-p_i^* = q_i \text{ for each } p_i \in \mathbf{p}; \\ &-F^* = F \text{ for any atom } F \not\in \mathbf{p}; \\ &-\bot^* = \bot; \quad \top^* = \top; \\ &-(\neg F)^* = \neg F; \\ &-(F \wedge G)^* = F^* \wedge G^*; \qquad (F \vee G)^* = F^* \vee G^*; \\ &-(F \rightarrow G)^* = (F^* \rightarrow G^*) \wedge (F \rightarrow G). \end{aligned}
```

 $^{^{1}}$ I(p) denotes the truth value of p under I. We identify a list with a set if there is no confusion.

Let I and J be two interpretations of σ , and let p be a subset of σ . We say $J \leq^{p} I$ if

- J and I agree on all atoms not in p, and
- for all $p \in \mathbf{p}$, if $J \models p$, then $I \models p$.

We say $J < \mathbf{p} I$ if $J \le \mathbf{p} I$ and $J \ne I$.

Definition 1. An interpretation I is a stable model of F relative to \mathbf{p} (denoted $I \models SM[F; \mathbf{p}]$)

- if $I \models F$, and
- there is no interpretation J such that $J < \mathbf{p} I$ and $I \cup J_{\mathbf{q}}^{\mathbf{p}} \models F^*(\mathbf{q})$.

Example 1. Consider a logic program

$$p \leftarrow not \ q, \quad q \leftarrow not \ p$$

which is understood as an alternative notation for propositional formula

$$F_1 = (\neg q \to p) \land (\neg p \to q).$$

 $F_1^*(u,v)$ is

$$(\neg q \to u) \land (\neg q \to p) \land (\neg p \to v) \land (\neg p \to q).$$

We check that $I_1 = \{p\}$ (that is, p is TRUE and q is FALSE) 2 is a stable model of F_1 (relative to $\{p,q\}$): I_1 satisfies F_1 , and \emptyset is the only interpretation J such that $J <^{pq} I_1$. However, $I_1 \cup J_{uv}^{pq} = \{p\}$ does not satisfy $F_1^*(u,v)$ because it does not satisfy the first conjunctive term of $F_1^*(u,v)$.

Similarly, we can check that $\{q\}$ is another stable model of F_1 .

2.2 Review: Fuzzy Logic

Let σ be a fuzzy propositional signature, which is a set of symbols called *fuzzy atoms*. In addition, we assume the presence of a set $\mathbb C$ of fuzzy conjunction symbols, a set $\mathbb D$ of fuzzy disjunction symbols, a set $\mathbb N$ of fuzzy negation symbols, and a set $\mathbb I$ of fuzzy implication symbols.

A fuzzy (propositional) formula of σ is defined recursively as follows.

- every fuzzy atom $p \in \sigma$ is a fuzzy formula;
- every numeric constant \overline{c} where c is a real number in [0,1] is a formula;
- if F is a formula, then $\neg F$ is a formula, where $\neg \in \mathbb{N}$;
- if F and G are formulas, then $F\otimes G$, $F\oplus G$ and $F\to G$ are formulas, where $\otimes\in\mathbb{C},\oplus\in\mathbb{D}$, and $\to\in\mathbb{I}$.

² We identify a propositional interpretation with the set of atoms that are true in it.

4 Joohyung Lee and Yi Wang

The models of a fuzzy formula are defined as follows [2]. The *fuzzy truth values* are the real numbers in the range [0,1]. A *fuzzy interpretation* I of σ is a mapping from σ into [0,1].

The fuzzy operators are functions mapping one or two truth values into a truth value. Among the operators, \neg denotes a function from [0,1] into [0,1]; \otimes , \oplus , and \rightarrow denote functions from $[0,1] \times [0,1]$ into [0,1]. The actual mapping performed by each operator can be defined in many different ways, but all of them satisfy the following conditions, which imply that they are generalizations of the corresponding classical propositional connectives:³

- a fuzzy negation \neg is decreasing, and satisfies $\neg(0) = 1$ and $\neg(1) = 0$;
- a fuzzy conjunction \otimes is increasing, commutative, associative, and $\otimes(1,x)=x$ for all $x\in[0,1]$;
- a fuzzy disjunction \oplus is increasing, commutative, associative, and $\oplus (0,x)=x$ for all $x\in [0,1];$
- a fuzzy implication \rightarrow is decreasing in its first argument and increasing in its second argument; and $\rightarrow (1, x) = x$ and $\rightarrow (0, 0) = 1$ for all $x \in [0, 1]$.

T. 1	1 1 1 /			C	operators	.1 .		•	.1 .	
Highira	licte	come	CHACITIC	T11771	Onergiore	that	1110 HC	2 1n	thic	naner
I IZUIC I	LHSIS	SOILIC	SUCCINC	IUZZV	oberators	mai	wc us	_ 111	ums	Daber.

Symbol	Name	Definition				
\otimes_l	Łukasiewicz t-norm	$\otimes_l(x,y) = max(x+y-1,0)$				
$\oplus \iota$	Łukasiewicz t-conorm	$\bigoplus_{l}(x,y) = min(x+y,1)$				
\otimes_m	minimum t-norm	$\otimes_m(x,y) = min(x,y)$				
\oplus_m	maximum t-conorm	$\oplus_m(x,y) = max(x,y)$				
\otimes_p	product t-norm	$\otimes_p(x,y) = x \cdot y$				
\oplus_p	product t-conorm	$\bigoplus_{p}(x,y) = x + y - x \cdot y$				
\neg_s	standard negator	$\neg_{s}(x) = 1 - x$				
\rightarrow_r	the residual implicator of \oplus_m	$\rightarrow_r (x, y) = \begin{cases} 1 & \text{if } x \le y \\ y & \text{otherwise} \end{cases}$				
\rightarrow_s	the S-implicator induced by \neg_s and \oplus_m					

Fig. 1. Some t-norms, t-conorms, negator, and implicators

The *truth value* of a formula F under I, denoted F^I , is defined recursively as follows:

