HyFOM Reasoner: Hybrid Integration of Fuzzy Ontology and Mamdani Reasoning

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Keywords: Knowledge Representation and Reasoning, Fuzzy Ontology, Mamdani Fuzzy Inference System, Hybrid Reasoner.

Abstract: Some real-world applications require representation and reasoning regarding imprecise or vague information. In this context, the appropriate combination of fuzzy ontologies and Mamdani fuzzy inference systems can provide meaningful inferences involving fuzzy rules and numerical property values. In general, this knowledge is not obtained through typical fuzzy ontology reasoning and can be relevant for some ontology reasoning tasks that depend on numerical property values. To address this issue, this paper proposes the HyFOM reasoner, which provides a hybrid integration of fuzzy ontology and Mamdani reasoning. A real-world case study involving the domain of food safety is presented, including comparative results with a state-of-the-art fuzzy description logic reasoner.

1 INTRODUCTION

Many applications use ontologies to represent semantic information that can be shared among people, software agents and systems. In special, ontologies support not only representational primitives but also reasoning tasks that reveal meaningful knowledge.

However, there are some concepts whose meaning cannot be fully captured using conventional ontologies. For instance, it is difficult to model concepts like *creamy*, *dark*, *hot*, *large* and *thick*, for which a clear and precise definition is not possible, as they involve so-called fuzzy or vague concepts (Straccia, 2006). Thus, there is a need for extending ontologies with concepts from the fuzzy set theory (Zadeh, 1965) to represent and reason over imprecise or vague information.

In this sense, a number of fuzzy extensions of ontologies have been developed, as pointed out by (Lukasiewicz and Straccia, 2008). Some proposals have incorporated concepts related to fuzzy variables and linguistic terms, as they capture the vagueness inherent in some real-world situations. These concepts have been exploited by Mamdani Fuzzy Inference Systems (Mamdani FIS) (Mamdani and Assilian, 1975) to infer numerical outputs based on fuzzy variables and fuzzy rules. This well-known reasoning approach could be also employed in fuzzy ontology-based applications, providing numerical property values that are not inferred by typical fuzzy ontology reasoning. The inferred values could be considered in other fuzzy ontology reasoning tasks, e.g. the fuzzy instance check depending on specific property values.

Although some proposals have been developed towards the combination of fuzzy ontology and fuzzy rule reasoning, there are some issues to be considered. Fuzzy rule semantics and defuzzification methods should meet application requirements in order to obtain meaningful results. The set of fuzzy inferences should not be limited to fuzzy rule reasoning, since fuzzy ontology reasoners also provide relevant inferences regarding fuzzy concept knowledge. It is important to incorporate fuzzy rule inferences to the fuzzy ontology, as they may contribute to perform other fuzzy ontology reasoning tasks.

Focusing on the mentioned issues, this paper describes the HyFOM reasoner (*Hybrid Integration of Fuzzy Ontology and Mamdani reasoning*). It follows a hybrid architecture to integrate fuzzy ontologies and Mamdani rules aiming at providing meaningful inferences to fuzzy ontology-based applications. The HyFOM approach is explained as follows. Section 2 dis-

A. Yaguinuma C., C. P. Magalhães Jr. W., T. P. Santos M., A. Camargo H. and Reformat M..
HyFOM Reasoner: Hybrid Integration of Fuzzy Ontology and Mamdani Reasoning.
DOI: 10.5220/0004452803700378
In *Proceedings of the 15th International Conference on Enterprise Information Systems* (ICEIS-2013), pages 370-378
ISBN: 978-989-8565-59-4

cusses related work on the combination of fuzzy ontologies and fuzzy inference systems. Section 3 describes the main features of the HyFOM reasoner. A case study about the domain of food safety, including a comparison with a fuzzy description logic reasoner, is presented in Section 4. Finally, Section 5 concludes this paper and points out ongoing research.

2 RELATED WORK

In relation to the current approaches aiming to combine fuzzy ontologies and fuzzy inference systems, there are some issues that should be considered:

1. Does the semantics provided to represent and reason over fuzzy rules meet the application needs?
2. Are fuzzy rule inferences integrated to the fuzzy ontology so that they can contribute to other ontology reasoning tasks?
3. Does the application need to control the interaction between fuzzy ontology and fuzzy rule inferences?
4. Does the set of possible fuzzy inferences comprise both fuzzy ontology and fuzzy rule reasoning?

