Fuzzy-based Interference Level Estimation in Cognitive Radio Networks

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Abstract—**Fuzzy logic is used in various areas such as economics, train systems, smart home systems, telecommunications. Recently, fuzzy logic has attracted researchers working in cognitive radio networks (CRNs). In this paper, we introduce a method that uses fuzzy logic to combine observed factors of the wireless environment (e.g., area overlapping and primary receivers density) to estimate interference level to primary receivers. The computed results reflect the precise impact that may be induced when a cognitive radio communication is operating nearby. This impact envisages the effects of CRNs over primary receivers. It can also be used as a routing metric that helps to choose the route with minimal impact - lowest interference level - to primary receivers.**

Keywords*–*Cognitive radio; fuzzy logic; routing metric; interference avoidance.

I. INTRODUCTION

In a Cognitive Radio Network (CRN), a cognitive radio node (CR) makes decisions based on its own observed information even though these knowledge may be incomplete. Fuzzy logic, however, can yield useful outputs with incomplete approximate and vague information (e.g., low or high interference, sufficient or not sufficient available radio resources). Furthermore, fuzzy logic does not require too complicated computation since the calculation is mostly based on If-then-else rules. Hence, we can use fuzzy logic in real-time cognitive radio applications for which the response time is crucial to the system performance [1]. Due to its simplicity, flexibility, and if-then-else rules composition, fuzzy logic processing time is minor.

Fuzzy logic introduces a logic theory that was developed to generalise 'true' and 'false' values to any value between 0 and 1 [2]. It also presents the approximate knowledge which may be difficult to express by conventional crisp method (i.e., bivalent set theory).

A fuzzy logic system with two inputs and one output is described in Figure 1. The fuzzy sets are sets of unsharp boundaries objects in which the membership is a matter of degree (in range of 0 to 1). For instance, a fuzzy set of $weekend$ may contain half of Friday, Saturday and Sunday and a set of $weekdays$ may contain from Monday to first half of Friday. So, Friday can be existing in both sets with distinctive degrees. To identify the degree of these variables, a membership function is used to reason the related information. The membership function assigns a value in the interval $[0, 1]$ to a fuzzy variable and denotes as $\mu(weekend(day))$, where $weekend$ is a fuzzy set, and day is a fuzzy variable.

Input crisp values are fuzzified to produce appropriate linguistic values according to defined membership functions.

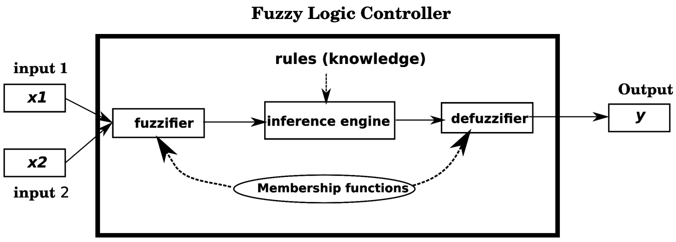

Figure 1: General fuzzy logic system

Then, the inference engine will extract the associated outputs based on the defined rules. These outputs are fuzzified based on output membership functions. Finally, fuzzified outputs are aggregated into a single crisp value by the defuzzifier.

In the previous articles [3] [4], we showed that reception overlapping associated with the interference could impact the primary radio (PR) receivers. However, we also noticed the case where node density also contributed to the impact. It is worth mentioning that we only consider non-zero overlapping situation since zero overlapping does not impact to the primary network.

The output can be used to investigate how the routing layer reacts and makes the right decisions to maximise spectrum resources while avoiding interference to the primary receivers. For instance, a CR can operate within an area having high overlap size but low operating primary receivers. We apply fuzzy logic to determine the overlap size and the probability of operating primary receivers (e.g., low or high). We also introduce in details the methodology of Mamdani inference system so that the audiences can easily follow the proposed solution.

The rest of the paper is organised as follows. Section II presents some recent work related to fuzzy logic applications. Our basic implementation is then discussed in Section III. The advance implementations in Cognitive Radio Networks (CRNs) context is presented in Section IV. We conclude the work with some future directions in Section V.