```
 \begin{array}{l} \textbf{-} \mbox{ for any atom } p \in \sigma, \ p^I = I(p); \\ \textbf{-} \mbox{ for any numeric constant } \overline{c}, \overline{c}^I = c; \\ \textbf{-} \mbox{ } (\neg F)^I = \neg (F^I); \\ \textbf{-} \mbox{ } (F \otimes G)^I = \otimes (F^I, G^I); \ (F \oplus G)^I = \oplus (F^I, G^I); \ (F \to G)^I = \to (F^I, G^I). \end{array}
```

³ We say that a function f of arity n is increasing in its i-th argument $(1 \le i \le n)$ if $f(arg_1, \ldots, arg_i, \ldots, arg_n) \le f(arg_1, \ldots, arg_i', \ldots, arg_n)$ for all arguments such that $arg_i \le arg_i'$; f is said to be increasing if it is increasing in all its arguments. The definition of decreasing is similar.

(For simplicity, we identify the symbols for the fuzzy operators with the truth value functions represented by them.)

Definition 2. We say that a fuzzy interpretation I satisfies a fuzzy formula F w.r.t. a threshold $y \in [0,1]$ if $F^I \geq y$, and denote it by $I \models_y F$. We call I a fuzzy y-model of F.

We often omit the threshold y when it is 1.

3 Definition and Examples

We extend the notion of $J <^{\mathbf{p}} I$ in Section 2.1 as follows. For any two fuzzy interpretations J and I of the same signature σ and any subset \mathbf{p} of σ , we say $J \leq^{\mathbf{p}} I$ if

```
- J and I agree on all fuzzy atoms not in p, and
```

```
- for all p \in \mathbf{p}, p^J \leq p^I.
```

We say $J < {}^{\mathbf{p}} I$ if $J \le {}^{\mathbf{p}} I$ and $J \ne I$.

As before, we assume a list \mathbf{q} of new, distinct fuzzy atoms, and define $I \cup J_{\mathbf{q}}^{\mathbf{p}}$ in the same way. That is, $I \cup J_{\mathbf{q}}^{\mathbf{p}}$ denotes the interpretation of $\sigma \cup \mathbf{q}$ that agrees with I and J on all atoms not in $\mathbf{p} \cup \mathbf{q}$, and

```
 \begin{array}{l} \textbf{-} \ \ \text{for each} \ p \in \mathbf{p}, \ (I \cup J^{\mathbf{p}}_{\mathbf{q}})(p) = I(p); \\ \textbf{-} \ \ \text{for each} \ q \in \mathbf{q}, \ (I \cup J^{\mathbf{p}}_{\mathbf{q}})(q) = J(p). \end{array}
```

The definition of F^* is also extended in a straightforward way: For any fuzzy formula F of signature σ , $F^*(\mathbf{q})$ is defined as follows.

```
\begin{array}{l} -\ p_i^*=q_i \ \text{for each} \ p_i\in \mathbf{p};\\ -\ F^*=F \ \text{for any atom} \ F\not\in \mathbf{p};\\ -\ \overline{c}^*=\overline{c} \ \text{for any numeric constant} \ \overline{c};\\ -\ (\neg F)^*=\neg F;\\ -\ (F\otimes G)^*=F^*\otimes G^*;\qquad (F\oplus G)^*=F^*\oplus G^*;\\ -\ (F\to G)^*=(F^*\to G^*)\otimes_m (F\to G). \end{array}
```

Definition 3. An interpretation I is a y-stable model of F relative to \mathbf{p} (denoted $I \models_y SM[F; \mathbf{p}]$) if