Some fuzzy ontology languages based on expressive fuzzy description logics, e.g. (Bobillo and Straccia, 2008; Bobillo and Straccia, 2009), provide implication operators that can be used to represent fuzzy rules. As described by (Guillaume and Charnomordic, 2012), these rules are called implicative rules, which are combined conjunctively. Nevertheless, such semantics can be too restrictive depending on the application, possibly resulting in knowledge base inconsistency even for allowed property values (question 1). Another approach provided by the fuzzyDL reasoner (Bobillo and Straccia, 2008) is representing fuzzy rules using fuzzy concept definitions along with a query interface to call defuzzification methods. However, the defuzzified output is not incorporated into the fuzzy ontology, unless explicitly done by application, affecting questions 2 and 3.

There are proposals that consider a *crisp* ontology integrated with Mamdani rules, as in (Bobillo et al., 2009; Wlodarczyk et al., 2010). In this context, an ontology reasoner is used for consistency checking regarding crisp definitions but the set of fuzzy inferences is limited to fuzzy rule reasoning (question 4).

Some studies (Lee et al., 2010; Huang et al., 2011) have adopted the *Fuzzy Markup Language* (FML) (Acampora and Loia, 2005) to express FIS-related information such as fuzzy rules, linguistic variables and fuzzy rule reasoning methods. OWL-FC (de Maio et al., 2012) also represents these elements with a high-level specification for fuzzy control systems that enables links to domain ontology concepts. In general, these proposals focus on fuzzy rule reasoning, mainly using the fuzzy ontology to represent a FIS knowledge base. Thus, their set of fuzzy inferences does not include fuzzy concept knowledge reasoning (question 4), provided by fuzzy ontology reasoners.

(Bragaglia et al., 2010) propose a hybrid architecture combining forward rules and fuzzy ontology reasoning. Although the set of fuzzy inferences covers both fuzzy ontological and fuzzy rule reasoning, their proposal does not exploit Mamdani reasoning neither defuzzification methods. As mentioned earlier, Mamdani FIS provides useful inferences that can complement the set of fuzzy inferences demanded by some applications, an issue related to question 1.

Aiming to deal with the discussed limitations, the HyFOM reasoner is described in Section 3, combining fuzzy ontology and Mamdani reasoning based on a hybrid architecture.

3 THE HyFOM REASONER

In this paper, the purpose of combining fuzzy ontology and fuzzy rule reasoning is providing expressive inferences that are not obtained through typical fuzzy ontology reasoning. Specifically, a Mamdani FIS can be used to infer numerical property values based on fuzzy rules combining different properties and their respective linguistic terms. In this sense, when applications require knowledge associated with a numerical property value, it can be inferred based on a Mamdani FIS by getting inputs from the fuzzy ontology. The inferred output is then returned to the ontology, possibly contributing to other fuzzy ontology reasoning tasks. Figure 1 presents a SADT diagram (Marca and McGowan, 1987) describing the HyFOM reasoner approach to integrate fuzzy ontology and Mamdani FIS reasoning.

According to Figure 1, the main inputs and controls of the HyFOM reasoner are *Mamdani rules* representing a Mamdani rule base; a *fuzzy ontology*; and an *individual* of the fuzzy ontology. The Mamdani rule base contains a set of rules combining numerical properties and linguistic terms in the antecedent (input properties) to infer the value of a property in the consequent (output property). An example of a Mamdani rule is: `If property1 is` *`high`* `and property2 is` *`medium`* `then property3 is` *`low`*, where *property1* and *property2* are input properties and *property3* is an output property, all of them described by linguistic terms (*high, medium* and *low*, respectively).