II. RELATED WORK

Many fuzzy logic based solutions have been proposed. For instance, fuzzy-decision based routing was introduced in [5] for MANET. It was developed on top of the classical Dynamic Source Routing (DSR) protocol in order to achieve the fairness of all the routing input metrics and prioritize the services differentiated packet routing, i.e., to route packets

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based on QoS priority. Wong et al. [5] proposed a routing protocol based on fuzzy decision engine that supports service differentiation and quality of service (e.g., routing protocol with service engineering or service-based routing in MANET).

Rea et al. [6] used fuzzy logic to instruct route caching during path exploration process to ensure that only the quality routes are cached in DSR. The solution also uses hop count as one of the metrics similarly to [7]. Furthermore, it uses link strength and energy available at a link vertex as fuzzy inputs. The outcome is whether a path in a route request is cached or not and continue with a route request rebroadcast. Though the solution at that stage was still not completely dealing with changes of the wireless environment, applying fuzzy theory in ad-hoc routing is convincing.

Chiang and Wang [8] used fuzzy logic to optimize routing path in a distributed manner. The objective of the proposed protocol is to minimize resource energy consumption in order to lengthen the lifetime of the sensor network. Since fuzzy logic is a system based on a conditional statements rule, resources consumption was reduced as expected in this proposal.

Santhi et al. [9] applied fuzzy logic to combine different QoS criteria to produce a routing metric. Ad-hoc mobile node uses this metric to predict and choose the most stable but least cost path to reach the destination. Similar approach can be used in CRNs but we have to consider the surrounding's changes that affect the routing decision as well as routing performance, such as the resource availability and operation interference on the legacy primary systems.

In CRN design development, Baldo et al. [10] suggested to use fuzzy logic in controlling transmitting power of the CR devices while it co-exists with PR devices. Le et al. [11] proposed a design of network accessing scheme based on fuzzy logic. Fuzzy logic was used to combine multiple feedbacks of a device on network performance such as delay, throughput and reliability. The output of the network selection outperformed conventional scheme on choosing an access based on a single parameter.

Masri et al. [12] proposed a strategy that used fuzzy logic to compose multiple independent environment parameters for multihop routing in CRNs. They accounted for instantaneous variations of the environment and proved that channel selection must be part of routing decision jointly with MAC layer support. In this work, we aim to extend the work described in [12] by adding impact factors that are derived from the environment observation. The solution proposes a metric that could guarantee the minimal impact to the primary system when it coexists with the secondary system.

III. BASIC IMPLEMENTATION AND RESULTS

We argue that when reception area of a CR emitter and reception area of a PR emitter overlap, it produces unavoidable effects on the primary system, especially to the PR receivers. This observation was mentioned in [3]. However, we also proved that not only the overlap size but also the number of existing primary receivers cause the impact [4]. In this work, our approach takes into account the overlap ratio and node density probability as two main factors. The ratio of the overlap size over the overall size of the PR emitter's disk, named overlap ratio while node density probability is the probability of possible node density within this PR emitter's disk.

We hence choose overlap ratio and node density probability to be the fuzzy inputs of our fuzzy inference system. Each of these two variables is composed of two fuzzy sets, i.e., *Low* and *High*. The fuzzy output variable is the interference level that is also a fuzzy set containing two fuzzy variables *Low* and *High*. A proper implication would be applied for each rule listed in the rules table. Result from implication rule is then aggregated and defuzzified to obtain the final result. This is the degree of impact on the primary system. A CR can consider this degree before using a frequency range when overlap happens.

A. Overlap Ratio Fuzzy Sets

Ratio of an overlap area to reception zone of an emitter is taken as the fuzzy input variable. To make it simple and easy to understand, we first define two simple fuzzy sets *Low* and *High* that represent the overlap ratio state. *Low* set contains all values that indicate the low overlap ratio. For instance, overlap ratio is considered low when it is less than 50%, otherwise, it is considered high. Note that, specific low and high boundaries are not precisely defined. We can have different definitions of *low* and *high*. We are declaring the simplest possibility in this context. It is said to be 100% low when the ratio is exactly from 0 to 20%. From 20% to further (e.g., 50%), the possibility of being low hence decreases while the possibility of being high increases. We describe the membership functions of these sets in trapezoidal or triangular-shape. Overlap ratio membership functions are described in equations (1) and (2).