```
- I \models_y F, and
```

- there is no interpretation J such that $J < \mathbf{p} I$ and $I \cup J_{\mathbf{q}}^{\mathbf{p}} \models_{y} F^{*}(\mathbf{q})$.

We often omit the threshold y when it is 1, and omit \mathbf{p} if it contains all atoms in σ . Clearly, when \mathbf{p} is empty, Definition 3 reduces to the definition of a fuzzy model in Definition 2 because there is no J such that $J <^{\emptyset} I$.

Also, Definition 3 is very similar to the definition of a stable model for classical propositional formulas in Definition 1. The main difference is that simply in the latter, atoms may have various degrees of truth, and accordingly the notion of $J <^{\mathbf{p}} I$ is more general. The precise relationship between the definitions is discussed in Section 5.

Example 2. Consider the formula $F = \neg_s p \rightarrow_r q$ and the interpretation $I = \{(p,0), (q,0.6)\}$. $F^*(u,v)$ is

$$((\neg_s p)^* \to_r q^*) \otimes_m (\neg_s p \to_r q) = (\neg_s p \to_r v) \otimes_m (\neg_s p \to_r q).$$

 $I \models_{0.6} SM[F; p, q]$. First, it is easy to see that $I \models_{0.6} F$, as

$$F^{I} = \rightarrow_{r} ((\neg_{s}p)^{I}, q^{I}) = \rightarrow_{r} (1 - p^{I}, q^{I}) = \rightarrow_{r} (1, 0.6) = 0.6.$$

Suppose there exists $J<^{pq}I$ such that $I\cup J^{pq}_{uv}\models_{0.6}F$, i.e.,

$$\begin{split} F^*(u,v)^{I \cup J^{pq}_{uv}} &= \min \left(\rightarrow_r (\lnot_s(p^I), v^{J^{pq}_{uv}}), \rightarrow_r (\lnot_s(p^I), q^I) \right) \\ &= \min \left(\rightarrow_r (1, v^{J^{pq}_{uv}}), 0.6 \right) \\ &= \min \left(v^{J^{pq}_{uv}}, 0.6 \right) \geq 0.6. \end{split}$$

So $v^{J^{pq}_{uv}} \geq 0.6$. Since $v^{J^{pq}_{uv}} \leq q^I = 0.6$, we conclude that $v^{J^{pq}_{uv}} = 0.6$. However, this contradicts the assumption that $J <^{pq} I$. Therefore, such J does not exist, and I is a 0.6-stable model of F.

Example 3. p and $\neg_s \neg_s p$ have the same fuzzy models, but their stable models are different. This is similar to the fact that p and $\neg \neg p$ have different stable models according to the semantics from [5].

Clearly, any interpretation $I = \{(p,y)\}$, where y is any positive real number in [0,1], is a y-stable model of p relative to $\{p\}$. On the other hand, $I = \{(p,y)\}$ is not a y-stable model of $F = \neg_s \neg_s p$ relative to $\{p\}$. Formula $F^*(q)$ is $\neg_s \neg_s F$, and although $I \models_y F$, we have $I \cup J_p^p \models_y F^*(q)$ regardless of any J.

Example 4. Let $F_1 = p \to_s p$ and $F_2 = \neg_s p \oplus_m p$. Their fuzzy models are the same, but their stable models are not. This is similar to the relation between $p \to p$ and $\neg p \lor p$ in the Boolean stable model semantics. Indeed, observe that $F_1^*(q) = (p \to_s p) \otimes_m (q \to_s q)$ and $F_2^*(q) = \neg_s p \oplus_m q$.

The interpretation $I = \{(p, 1)\}$ is not a 1-stable model of F_1 relative to p, as witnessed by $J = \{(p, 0)\}$. However, I is a 1-stable model of F_2 relative to p: for any J_q^p ,

$$F_2^*(q)^{I\cup J_q^p} = \max\left(1-p^I,q^{J_q^p}\right) = \max\left(0,q^{J_q^p}\right) = q^{J_q^p}.$$

So, for $I \cup J_q^p$ to satisfy $F_2^*(q)$ to degree 1, $q^{J_q^p}$ should be 1, or equivalently, p^J should be 1. Consequently, it is not possible to have $J <^p I$.

The following example illustrates how the commonsense law of inertia involving fuzzy truth values can be represented.