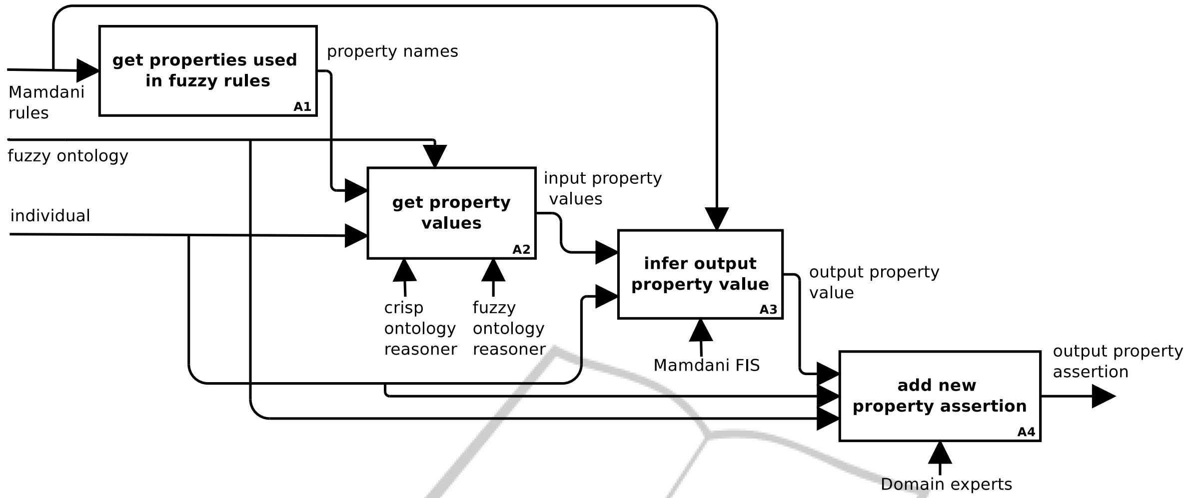

Figure 1: Main steps for integrating fuzzy ontology and Mamdani FIS reasoning with HyFOM reasoner.

The fuzzy ontology models a specific domain in terms of concepts, properties, relationships, instances and linguistic terms associated with numerical properties. The properties and linguistic terms used in Mamdani rules should be defined in the fuzzy ontology with equal names, for mapping purposes. Applications pass an individual of the fuzzy ontology to check if it has any property value that can be inferred based on Mamdani reasoning. If a class is passed as input, the integration approach is done for all its individuals.

The mechanisms (arrows at the bottom of activity boxes) are the resources required to complete a process, which may include people with particular skills and computational tools, according to the SADT specification. In the proposed approach, the mechanisms are inference engines and domain experts who supervise the outputs of the integration process. Following a hybrid architecture, inference engine implementations are reused, including a *crisp ontology reasoner*, a *fuzzy ontology reasoner* and a *Mamdani FIS*. The *crisp ontology reasoner* performs efficient query answering and reasoning related to crisp definitions and assertions in the ontology. The *fuzzy ontology reasoner* provides reasoning tasks regarding fuzzy definitions and assertions, such as fuzzy concept subsumption and fuzzy instance check. The *Mamdani FIS* is responsible to infer the value of a numerical property based on fuzzy rules and fuzzy operations.

The activity boxes presented in Figure 1 combine inputs, controls and mechanisms to produce outputs. In the activity A1, the HyFOM reasoner identifies which are the input and output properties used in Mamdani rules so that their values can be obtained from the fuzzy ontology. In the activity A2, the HyFOM reasoner firstly checks if the output property value for a particular individual can be obtained from the fuzzy ontology. If so, then the fuzzy ontology is able to provide its value thus there is no need to involve Mamdani rules. If not, the appropriate input property values should be obtained from the fuzzy ontology so that the Mamdani FIS can be invoked to infer the output property value.

Still in the activity A2, property values (either output or input) are obtained from the fuzzy ontology based on the following procedure. The crisp ontology reasoner is invoked to check if the property value is either asserted or inferred based on crisp definitions. The main reason for using a crisp ontology reasoner is due to its optimized access to assertions and conventional ontology reasoning tasks. Still, if property values cannot be obtained, the fuzzy ontology reasoner is invoked because fuzzy concept definitions and implications can support reasoning associated with property values. For example, a fuzzy concept definition such as $\texttt{C1} \equiv \exists \texttt{property1.high}$ along with an assertion $\texttt{C1}(\texttt{ind1})$ indicates that individual `ind1` has value `high` for `property1`. Thus, even if property values are not explicit, they may be inferred based on fuzzy ontology axioms and definitions. The inferred values can be crisp (a specific number) or fuzzy (a fuzzy set), depending on application preferences.

After the input values are obtained, the activity A3 invokes the Mamdani FIS to infer the corresponding output based on Mamdani rules. In the Mamdani FIS, the fuzzy operations considered are min-max composition, minimum for rule semantics and maximum for aggregation of outputs (Mamdani and Assilian, 1975). Several defuzzification methods are provided to obtain a numerical value from the aggregated fuzzy output, such as Center of Area (COA), Moment defuzzification and Mean of Maxima (MOM). Finally, a new property assertion associating the output property, the individual and the defuzzified value is added to the fuzzy ontology under domain expert supervision (activity A4). As a result, the output generated by Mamdani FIS will be available for other fuzzy ontology reasoning tasks that may depend on it.