$$\mu_{Low}(x) = \begin{cases} 1 & 0 \le x \le 20\% \\ \frac{50\% - x}{30\%} & 20\% < x \le 50\% \\ 0 & x \ge 50\% \end{cases} \tag{1}$$

$$\mu_{High}(x) = \begin{cases} \frac{x - 25\%}{50\%} & 25\% \le x \le 75\% \\ 1 & x \ge 75\% \end{cases} \tag{2}$$

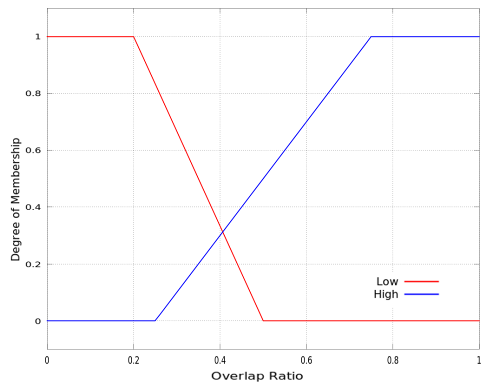

Figure 2: Membership function of Overlap Ratio.

To interpret the output of antecedents (i.e., the overlap ratio), we use Mamdani Min Implication rules [2] to extract the final result for the overlap ratio fuzzy set. For instance, at intersection part of two functions, an *or* operator is used to connect two sets, the maximum of two membership functions is evaluated for the antecedent part of the fuzzy rules.

$$\begin{aligned}\mu_{OverlapRatio}(x) &= \mu_{Low}(x) \vee \mu_{High}(x) \\ &= max[\mu_{Low}(x), \mu_{High}(x)] \qquad (3)\end{aligned}$$

B. Node Density Fuzzy Sets

Similarly to Overlap Ratio sets, we also define two simple fuzzy sets *Low* and *High* in order to reflect how PR receivers are scattered within an area. The characteristics of the mobile receivers are discrete, independent and randomly distributed. Therefore, the distribution of the nodes in this context is assumed to follow Poisson distribution. The expected density value X yields from Grey Model [4]. Since the node density appearance is a mutual independent event occurring at a known and constant rate r per unit (of time or space) are observed through a certain window (a unit of time or space), it follows the principle of Poisson distribution.

From the historical data (i.e., the input series for Grey Model), we can compute the possible average density m that represents the estimated rate λ. The probability the area has at most X receivers within an area unit is the Poisson accumulate density function of $P(X \leq x)$ illustrated in (III-B), $P(X \leq x) = \frac{e^{-\lambda} \sum_{i=0}^{x} \lambda^i}{i!}$

Higher probability of predicted density is, higher chance the receivers get impact. We consider that the low value of $P(x)$ belongs to fuzzy set *Low* and the other belongs to fuzzy set *High*. The membership functions of Node Density are also presented in a trapezoid-shape similarly to Overlap Ratio fuzzy sets

C. Fuzzy Process for Overlap and Node Density sets

Since Overlap ratio and Node Density are two independent entities with different properties and characteristics, we combine these two sets using a rules table. Output of the combination represents the interference level (e.g., *Low* or *High* level of interference) to the primary system under specific overlap degree $\mu_{OverlapRatio}(ratio)$ and primary receiver density degree - defined as $\mu_{Density}(P_x)$. The interference level is used to foresee how much impact primary receiver would be tolerated, density of these nodes are hence prioritized in this rules table (Table I).

TABLE I. INTERFERENCE LEVEL RULES TABLE

Overlap Degree	Density Degree	Interference Level
Low	Low	Low
High	Low	Low
Low	High	High
High	High	High

The rules table is expressed in the If-then construct. For instance, if both the overlap ratio and the density are *Low*, interference level is *Low*. However, interference level is *Low* when overlap ratio is *High* and the density is *How*. This explains the case where we have big overlap and low receivers operating in the emitter's reception zone. The statement if-part

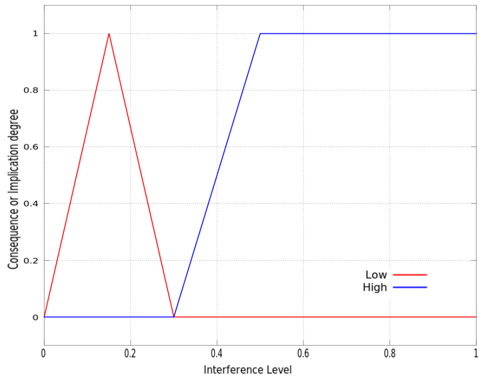

Figure 3: Membership function of the output Interference Degree.

of the rule is called *antecedent* or premise, while the then-part of the rule is called *consequence* or conclusion. In this context, the premises are the overlap ratio and the density degree, while the consequence is the interference level. The consequence is also a fuzzy set. We define the fuzzy sets of interference level in Figure 3.