Example 5. Let σ be $\{p, \sim p, q, \sim q\}^4$ and let F be $F_1 \otimes_m F_2$, where F_1 represents that p and $\sim p$ are complementary, i.e., the sum of their truth values is 1:

$$F_1 = \neg_s(p \otimes_l \sim p) \otimes_m \neg_s \neg_s(p \oplus_l \sim p).$$

 $^{^4}$ Note that \sim is not a connective; it is just a part of the symbol representing an atom.

 F_2 represents that by default p has the truth value of q, and $\sim p$ has the truth value of $\sim q$:

$$F_2 = ((q \otimes_m \neg_s \neg_s p) \to_r p) \otimes_m ((\sim q \otimes_m \neg_s \neg_s \sim p) \to_r \sim p).$$
 Let $\mathbf{p} = \{p, \sim p\}$ and $\mathbf{u} = \{u, \sim u\}. F^*(\mathbf{u})$ is
$$\neg_s (p \otimes_l \sim p) \otimes_m \neg_s \neg_s (p \oplus_l \sim p) \\ \otimes_m ((q \otimes_m \neg_s \neg_s p) \to_r u) \otimes_m ((q \otimes_m \neg_s \neg_s p) \to_r p) \\ \otimes_m ((\sim q \otimes_m \neg_s \neg_s \sim p) \to_r \sim u) \otimes_m ((\sim q \otimes_m \neg_s \neg_s \sim p) \to_r \sim p).$$

One can check that the interpretation $I_1 = \{(p,x), (\sim p, 1-x), (q,x), (\sim q, 1-x)\}$ (x is any value in [0,1]) is a 1-stable model of F relative to $(p,\sim p)$; The interpretation $I_2 = \{(p,y), (\sim p, 1-y), (q,x), (\sim q, 1-x)\}$, where y > x, is not. Similarly, if y < x, I_2 is not a 1-stable model of F relative to $(p,\sim p)$.

On the other hand, if we conjoin F with $\overline{y} \to_r p$ to yield $F \otimes_m (\overline{y} \to_r p)$, then the default behavior is overridden, and I_2 is a 1-stable model of $F \otimes_m (\overline{y} \to_r p)$ relative to $(p, \sim p)$.

This behavior is useful in expressing the commonsense law of inertia involving fuzzy values. Suppose q represents some fluent at time t, and p represents the fluent at time t+1. Then F states that, "by default, the fluent retains the previous value." The default value is overridden if there is an action that sets p to a different value.

4 Further Examples

The trust example in the introduction can be formalized in the fuzzy stable model semantics as follows. Below x, y, z are schematic variables ranging over people, and t is a schematic variable ranging over time steps. Trust(x,y,t) is a fuzzy atom representing that "x trusts y at time t." Similarly, Distrust(x,y,t) is a fuzzy atom representing that "x distrusts y at time t."

The trust relation is reflexive:

$$F_1 = Trust(x, x, t).$$

The trust and distrust degrees are complementary, i.e., their sum is 1 (similar to Example 5):

$$F_2 = \neg_s(Trust(x, y, t) \otimes_l Distrust(x, y, t)),$$

$$F_3 = \neg_s \neg_s(Trust(x, y, t) \oplus_l Distrust(x, y, t)).$$

Initially, if x trusts y to degree d_1 and y trusts z to degree d_2 , then x trusts z to degree $d_1 \times d_2$; further the initial distrust degree is 1 minus the initial trust degree.

$$\begin{aligned} F_4 &= \mathit{Trust}(x,y,0) \otimes_p \mathit{Trust}(y,z,0) \to_r \mathit{Trust}(x,z,0), \\ F_5 &= \neg_s \mathit{Trust}(x,y,0) \to_r \mathit{Distrust}(x,y,0). \end{aligned}$$

The inertia assumption (similar to Example 5):

$$F_6 = Trust(x, y, t) \otimes_m \neg_s \neg_s Trust(x, y, t+1) \rightarrow_r Trust(x, y, t+1),$$

$$F_7 = Distrust(x, y, t) \otimes_m \neg_s \neg_s Distrust(x, y, t+1) \rightarrow_r Distrust(x, y, t+1).$$

A conflict increases the distrust degree by the conflict degree:

```
F_8 = Conflict(x, y, t) \oplus_l Distrust(x, y, t) \rightarrow_r Distrust(x, y, t+1),

F_9 = \neg_s(Conflict(x, y, t) \oplus_l Distrust(x, y, t)) \rightarrow_r Trust(x, y, t+1).
```

Let F_{TW} be $F_1 \otimes_m F_2 \otimes_m \cdots \otimes_m F_9$. Suppose we have the formula $F_{Fact} = Fact_1 \otimes_m Fact_2$ that gives the initial trust degree.

$$Fact_1 = \overline{0.8} \rightarrow_r Trust(Alice, Bob, 0),$$

 $Fact_2 = \overline{0.7} \rightarrow_r Trust(Bob, Carol, 0).$

Although there is no fact about how much *Alice* trusts *Carol*, any 1-stable model of $F_{TW} \otimes_m F_{Fact}$ assigns value 0.56 to the atom Trust(Alice, Carol, 0). On the other hand, the 1-stable model assigns value 0 to Trust(Alice, David, 0) due to the closed world assumption under the stable model semantics.

When we conjoin $F_{TW} \otimes F_{Fact}$ with $\overline{0.2} \to Conflict(Alice, Carol, 0)$, the 1-stable model of $F_{TW} \otimes_m F_{Fact} \otimes_m (\overline{0.2} \to Conflict(Alice, Carol, 0))$, manifests that the trust degree between Alice and Carol decreases to 0.36 at time 1. More generally, if we have more actions that change the trust degree in various ways, by specifying the entire history of actions, we can determine the evolution of the trust distribution among all the participants. Useful decisions can be made based on this information. For example, Alice may decide not to share her personal pictures to those whom she trusts less than degree 0.48.

Note that this example, like Example 5, uses nested connectives, such as $\neg_s \neg_s$, that are not available in previous fuzzy ASP semantics, such as [3, 4].

5 Relation to Boolean-Valued Stable Models

The Boolean stable model semantics in Section 2.1 can be embedded into the fuzzy stable model semantics as follows:

For any classical propositional formula F, define F^{fuzzy} to be the fuzzy propositional formula obtained from F by replacing \bot with $\overline{0}$, \top with $\overline{1}$, \neg with \neg_s , \wedge with \otimes_m , \vee with \oplus_m , and \rightarrow with \rightarrow_s . We identify the signature of F^{fuzzy} with the signature of F. Also, for any interpretation I, we define the corresponding fuzzy interpretation I^{fuzzy} as

```
- I^{fuzzy}(p) = 1 if I(p) = \text{TRUE};
- I^{fuzzy}(p) = 0 otherwise.
```

The following theorem tells us that the Boolean-valued stable model semantics can be viewed as a special case of the fuzzy stable model semantics.

Theorem 1 For any classical propositional formula F and any classical propositional interpretation I, I is a stable model of F relative to \mathbf{p} iff I^{fuzzy} is a 1-stable model of F^{fuzzy} relative to \mathbf{p} .

Example 6. Let F be the classical propositional formula $\neg p \to q$. F has only one stable model $I = \{q\}$. Clearly $I^{fuzzy} = \{(p,0),(q,1)\}$ is a 1-stable model of $F^{fuzzy} = \neg_s p \to_s q$.

Theorem 1 does not hold for an arbitrary choice of operators, as illustrated by the following example.

Example 7. Let F be the classical propositional formula $p \vee p$. Classical interpretation $I = \{p\}$ is a stable model of F. However, $I^{fuzzy} = \{(p,1)\}$ is not a stable model of $F' = p \oplus_l p$ because there is $J = \{(p,0.5)\}$ such that $I \cup J_q^p \models_1 q \oplus_l q$.

However, one direction of Theorem 1 holds for arbitrary choice of fuzzy operators.

Theorem 2 For any classical propositional formula F, let F_1^{fuzzy} be the formula obtained from F by replacing \bot with $\overline{0}$, \top with $\overline{1}$, \neg with any fuzzy negation symbol, \wedge with any fuzzy conjunction symbol, \vee with any fuzzy disjunction symbol, and \rightarrow with any fuzzy implication symbol. For any classical propositional interpretation I, if I^{fuzzy} is a 1-stable model of F_1^{fuzzy} relative to \mathbf{p} , then I is a stable model of F relative to \mathbf{p} .

6 Relation to Other Approaches to Fuzzy ASP

6.1 Relation to Stable Models of Normal FASP Programs

A normal FASP program is a finite set of rules of the form

$$a \leftarrow b_1 \otimes \ldots \otimes b_m \otimes \neg b_{m+1} \otimes \ldots \otimes \neg b_n$$

where $n \ge m \ge 0$, a, b_1, \dots, b_n are fuzzy atoms or numeric constants in [0, 1], and \otimes is any fuzzy conjunction. We identify the rule with the fuzzy implication

$$b_1 \otimes \ldots \otimes b_m \otimes \neg_s b_{m+1} \otimes \ldots \otimes \neg_s b_n \rightarrow_r a.$$

We say that a fuzzy interpretation I of signature σ satisfies a rule R if $R^I=1$. I satisfies an FASP program Π if $I\models R$ for every rule R in Π . According to [3], an interpretation I is a fuzzy answer set of a normal FASP program Π if I satisfies Π , and no interpretation J such that $J<^\sigma I$ satisfies the reduct of Π w.r.t. I, which is the program obtained from Π by replacing each negative literal $\neg b$ with the constant for $1-b^I$.

Theorem 3 For any normal FASP program $\Pi = \{r_1, ..., r_n\}$, let F be the formula $r_1 \otimes_m ... \otimes_m r_n$. An interpretation I is a fuzzy answer set of Π in the sense of [3] if and only if I is a 1-stable model of F.

Example 8. Let Π be the following program

$$p \leftarrow \neg q, \quad q \leftarrow \neg p.$$

The answer sets of Π according to [3] are $\{(p,x),(q,1-x)\}$, where x is any value in [0,1]: the corresponding fuzzy formula F is $(\neg_s q \rightarrow_r p) \otimes_m (\neg_s p \rightarrow_r q)$; $F^*(u,v)$ is

$$F \otimes_m ((\neg_s q \to_r u) \otimes_m (\neg_s p \to_r v)).$$

One can check that the 1-stable models of F are also $\{(p,x),(q,1-x)\}$, where $x\in[0,1]$.

6.2 Relation to Fuzzy Equilibrium Logic

Like our fuzzy stable model semantics, fuzzy equilibrium logic [6] generalizes fuzzy ASP programs to arbitrary propositional formulas, but its definition is highly complex. Nonetheless we show that if we disregard strong negation considered there, fuzzy equilibrium logic is essentially equivalent to the fuzzy stable model semantics where the threshold is set to 1 and all atoms are subject to minimization.⁵

We review the definition of fuzzy equilibrium logic in the absence of strong negation. For any fuzzy propositional signature σ , a (fuzzy N5) valuation is a mapping from $\{h,t\}\times\sigma$ to subintervals of [0,1] such that $V(t,a)\subseteq V(h,a)$ for each atom $a\in\sigma$. For V(w,a)=[u,v], where $w\in\{h,t\}$, we write $V^-(w,a)$ to denote the lower bound u and $V^+(w,a)$ to denote the upper bound v. The truth value of a formula under V is defined as follows.