The HyFOM reasoner was implemented using reasoners and frameworks available for fuzzy ontology-based applications and FIS. The crisp ontology reasoner is based on the OWL API (Horridge and Bechhofer, 2011) and Hermit (Motik et al., 2009), an optimized reasoner providing efficient access to crisp ontology assertions and inferences. The fuzzy ontology reasoner used is the fuzzyDL reasoner (Bobillo and Straccia, 2008), which supports fuzzy concepts, linguistic terms and fuzzy axioms, with a Java API to access reasoning tasks. The Mamdani FIS is provided by FuzzyJ Toolkit and Fuzzy Jess (Orchard, 2001), including a Java API for handling fuzzy sets, fuzzy rules, Mamdani inference and defuzzification methods.

Based on this platform, domain experts can model the fuzzy ontology using the Protégé ontology editor with the FuzzyOWL2 plugin (Bobillo and Straccia, 2011). The resulted ontology can be processed by OWL API, Hermit and fuzzyDL, provided that it is parsed to the fuzzyDL syntax to allow fuzzy ontology reasoning. The results inferred by the Mamdani FIS are integrated to the fuzzy ontology using the OWL API support for including new assertions.

Some contributions of the HyFOM reasoner are demonstrated in a real-world case study described in Section 4.

4 CASE STUDY ON FOOD SAFETY

The HyFOM reasoner was applied in a case study to support domain experts in evaluating the chemical risk of analytes (residues and contaminants) detected in food samples. The experiments were sponsored by the Brazilian Ministry of Agriculture, Livestock and Supply (MAPA), focusing on the National Plan for Control of Residues and Contaminants (PNCRC). PNCRC is responsible for monitoring the presence of residues of pesticides and veterinary drugs as well as environmental contaminants in food products. More details on MAPA and PNCRC are available in (de Magalhães Junior et al., 2012).

According to the methodology explained by (de Magalhães Junior et al., 2012), laboratory analyses obtain the concentration of different analytes in food samples. For each analyte, there is a *maximum level* established by the Codex Alimentarius Commission, which is the maximum concentration of that substance officially permitted in a specific food. Each analyte concentration is confronted with its respective maximum level (in percentage) to obtain the *Concentration Risk* (CR) of the analyte detected in a food sample. In this sense, if an analyte concentration is lower or equal than its maximum level it is called a *compliant* analyte in the sample; otherwise it is called *non-compliant*. In addition to CR, there are other risk factors determined by PNCRC experts:

- Trends associated with analyte concentration: indicate whether the analyte concentration has a tendency of decreasing, stabilizing or increasing in a short, medium or long period of time, according to its toxicological profile;
- Adjustment period: estimated time for the provider of the food sample to be brought into compliance with MAPA's requirements concerning a specific analyte;
- Adjustment cost: estimated costs for the provider of the food sample to be brought into compliance with MAPA's requirements concerning a specific analyte.

The risk factors are combined to obtain the Aggregate Risk (AR) associated with an analyte detected in a food sample. Depending on the AR value, interventions should be applied to the providers of food samples. Some types of intervention are: *no intervention* for compliant analytes with negligible AR; *preventive intervention* for analytes that have a short-term increasing trend and medium AR; and *maximum intervention* for non-compliant analytes that have intolerable AR.