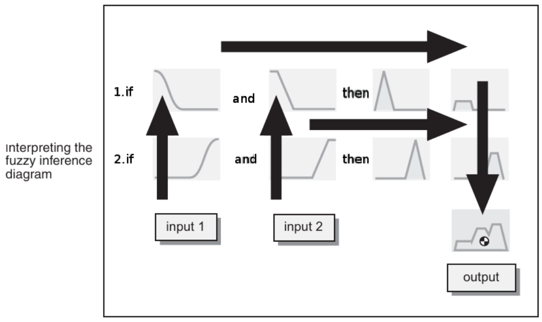

Figure 4: Fuzzy Inference Mapping Diagram.

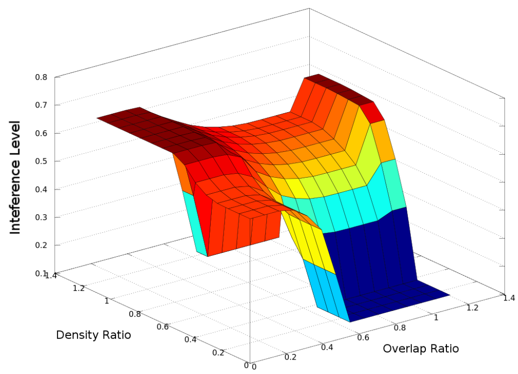

Figure 5: Interference Level Output as function of Overlap and Node Density - Rule set of 4.

In general, the inputs to these rules are the current values of overlap and density degrees and the output would be the entire fuzzy set of interference level (e.g., Low or $High$ set). This set is then defuzzified that assigns a single value to indicate the interference ratio. The mapping is done from-left-to-right flows as shown in Figure 4 [13]. The graphical view of the interference level according to the overlap ratio and the node density is presented in Figure 5.

TABLE II. OVERLAP DEGREE FUZZIFICATION OUTPUT

Index	Overlap Ratio	$\mu(x)$ Low	$\mu(x)$ High	$\mu(x)$ Overlap Ratio	Overlap Degree
1	0.06718	1	0	1	Low
2	0.25534	0.81552	0.01069	0.81552	Low
3	0.42753	0.24155	0.35507	0.35507	High
4	0.65681	0	0.81362	0.81362	High

Table II represents the numerical data after fuzzification and defuzzification process of Overlap Ratio fuzzy sets. $Ratio$ is the overlap ratio of overlap region to the emitter reception zone. This is the fuzzy input of fuzzification process to map this value to the linguistic variables *Low* and *High*. Fuzzy logic controller (FLC) uses the membership functions defined in Figure 2 to fuzzify the input ratio. $\mu(x)Low$ and $\mu(x)High$ present the fuzzified values obtained from equations (1) and (2) respectively. For example, at index 2 input ratio that equals 0.25534 is interpreted as 81.56% Low and 1.07% High according to the membership functions defined in Figure 2. These outputs are evaluated as 81.56% low overlap (e.g., columns $\mu(x)$ Overlap Ratio and Overlap Degree) by Mamdani Min Implication in equation (3).