```
 \begin{array}{l} -\ V(w,\overline{c}) = [c,\ c] \ \text{for any numeric constant } \overline{c}; \\ -\ V(w,F\otimes G) = [V^-(w,F)\otimes V^-(w,G),\ V^+(w,F)\otimes V^+(w,G)]; \ ^6 \\ -\ V(w,F\oplus G) = [V^-(w,F)\oplus V^-(w,G),\ V^+(w,F)\oplus V^+(w,G)]; \\ -\ V(h,\neg F) = [1-V^-(t,F),\ 1-V^-(h,F)]; \\ -\ V(t,\neg F) = [1-V^-(t,F),\ 1-V^-(t,F)]; \\ -\ V(h,F\to G) = [\min(V^-(h,F)\to V^-(h,G),V^-(t,F)\to V^-(t,G)),\ V^-(h,F)\to V^+(h,G)]; \\ -\ V(t,F\to G) = [V^-(t,F)\to V^-(t,G),\ V^-(t,F)\to V^+(t,G)]. \end{array}
```

A valuation V is a (fuzzy N5) model of a formula F if $V^-(h,F)=1$, which implies $V^+(h,F)=V^-(t,F)=V^+(t,F)=1$. For two valuations V and V', we say $V' \preceq V$ if V'(t,a)=V(t,a) and $V(h,a)\subseteq V'(h,a)$ for all atoms a. We say $V' \prec V$ if $V' \preceq V$ and $V' \neq V$. We say that a model V of V' is V' if there is no model V' of V' such that $V' \prec V$. An h-minimal fuzzy N5 model V' of V' is a fuzzy equilibrium model of V' if V' is a fuzzy equilibrium V' if V'

For two fuzzy interpretations I, J of signature σ such that $J \leq^{\sigma} I$, define the N5 fuzzy valuation $V_{J,I}$ as $V_{J,I}(h,a) = \begin{bmatrix} a^J,1 \end{bmatrix}, V_{J,I}(t,a) = \begin{bmatrix} a^I,1 \end{bmatrix}$ for all atoms a in σ . Since $J \leq^{\sigma} I$, we have $a^J \leq a^I$, and $V_{J,I}(t,a) \subseteq V_{J,I}(h,a)$ for all atoms a.

As in [6], we assume that the fuzzy negation \neg is \neg_s .

The following proposition relates the notions used in the fuzzy equilibrium models and the fuzzy stable models.

```
Proposition 1 (a) I \models_1 F if and only if V_{I,I} is a model of F.

(b) For \mathbf{p} = \sigma, I \cup J^{\mathbf{p}}_{\mathbf{q}} \models_1 F^*(\mathbf{q}) if and only if V_{J,I} is a model of F.

(c) For two interpretations I and J, we have V_{J,I} \prec V_{I,I} if and only if J < I.
```

The theorem below shows that the fuzzy stable model semantics can be reduced to fuzzy equilibrium logic semantics.

Theorem 4 For any fuzzy formula F (that contains no strong negation) and any fuzzy interpretation I, I is a 1-stable model of F if and only if $V_{I,I}$ is a fuzzy equilibrium model of F.

⁵ Strong negation can be simulated in our semantics using new atoms as illustrated in Example 5.

⁶ For readability, we write the infix notation $(x \odot y)$ in place of $\odot(x, y)$.

Next we show the other direction, i.e., reducing fuzzy equilibrium logic to the fuzzy stable model semantics. For any valuation V, define the fuzzy interpretation I_V as $a^{I_V} = V^-(h,a)$ for all atoms a.

Theorem 5 For any fuzzy formula F (that contains no strong negation) and any valuation V, we have that V is an equilibrium model of F if and only if

- (i) $V^{+}(h, a) = V^{+}(t, a) = 1$ for all atoms a, and
- (ii) I_V is a 1-stable model of F relative to σ .

Theorem 5 tells us that in the absence of strong negation, the upper bounds of both worlds in any equilibrium model are always 1.

7 Properties of Fuzzy Stable Models

In this section, we show that several well-known properties of the Boolean stable model semantics can be naturally extended to the fuzzy stable model semantics.

7.1 Alternative Definition of F^*

Proposition 2 For any fuzzy formula F and any fuzzy interpretations I, J with $J \leq^{\mathbf{p}} I$,