With support of PNCRC experts, the main concepts related to the chemical risk of analytes were modeled in a fuzzy ontology. Initially, Protégé and FuzzyOWL2 plugin were used to model the main concepts and properties, later parsed to the fuzzyDL syntax to enable fuzzy ontology reasoning. Listing 1 shows how the risk factors were modeled in the fuzzy ontology (fuzzyDL syntax), all of them associated with linguistic terms defined by the experts. At the moment, the linguistic terms related to the properties *hasConcentrationTrend*, *hasAdjustmentPeriod* and *hasAdjustmentCost* are nominal (crisp) values due to the available data, but there is an ongoing work with PNCRC experts to fuzzify such definitions. Listing 2 describes concept definitions representing the types of intervention, which are based on the risk factors and their linguistic terms. An instance of an analyte-sample analysis is illustrated as well.

```
(functional hasConcentrationRisk )
(range hasConcentrationRisk *real* 0.0 200.0 )
(define-fuzzy-concept negligibleCR
    left-shoulder(0.0, 200.0, 20.0, 40.0) )
(define-fuzzy-concept acceptableCR
    trapezoidal(0.0, 200.0, 20.0, 40.0, 80.0, 90.0) )
(define-fuzzy-concept nearCR
    trapezoidal(0.0, 200.0, 80.0, 90, 100.0, 100.0) )
(define-fuzzy-concept equivalentCR
    crisp(0.0, 200.0, 100.0, 100.0) )
(define-fuzzy-concept highCR
    trapezoidal(0.0, 200.0, 100.0, 100, 120.0, 130.0) )
(define-fuzzy-concept intolerableCR
    right-shoulder(0.0, 200.0, 120.0, 130.0) )

(functional hasConcentrationTrend )
(range hasConcentrationTrend *real* 0.0 3.0 )
(define-fuzzy-concept decreaseOrStabilize
    crisp(0.0, 3.0, 0.0, 0.0) )
(define-fuzzy-concept longTermIncrease
    crisp(0.0, 3.0, 1.0, 1.0) )
(define-fuzzy-concept mediumTermIncrease
    crisp(0.0, 3.0, 2.0, 2.0) )
(define-fuzzy-concept shortTermIncrease
    crisp(0.0, 3.0, 3.0, 3.0) )

(functional hasAdjustmentPeriod )
(range hasAdjustmentPeriod *real* 0.0 3.0)
(define-fuzzy-concept unnecessaryAP
    crisp(0.0, 3.0, 0.0, 0.0))
(define-fuzzy-concept shortAP crisp(0.0, 3.0, 1.0, 1.0))
(define-fuzzy-concept mediumAP crisp(0.0, 3.0, 2.0, 2.0))
(define-fuzzy-concept longAP crisp(0.0, 3.0, 3.0, 3.0))

(functional hasAdjustmentCost )
(range hasAdjustmentCost *real* 0.0 3.0 )
(define-fuzzy-concept unnecessaryAC
    crisp(0.0, 3.0, 0.0, 0.0))
(define-fuzzy-concept lowAC crisp(0.0, 3.0, 1.0, 1.0))
(define-fuzzy-concept mediumAC crisp(0.0, 3.0, 2.0, 2.0))
(define-fuzzy-concept highAC crisp(0.0, 3.0, 3.0, 3.0))

(functional hasAggregateRisk )
(range hasAggregateRisk *real* 1.0 15.0 )
(define-fuzzy-concept negligibleAR
    crisp(1.0, 15.0, 1.0, 1.5) )
(define-fuzzy-concept veryLowAR
    triangular(1.0, 15.0, 1.5, 1.5, 4.75) )
(define-fuzzy-concept lowAR
    triangular(1.0, 15.0, 1.5, 4.75, 8.0) )
(define-fuzzy-concept mediumAR
    triangular(1.0, 15.0, 4.75, 8.0, 11.25) )
(define-fuzzy-concept highAR
    triangular(1.0, 15.0, 8.0, 11.25, 14.5) )
(define-fuzzy-concept veryHighAR
    triangular(1.0, 15.0, 11.25, 14.5, 14.5) )
(define-fuzzy-concept intolerableAR
    crisp(1.0, 15.0, 14.5, 15.0) )
```

Listing 1: Risk factors defined in the fuzzy ontology.

```
(define-concept CompliantAnalysis
(and AnalyteSampleAnalysis
(<= hasConcentrationRisk 100.0 )))

(define-concept NonCompliantAnalysis
(and AnalyteSampleAnalysis
(> hasConcentrationRisk 100.0 )))

(define-concept NoIntervention (and CompliantAnalysis
(some hasAggregateRisk negligibleAR)))

(define-concept PreventiveIntervention
(and (some hasConcentrationTrend shortTermIncrease)
(some hasAggregateRisk mediumAR)))

(define-concept MaximumIntervention
(and NonCompliantAnalysis
(some hasAggregateRisk intolerableAR)))

(instance analysis1 AnalyteSampleAnalysis)
(related analysis1 metidation hasAnalyte)
(related analysis1 milkSample1 hasSample)
(instance analysis1 (= hasConcentrationRisk 121.2 ))
(instance analysis1 (= hasConcentrationTrend 3.0 ))
(instance analysis1 (= hasAdjustmentPeriod 3.0 ))
(instance analysis1 (= hasAdjustmentCost 2.0 ))
```

Listing 2: Concept definitions in the fuzzy ontology.