TABLE III. DENSITY DEGREE FUZZIFICATION OUTPUT

Index	Poisson Distribution of Node Density	$\mu(x)$ Low	$\mu(x)$ High	$\mu(x)$ Density	Density Degree
1	0.26119	0.79601	0.0224	0.79601	Low
2	0.89204	0	1	1	High
3	0.94045	0	1	1	High
4	0.77162	0	1	1	High

The same processes are done and presented in Table III. Density degree and overlap degree are composed by applying Larsen implication rule with the rule explained in Table I. *Low* overlap ratio combined with *low* density probability would result a *low* interference level. Defuzzified value of this result is produced by multiplying the crisp values of overlap ratio and density probability. Table IV shows the final output result after aggregating the two fuzzy sets Overlap Degree and Density Degree. We can see that if overlap is *low* and density degree is *low*, interference level is hence *low* (first row of the table in Table IV). Crisp value column represents defuzzified output of overlap and density degree sets. Interference level is at 79.6% *low* when overlap degree is 100% *low* and density degree is 79.6% *low* for instance at index 1. The corresponding outputs of overlap and density degree antecedents are presented in Table II and Table III.

TABLE IV. INTERFERENCE LEVEL FUZZIFICATION OUTPUT

Index	Overlap Degree	Density Degree	Interference Level	Crisp value
1	Low	Low	Low	0.79601
2	Low	High	High	0.81552
3	High	High	High	0.35507
4	High	High	High	0.81362

With this simple approach, we can see that interference level depends on the predicted density degree. However, it provides the glimpse of considering overlap and density for better protecting primary receivers in CRNs. Moreover, considering binary variables as Low and $High$ is not sufficient enough to evaluate how interference level is good enough to make a judgement when it comes to path selection. Clearly, the rule table as well as the outcome of the defuzzification process does not reflect any impact of the overlap size. A middle level of impact may happen due to low overlap even with high density receivers. An extension of this approach is hence introduced briefly below. This enhances overlap and density fuzzy sets, as well as refines rules table, accordingly.

IV. ADVANCE INTERFERENCE LEVEL IMPLEMENTATION

A. Extended Overlap Ratio Fuzzy Sets

As explained, we need more elaborate definition for the input of FLC that covers all possible cases of the overlap and density effects. We redesigned the input fuzzy sets that now contain four linguistics variables $O_{fuzzyset} = \{low, medium, high, veryhigh\}$ in which, for example, the overlap ratio:

- $low : 0 < \frac{A_{overlap}}{A_P} \leq \frac{3}{10}$
- $medium : \frac{2}{10} < \frac{A_{overlap}}{A_P} \leq \frac{5}{10}$
- $high : \frac{4}{10} < \frac{A_{overlap}}{A_P} \leq \frac{7}{10}$
- $veryhigh : \frac{A_{overlap}}{A_P} > \frac{6}{10}$

We consider that the overlap ratio is low when the ratio is from 0 to 10%. The membership function of *low* overlap ratio reflects the degree of low overlapping which follows the idea of the possibility that overlap is lower and lower after 10% of overlap. The possibility of *low* overlap decreases when the ratio increases. Other possibilities could be *medium* or *high* overlap after a specific boundary. For instance, the input value of an overlap ratio is at 25%, the probability of it to *low* is 25%. Moreover, the probability of it to *medium* is 33%. We can conclude that the input may be possibly at *medium* overlap degree.

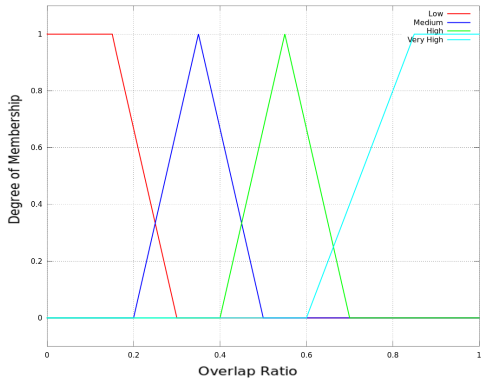

Figure 6: Enhanced Overlap Ratio membership function.

B. Extended Node Density Fuzzy Sets

Applying the same principle in IV-A, we define four linguistic variables corresponding to four fuzzy sets *Low*, *Medium*, *High* and *Very High*. Assume that density of the receivers is defined as $d_r = \frac{N}{A_P}$.

where N, the total number of receivers within the reception zone of an emitter, A_P the total area size of the zone. Therefore, within a specific area A_0, the average number of receivers is $n_{avg} = d_r * A_0$.