```
-I \cup J_{\mathbf{q}}^{\mathbf{p}} \models_{y} \neg F^{*}(\mathbf{q}) \otimes_{m} \neg F \quad iff \quad I \cup J_{\mathbf{q}}^{\mathbf{p}} \models_{y} \neg F.
-I \cup J_{\mathbf{q}}^{\mathbf{p}} \models_{y} (F^{*} \otimes G^{*})(\mathbf{q}) \otimes_{m} (F \otimes G) \quad iff \quad I \cup J_{\mathbf{q}}^{\mathbf{p}} \models_{y} (F^{*} \otimes G^{*})(\mathbf{q}).
-I \cup J_{\mathbf{q}}^{\mathbf{p}} \models_{y} (F^{*} \oplus G^{*})(\mathbf{q}) \otimes_{m} (F \oplus G) \quad iff \quad I \cup J_{\mathbf{q}}^{\mathbf{p}} \models_{y} (F^{*} \oplus G^{*})(\mathbf{q}).
```

This proposition tells us that F^* in Section 3 can be equivalently defined by treating the fuzzy operators in the uniform way:

```
- (\neg F)^* = \neg F^* \otimes_m \neg F;

- (F \odot G)^* = (F^* \odot G^*) \otimes_m (F \odot G) for any binary operator \odot.
```

7.2 Theorem on Constraints

In answer set programming, constraints—rules with \bot in the head—play an important role in view of the fact that adding a constraint eliminates the stable models that "violate" the constraint. The following theorem is the counterpart of Theorem 3 from [5] for fuzzy propositional formulas.

Theorem 6 For any fuzzy formulas F and G, I is a 1-stable model of $F \otimes \neg G$ (relative to \mathbf{p}) if and only if I is a 1-stable model of F (relative to \mathbf{p}) and $I \models_{\mathbf{1}} \neg G$.

Example 9. Consider $F = (\neg_s p \to_r q) \otimes_m (\neg_s q \to_r p) \otimes_m \neg_s p$. Formula F has only one 1-stable model $I = \{(p,0), (q,1)\}$, which is the only 1-stable model of $(\neg_s p \to_r q) \otimes_m (\neg_s q \to_r p)$ that satisfies $\neg_s p$ to degree 1.

If we consider a more general y-stable model, then only one direction holds.

Theorem 7 For any fuzzy formulas F and G, if I is a y-stable model of $F \otimes \neg G$ (relative to \mathbf{p}), then I is a y-stable model of F (relative to \mathbf{p}) and $I \models_y \neg G$.

Example 10. The other direction, that is, "if I is a y-stable model of F and $I \models_y \neg G$, then I is a y-stable model of $F \otimes \neg G$," does not hold in general. For example, consider F = G = p and \otimes to be \otimes_l , and interpretation $I = \{(p, 0.4)\}$. Clearly I is a 0.4-stable model of p and $I \models_{0.4} \neg p$, but I is not a 0.4-stable model of $p \otimes_l \neg p$. In fact, I is not even a 0.4-model of the formula.

7.3 Theorem on Choice Formulas

In the Boolean stable model semantics, formulas of the form $p \lor \neg p$ are called *choice formulas*, and adding them to the program makes atoms p exempt from minimization. Choice formulas have been shown to be useful in composing a program in the "Generate-and-Test" method. This section shows their counterpart in the fuzzy stable model semantics.

For any fuzzy atom p, Choice(p) stands for $p \oplus_l \neg_s p$. For any list $\mathbf{p} = (p_1, \dots p_n)$ of fuzzy atoms, $Choice(\mathbf{p})$ stands for

$$Choice(p_1) \otimes \ldots \otimes Choice(p_n),$$

where \otimes is any fuzzy conjunction.

The following proposition tells that choice formulas are tautological.

Proposition 3 For any fuzzy interpretation I and any list \mathbf{p} of fuzzy atoms, $I \models_1 Choice(\mathbf{p})$.

Theorem 8 is an extension of Theorem 2 from [5].

Theorem 8 (a) If I is a y-stable model of F relative to $\mathbf{p} \cup \mathbf{q}$, then I is a y-stable model of F relative to \mathbf{p} .

(b) I is a 1-stable model of F relative to \mathbf{p} iff I is a 1-stable model of $F \otimes Choice(\mathbf{q})$ relative to $\mathbf{p} \cup \mathbf{q}$.

Theorem 8 (b) does not hold for arbitrary threshold y (i.e., if "1—" is replaced with "y—"). For example, consider $F = \neg_s \neg_s q$ and $I = \{(q, 0.5)\}$. Clearly I is a 0.5-model of F, and thus I is a 0.5-stable model of F relative to \emptyset . However, I is not a 0.5-stable model of $F \otimes_m Choice(q) = \neg_s \neg_s q \otimes_m (q \oplus_l \neg_s q)$ relative to $\emptyset \cup \{q\}$, as witnessed by $J = \{(q, 0)\}$.