Instead of using the Chem-risk approach (de Magalhes Junior, 2011) to compute AR, domain experts were requested to express their knowledge using Mamdani rules combining the risk factors to infer AR. In this case study, fuzzy rules contribute to make the process more transparent and interpretable for PNCRC and MAPA decision makers, due to the linguistic terms that are closer to human language. Then, the results obtained with the hybrid reasoner were compared with Chem-risk, which provides appropriate results according to PNCRC experts. A total of 17 Mamdani rules were modeled, some of them illustrated in Listing 3 using Fuzzy Jess.

Using the fuzzy ontology and Mamdani rules, the HyFOM reasoner was applied to provide recommendations on aggregate risk and intervention actions related to food samples. Following the approach described in Section 3, individuals of the concept *AnalyteSampleAnalysis* (see an example in Listing 2) are passed to the HyFOM reasoner to obtain AR values based on Mamdani rules. The corresponding input property values are obtained from the fuzzy ontology, as they are modeled as property assertions. Then, the Mamdani FIS generates the output values, which are returned to the fuzzy ontology under expert supervision. After that, the outputs can be considered in the fuzzy instance check involving the concepts *NoIntervention*, *PreventiveIntervention* and *MaximumIntervention* to recommend the appropriate intervention.

```
(defrule rule1
(hasAdjustmentCost ?c&:(fuzzy-match ?c "unnecessaryAC"))
(hasConcentrationRisk ?v&:(fuzzy-match ?v "negligibleCR"))
=>
(assert (hasAggregateRisk
(new FuzzyValue ?*hasAggregateRiskFvar* "negligibleAR"))))

(defrule rule2
(hasAdjustmentCost ?c&:(fuzzy-match ?c "unnecessaryAC"))
(hasConcentrationRisk ?v&:(fuzzy-match ?v "acceptableCR"))
=>
(assert (hasAggregateRisk
(new FuzzyValue ?*hasAggregateRiskFvar* "veryLowAR"))))

(defrule rule3
(hasAdjustmentCost ?c&:(fuzzy-match ?c "unnecessaryAC"))
(hasConcentrationRisk ?v&:(fuzzy-match ?v "nearCR"))
=>
(assert (hasAggregateRisk
(new FuzzyValue ?*hasAggregateRiskFvar* "veryLowAR"))))

(defrule rule4
(hasAdjustmentCost ?c&:(fuzzy-match ?c "unnecessaryAC"))
(hasConcentrationRisk ?v&:(fuzzy-match ?v "equivalentCR"))
=>
(assert (hasAggregateRisk
(new FuzzyValue ?*hasAggregateRiskFvar* "lowAR"))))

(defrule rule5
(hasAdjustmentCost ?c&:(fuzzy-match ?c "lowAC"))
(hasAdjustmentPeriod ?p&:(fuzzy-match ?p "unnecessaryAP"))
(hasConcentrationRisk ?v&:(fuzzy-match ?v "negligibleCR"))
=>
(assert (hasAggregateRisk
(new FuzzyValue ?*hasAggregateRiskFvar* "veryLowAR"))))

(defrule rule6
(hasAdjustmentCost ?c&:(fuzzy-match ?c "lowAC"))
(hasAdjustmentPeriod ?p&:(fuzzy-match ?p "unnecessaryAP"))
(hasConcentrationRisk ?v&:(fuzzy-match ?v "acceptableCR"))
=>
(assert (hasAggregateRisk
(new FuzzyValue ?*hasAggregateRiskFvar* "veryLowAR"))))
```

Listing 3: Mamdani rules to infer aggregate risk.

Based on this case study, some experiments were conducted using data provided by PNCRC. A total of 114 beef sample analyses were available, involving 19 different analytes. The HyFOM reasoner was executed with the 114 individuals of *AnalyteSampleAnalysis* defined in the fuzzy ontology, using the Moment and COA defuzzification methods for generating the AR values. The results obtained with the HyFOM reasoner were compared to the results provided by Chem-risk approach and fuzzyDL reasoner.