As a node existence is independent from the others within an area, the probability of x nodes which exist within A_0 follows Poisson process with mean $\lambda = n_{avg}$ is yield by (4) following the Poisson density function.

$$f(x) = P(X = x) = \frac{\lambda^x}{x!}e^{-\lambda} \tag{4}$$

The probability the area has more than the average number of receivers within A_0 is the Poisson accumulate density function of $P(X \geq x)$ with $x \geq \lambda$ becomes $P(X \geq x) = \frac{e^{-\lambda}(e\lambda)^x}{x^x}$

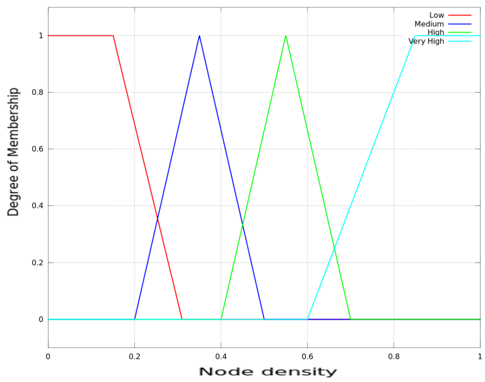

Figure 7: Enhanced Node Density membership function.

Practically, we can have a prediction system that generates the node density. However, in the context of this paper, the value is generated via a Poisson process. This value is converted into an appropriate linguistic value via the fuzzy logic controller. The membership function of this fuzzy set follows the definition from the overlap membership function above as described in Figure 7.

C. Interference Level Rules and Outputs

As the inputs are refined, the output of this enhanced inference system is also refined. A proposed rule table for these fuzzy sets is defined in table V, note that the rules subject to feasibly change depending on realistic observation later. As we could see, with the simple approach in section III, the rules illustrate only two states of the interference level, *low* or *high*. However, we introduced two more variables of reach input fuzzy sets (*medium* and *veryhigh*), the rules should also reflect the changes associated with these variables.

Practically, the level of interference can be at a reasonable degree such as medium. Based on application needs, the level could be adapted accordingly.

For instance, the above rules infer the followings.

- If (Overlap-Ratio is *Low*) or (Density-Ratio is *Low*), then (Interference Level is *Low*) (1)

TABLE V. ENHANCE INTERFERENCE LEVEL RULES TABLE

Index	Overlap Ratio	Density	Interference Level
1	Low	Low	Low
2	Low	Medium	rather Medium
3	Low	High	somewhat High
4	Low	Very High	High
5	Medium	Low	somewhat Low
6	Medium	Medium	Medium
7	Medium	High	High
8	Medium	Very High	Very High
9	High	Low	Medium
10	High	medium	somewhat High
11	High	High	High
12	High	Very High	Very High
13	Very High	Low	Medium
14	Very High	Medium	very High
15	Very High	High	extremely High
16	Very High	Very High	extremely very High

- If (Overlap-Ratio is *Low*) and (Density-Ratio is *Medium*), then (Interference Level isn't *Low* or rather *medium*) (0.5000)
- If (Overlap-Ratio is *High*) or (Density-Ratio is *Medium*), then (Interference Level is somewhat *High*) (1)
- If (Overlap-Ratio is *High*) or (Density-Ratio is *High*), then (Interference Level is *High*) (1)
- If (Overlap-Ratio is Very *High*) and (Density-Ratio is *High*), then (Interference Level is extremely *High*) (1)
- If (Overlap-Ratio is Very *High*) or (Density-Ratio is Very *High*), then (Interference Level is extremely Very *High*) (1)

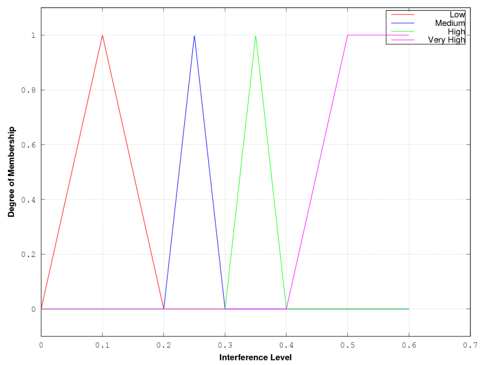

Figure 8: Enhanced Interference Level membership function.

The fuzzy inference engine combines the rules to obtain the aggregated fuzzy output. The output is the fuzzy set of the interference level that is defined in Figure 8. Fuzzy controller has to defuzzify these outputs into crisp values using centroid method to make the final decisions. Figure 9 shows the system output as a function of 2 variables, overlap ratio and node density, with the rules set of 16 conditional statements.