Since the 1-stable models of F relative to \emptyset are the models of F, it follows from Theorem 8 (b) that the 1-stable models of $F \otimes Choice(\sigma)$ relative to σ are exactly the 1-models of F.

Corollary 1 *Let* F *be a formula of a finite signature* σ . I *is a* 1-model of F *relative to* σ *iff* I *is a* 1-stable model of $F \otimes Choice(\sigma)$.

Example 11. Consider the formula $F = \neg_s p \to_r q$. Although any interpretation I that satisfies $1 - p^I \le q^I$ is a 1-model of F, among them only $\{(p,0),(q,1)\}$ is a 1-stable

model of F. However, we check that all 1-models of F are exactly the 1-stable models of $G = F \otimes_m Choice(p) \otimes_m Choice(q)$: $G^*(u, v)$ is

$$(\neg_s p \to_r q) \otimes_m (\neg_s p \to_r v) \otimes_m (u \oplus_l \neg_s p) \otimes_m (v \oplus_l \neg_s q)$$

and for $K = I \cup J_{uv}^{pq}$,

$$G^*(u, v)^K = 1 \otimes_m ((1 - p^K) \to_r v^K) \otimes_m (u^K \oplus_l (1 - p^K)) \otimes_m (v^K \oplus_l (1 - q^K)).$$

So, for K to satisfy $G^*(u,v)$ to degree $1, u^K$ should be at least p^K and v^K should be at least q^K . So there does not exist $J <^{pq} I$ such that $I \cup J_{uv}^{pq} \models_1 G^*(u,v)$, from which it follows that I is a 1-stable model of G.

8 Conclusion

We introduced a general stable model semantics for fuzzy propositional formulas, which generalizes both the Boolean stable model semantics and fuzzy propositional logic. The syntax is the same as the syntax of fuzzy propositional logic, but the semantics defines *stable models* instead of *models*. The formalism allows highly configurable default reasoning involving fuzzy truth values. Our semantics, when we restrict threshold to be 1 and assume all atoms to be subject to minimization, is equivalent to fuzzy equilibrium logic in the absence of strong negation, but is much more simpler. To the best of our knowledge, our representation of commonsense law of inertia involving fuzzy values is new. The representation uses nested fuzzy operators, which are not available in earlier fuzzy ASP semantics for a restricted syntax.

We showed that several traditional results in answer set programming can be naturally extended to this formalism, and expect that more results can be carried over. Future work includes implementing this language using mixed integer programming solvers or bilevel programming solvers [7].

Acknowledgements We are grateful to Joseph Babb, Michael Bartholomew, Enrico Marchioni, and the anonymous referees for their useful comments and discussions related to this paper. This work was partially supported by the National Science Foundation under Grant IIS-1319794 and by the South Korea IT R&D program MKE/KIAT 2010-TD-300404-001.

References

- Lifschitz, V.: What is answer set programming? In: Proceedings of the AAAI Conference on Artificial Intelligence, MIT Press (2008) 1594–1597
- 2. Hajek, P.: Mathematics of Fuzzy Logic. Kluwer (1998)
- Lukasiewicz, T.: Fuzzy description logic programs under the answer set semantics for the semantic web. In Eiter, T., Franconi, E., Hodgson, R., Stephens, S., eds.: RuleML, IEEE Computer Society (2006) 89–96
- Janssen, J., Vermeir, D., Schockaert, S., Cock, M.D.: Reducing fuzzy answer set programming to model finding in fuzzy logics. TPLP 12(6) (2012) 811–842
- Ferraris, P., Lee, J., Lifschitz, V.: Stable models and circumscription. Artificial Intelligence 175 (2011) 236–263
- Schockaert, S., Janssen, J., Vermeir, D.: Fuzzy equilibrium logic: Declarative problem solving in continuous domains. ACM Trans. Comput. Log. 13(4) (2012) 33
- 7. Alviano, M., Peñaloza, R.: Fuzzy answer sets approximations. TPLP 13(4-5) (2013) 753–767