The fuzzyDL reasoner was chosen for comparision since it is one of the state-of-the-art fuzzy description logic reasoners. In addition, it supports Mamdani FIS semantics with 3 defuzzification methods - Smallest of Maxima (SOM), Largest of Maxima (LOM) and MOM. In general, MOM generates more appropriate outputs compared with SOM and LOM, as it takes the average between them. Note that the HyFOM reasoner already uses fuzzyDL as a fuzzy ontology reasoner, but only for inferences related to fuzzy concept knowledge. Therefore, in the tests, a ”standalone” fuzzyDL reasoner is compared with the HyFOM reasoner. As fuzzyDL does not provide specific constructors for handling Mamdani rules, two fuzzyDL approaches for modeling fuzzy rules were considered: (1) fuzzy implications and (2) fuzzy concept constructors with MOM defuzzification. In these two situations, the fuzzy ontology (Listings 1 and 2) is reused but the rule set is replaced by the corresponding fuzzy rules according to the two fuzzyDL approaches.

Figure 2 presents the results obtained with HyFOM reasoner, fuzzyDL and Chem-risk, which is the reference for comparison. Some individuals of *AnalyteSampleAnalysis* are omitted because the AR values remain unchanged for individuals with $id \leq 66$. In terms of mean squared error (*mse*), the HyFOM reasoner achieved a better overall performance with moment defuzzification ($mse = 0.195$) and COA ($mse = 0.199$) against fuzzyDL implications ($mse = 0.295$) and fuzzyDL with MOM ($mse = 0.342$). The Friedman test was applied over the squared error values, concluding that at least one of the means differs from the rest. Dunn’s post test revealed that the fuzzyDL implications results are significantly different from the rest, reflecting the distinct reasoning semantics involved (Mamdani rules with defuzzification versus implication rules). However, it is important to analyze the specific situations in which one approach performs better than the others, to have a comprehensive understanding of the results.

For analyses with $AR = 1$ according to Chem-risk, the results from fuzzyDL implications are more precise than results provided by Mamdani rules with defuzzification. Implicative rules in fuzzyDL generate a numerical output corresponding to the minimum value in the domain of discourse which belongs to the conjunction of rule consequents. Thus, the numerical output is not influenced by the shape of the fuzzy set, as it happens with COA, Moment and MOM defuzzification methods, which generate a $mse = 0.0625$ in this specific situation. On the other hand, such characteristic favored the HyFOM reasoner results when $1 < AR \leq 5$ according to Chem-risk. In this case, the defuzzification methods based on shape of the fuzzy sets provided more precise results, differently from the fuzzyDL implications and MOM that are influenced by the extremes of maximum degree.

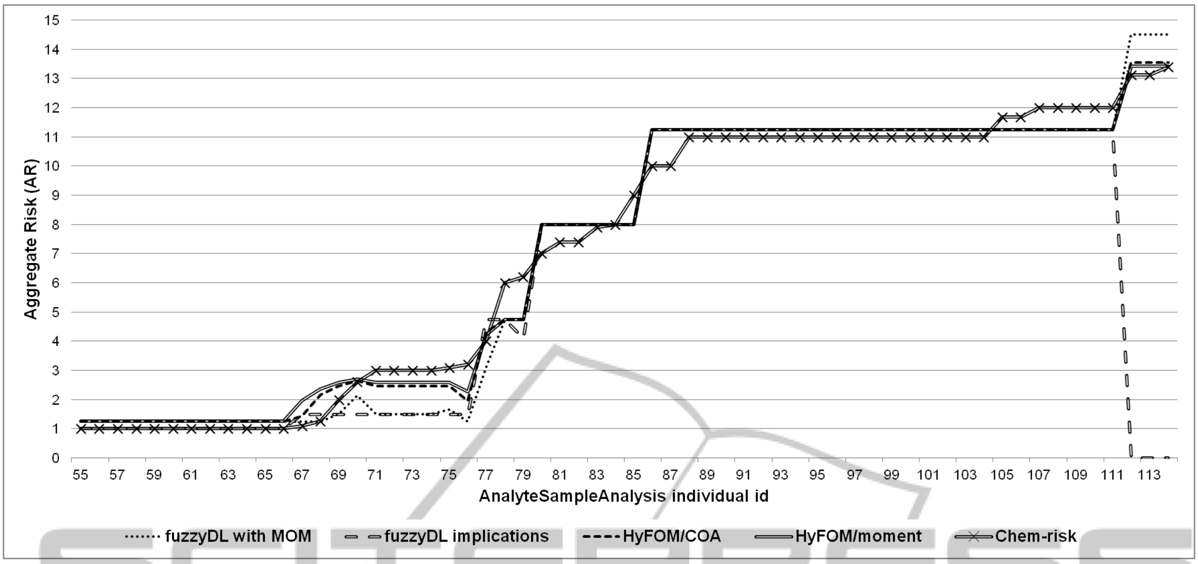

Figure 2: Aggregate risk obtained with fuzzyDL, HyFOM reasoner and Chem-risk.