Table VI and Table VII show the fuzzified data of the inputs based on their defined membership functions. We can observe that the crisp values are converted into linguistic values thanks to the membership functions in Figure 6 and Figure 7. Table VIII shows the output of the inference system. The aggregated values are processed according to the Interference

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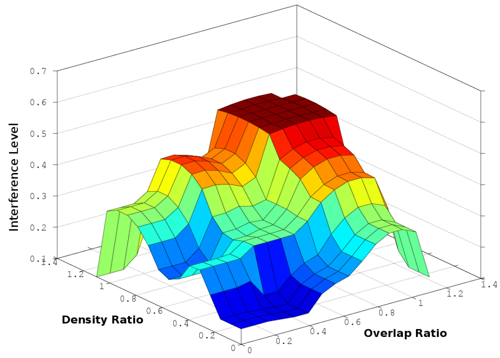

Figure 9: Interference Level Output as function of Overlap and Node Density - Rule set of 16.

Membership function in Figure 8. The rules are applied correspondingly in defuzzification process to produce the final crisp value of the Interference level.

TABLE VI. OVERLAP DEGREE FUZZIFICATION OUTPUT

Index	overlap ratio	$\mu(x)$ Low	$\mu(x)$ Medium	$\mu(x)$High	$\mu(x)$ Very High
1	0.25596	0.29362	0.37305	0	0
2	0.57829	0	0	0.81143	0
3	0.44402	0	0.37322	0.29345	0
4	0.66566	0	0	0.22894	0.26264
5	0.53420	0	0	0.89467	0
6	0.65453	0	0	0.30314	0.21811

TABLE VII. DENSITY DEGREE FUZZIFICATION OUTPUT

Index	Density probability	$\mu(x)$ Low	$\mu(x)$ Medium	$\mu(x)$ High	$\mu(x)$ Very High
1	0.08049	1	0	0	0
2	0.19908	0.67281	0	0	0
3	0.66764	0	0	0.21574	0.27056
4	0.81842	0	0	0	0.87370
5	0.28182	0.12118	0.54548	0	0
6	0.57480	0	0	0.83466	0

Precisely, FLC maps the fuzzified outputs (a.k.a. the output of each linguistic variable of overlap ratio and node density probability) of the inputs to infer the associated consequences. For instance, the inference engine decomposes an input of overlap ratio of 0.25596 into $\mu(low)$ at 0.29362 and input of density probability of 0.08049 into $\mu(low)$ at 1. This composition matches the first rule in Table V - *If (Overlap-Ratio is Low) or (Density-Ratio is Low), then (Interference Level is Low).*

Depending on the method that we defined at the beginning, the consequence of these antecedents is calculated and mapped to the membership functions of the interference level fuzzy set. With this current example, we opt to use Min implication method to evaluate the outcome, and compute the interference output is at 0.14236 for this rule. However, this is not yet the final outcome since after matching all the possible fuzzified inputs with the rule knowledge, all the outcomes are decomposed/defuzzified to produce a single crisp value (refers to the diagram in Figure 4). This will be the final output of the whole process.

V. Conclusion

In this paper, we provide an approach to estimate the interference level based on fuzzy logic. Overlap radio and node density are two critical inputs of the fuzzy system. Convincing numerical results confirm the feasibility of using fuzzy logic in Cognitive Radio Networks for estimating interference. The decision making process can leverage this information when a CR selects a possible accessing channel that minimizes the impact on the primary system. Moreover, the estimation can also be used in extracting a routing metric that considers a path with minimal interference level. In cross-layer design, this approach can also be integrated with other factors such as transmitting power and application requirements for engineering the traffic flow accordingly.

TABLE VIII. INTERFERENCE LEVEL FUZZIFICATION OUTPUT

Index	Overlap input	Density input	Interference Level	Crisp Value
1	0.25596	0.08049	Low	0.14236
2	0.57829	0.19908	Medium	0.21464
3	0.44401	0.66764	High	0.39495
4	0.66566	0.81842	Very High	0.47103
5	0.53420	0.28182	Medium	0.27273
6	0.65453	0.57480	High	0.37930

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