For analyses with $5 < AR \leq 12$, there is no difference in the results provided by both HyFOM reasoner and fuzzyDL. In such situation, the fired rules involve input properties with nominal values (*hasConcentrationTrend*, *hasAdjustmentPeriod* and *hasAdjustmentCost*), thus fuzziness is not considered in the results. As it was mentioned previously, there is an ongoing work to fuzzify these properties with support of PN-CRC experts, so that more precise results can be obtained in comparison with Chem-risk approach.

Finally, the HyFOM reasoner presents better results for analyses with $AR > 12$. In this situation, fuzzyDL implications do not infer AR values due to knowledge base inconsistency, since different rule consequents not having an intersection are combined *conjunctively*. This problem does not happen with Mamdani rules, which are able to infer pertinent outputs. In addition, the defuzzification methods provided by the HyFOM reasoner generate a better approximation than MOM, one of the methods available in fuzzyDL. Therefore, in relation to question 1 (Section 2), the HyFOM reasoner can be considered more appropriate for this case study as it provides rule semantics and defuzzification methods that better meet the application needs.

After fuzzy rule reasoning was performed, the AR values should be available for other fuzzy ontology reasoning tasks that depend on them. For example, the fuzzy ontology reasoner should consider the AR values to obtain the membership degree of an individual of *AnalyteSampleAnalysis* to the concept *PreventiveIntervention*.

As the HyFOM reasoner incorporates the AR values to the fuzzy ontology as new property assertions, the fuzzy instance check task is performed as expected. The AR inferred by the implicative rules is also considered by the fuzzy ontology reasoning task. However, when using fuzzyDL with Mamdani FIS semantics and MOM, the generated outputs are not taken into consideration by the fuzzy instance check. In this case, the application should be aware that the defuzzification results are not integrated and should take appropriate actions regarding fuzzy concept reasoning. This issue is related to the questions 2 and 3 (Section 2), which point out that fuzzy rule inferences should be automatically integrated with the fuzzy ontology. Thus, both the HyFOM reasoner and fuzzyDL implications meet these integration requirements, while the other fuzzyDL approach does not.

5 CONCLUSIONS AND FUTURE WORK

The proposed hybrid reasoning system was designed focusing on addressing issues discussed in Section 2, which are not fully accomplished by related work. Regarding rule semantics, the HyFOM reasoner is based on Mamdani rules while some fuzzy description logic reasoners support implicative rules that can be too restrictive for some applications. Moreover, the defuzzification methods provided are based on the shape of the fuzzy set, generating outputs that represent a suitable balance among multiple fired rules.

The case study involving the domain of food safety demonstrated that the HyFOM reasoner produces appropriate results comparable with the Chem-risk approach already used in this domain. Fuzzy ontologies and Mamdani rules are interesting for this context as they provide advantages regarding interpretability and treatment of imprecision, inherent in expert knowledge.

In terms of integration approach, the HyFOM reasoner automatically provides Mamdani FIS outputs to other fuzzy ontology reasoning tasks. As the HyFOM reasoner includes a fuzzy ontology reasoner (fuzzyDL), the set of possible fuzzy inferences comprise both fuzzy ontology and fuzzy rule reasoning. As illustrated by the case study, the integration of the outputs from Mamdani FIS is important for the fuzzy instance check task involving intervention actions that depend on aggregate risk values.

As for future work, more real-world applications of the HyFOM reasoner are being developed. In addition, there is an ongoing research about an integration architecture involving a fuzzy tableau-based reasoner and a fuzzy inference system. Other types of fuzzy inference systems can be considered as well, such as the non-parametric fuzzy system model proposed by (Angelov and Yager, 2012), which is a new type of simplified fuzzy rule-based system as an alternative to the Mamdani and Takagi-Sugeno models.

ACKNOWLEDGEMENTS

The authors would like to thank the Brazilian research agency CAPES for supporting this research. Special thanks to the Embrapa Dairy Cattle and the Brazilian Ministry of Agriculture, Livestock and Supply for providing real-world data and domain expert support for the case study.

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