Assessing Aggregate Interference with Mamdani Fuzzy Inference Systems

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*Abstract*—In dynamic spectrum allocation, estimating potential aggregate interference to receivers is crucial in setting transmission spectral and spatial limitations. The challenge of achieving accurate aggregate interference assessments is heightened by variability in environmental factors and limitations of static modeling. This often leads to protection levels that are either excessively stringent or overly permissive. Dynamic spectrum access (DSA) systems commonly rely on the ability to precisely model transmissions and estimate interference prior to frequency assignment, where total interference is acquired by means of summing individual contributions to a victim receiver. As an alternative to the worst-case static calculations, this paper proposes the implementation of a Mamdani-type fuzzy inference system as the assessment mechanism for interference levels prior to aggregation. In this approach, transmission parameters and path losses are encoded as linguistic variables to be provided as antecedents of a conjunctive rule base. The implications of the predefined rules give an estimation of interference levels that may be adjusted by altering the membership grade of input parameters with the respective linguistic variable to tune the final aggregate result. Simulation results demonstrated 93.52% aggregate interference prediction accuracy which demonstrates the system’s ability to adaptively tune to varying levels of agreement with static calculations, providing flexibility in modeling interference levels where necessary protection levels are ambiguous.

Keywords—aggregate interference, spectrum management, fuzzy inference systems, dynamic spectrum access, Mamdani, membership functions

# Introduction

The advent of fifth-generation (5G) mobile broadband has introduced a number of improvements over previous generations including higher data rates, reduced latency, and improved coverage in rural areas. The tradeoffs necessary to achieve these improvements have proved cumbersome for other wireless services. High bandwidth needs have resulted in the allocation of large blocks of spectrum to 5G in recent years in addition to many allocations interleaved among previously established services. While the 5G standard and spectrum policy have introduced measures to prevent harmful interference to services adjacent in spectrum, concern regarding their effectiveness in scenarios involving passive systems remains due to disagreement between compatibility studies conducted to inform policy makers [1]. For example, the auction of 24 GHz spectrum to 5G wireless services has created such a scenario and presents a notable risk to passive radiometers operating in the 23.6 – 24.0 GHz Earth Exploration-Satellite Service (EESS) band. Unable to adjust frequency or tolerance due to the need to sense trace atmospheric microwave emissions, these radiometers are subject to interference from unwanted adjacent-band emissions, creating potential for delayed and less accurate weather forecasts [2].

Dynamic spectrum access (DSA) systems can coordinate frequency assignment independent of prior allocations and use spectrum opportunistically, a capability that may reduce harmful interference in services such as the EESS. In order for these systems to predict and prevent interference scenarios, the estimated path loss of an emission is used in conjunction with transmitter operational parameters and receiver characteristics such as location, power, radiation pattern and gain to determine whether the received power will exceed the interference tolerance of the victim receiver in question. It can be difficult to acquire this information with low error and choose an appropriate propagation model for the given environment. This makes calculations to classify interference difficult to execute with high precision and reasonableness for complex propagation environments. At millimeter wavelengths, minor errors in location and antenna positioning data coupled with phenomena such as multipath effects can make deterministic interference calculations intractable. The issue of complexity is further exacerbated when considering the aggregation of interferences from simultaneous transmissions.

In response to the difficulties of precisely modeling devices and their propagation environments, statistical approaches to predicting aggregate interference have been developed. The statistical methods aim to reduce computational complexity by assigning probability distributions to parameters with random variations. The International Telecommunication Union’s (ITU) recommendation for aggregating interference levels in EESS bands is to sum the means and weighted standard deviations of interfering powers acquired through dynamic simulation, assuming the contributions from different active services are independent of one another [3]. Ghasemi and Sousa develop a statistical model for interference aggregation by characterizing variability of factors such as sensitivity, transmit power, path loss and channel fading in [4]. Kusaladharma and Vijayandran attempt to provide less cumbersome expressions by deriving an interference moment generating function for finite area networks [5, 6]. Peng et al. describe another simplified method of aggregating interference to deep-space Earth stations from high-density fixed service (HDFS) emitters in which the area surrounding deep-space Earth stations is geometrically partitioned and used to model the correlation of interferences [7]. Bhattarai et al. find the log-normal distribution provides good estimations of aggregate interference when a fixed number of emitters are distributed uniformly over a region [8]. This result is incorporated into their following work in spectrum sharing [9].

Another method of predicting aggregate interference that has been explored more recently is to leverage machine learning (ML) algorithms to handle analytically intractable calculations. Padilla presents a nonlinear autoregressive neural network (NARNN) to predict interference and aid in efficient resource allocation [10]. Saija evaluates the ability of various ML algorithms to estimate channel state information (CSI) in 5G systems by predicting signal-to-noise (SNR) and shows that the ML approaches outperform traditional methods in terms of error [11]. Zhao demonstrates a method wherein location, path loss information, and transmit power are supplied from a network of transmitters to a backpropagation neural network trained to predict aggregate interference at a receiver [12].

These prior works have produced important results by successfully reducing the complexity of the aggregate interference problem but many existing techniques remain unsuitable for real-time spectrum management applications. For example, the Citizens Broadband Radio Service (CBRS) Spectrum Access System (SAS) aggregate interference assessments encompass millions of path loss calculations, often delaying spectrum assignment for 24 or more hours [13]. ML-based approaches provide adequate speed but lack an explanation facility able to offer insights regarding the decisions of the assessment mechanism, a feature that may be desirable when mischaracterizations occur. In the event inconsistent results are produced by ML-based approaches actions are generally limited to error analysis, data inspection, and further training of the network to address the unknown contingencies introducing error. An approach offering further improvement would be capable of handling imprecise information and adapting to varying propagation environments in addition to offering an intuitive decision-making process that allows for understandable, quick evaluations of aggregate interference in near real-time scenarios.

Fuzzy inference systems (FIS) lend themselves well to the problem at hand due to their tolerance for ambiguous data, nonlinear classification capabilities, and inherent explanation facility. Incorporated with a DSA system such as the spectral broker [14], an FIS accepts precise and ambiguous information alike and can perform the evaluation within the time and computational constraints of the brokering system. This paper introduces the design of a Mamdani-type FIS tuned to a coexistence scenario between 5G devices and passive radiometers whose frequency assignments are managed by a spectral brokering system.

# Background

## Fuzzy Inference Primer

In conventional crisp logic, an element’s membership in a set is binary. As an alternative, L. A. Zadeh proposed Fuzzy Sets in 1964 [15]. These sets describe the degree to which an element belongs to a set. As with crisp logic, union and intersection operations are defined that facilitate the comparison of sets. By applying fuzzy logic to control systems, fuzzy inference systems can accurately model system behavior. This has been validated by reduction to practice. In a study on the impact of Fuzzy Logic conducted in 2013, there were 26 journals, over 100,000 publications, and over 2500 patents in the United States and Japan alone [16].

Fuzzy Inference Systems have three stages: fuzzification, rule evaluation, and defuzzification. Membership functions are the mathematical backbone that allows us to evaluate fuzzy membership. The following paragraphs describe how each of these systems can be implemented and the system benefits associated with each state.

Fuzzification evaluates each input against a number of antecedent membership functions and outputs a value between 0 and 1 describing the degree of membership in each set. Feature Engineering attempts to reduce the number of inputs to a lower dimensional latent space that captures the underlying behavior of the system. Feature Engineering at this stage has the potential to yield significant benefits by reducing the amount of information each transmitter and receiver sends across the network to predict aggregate interference compared to statistical prediction methods such as those used in CBRS [13].

For purposes of continuity and clarity, a tutorial example of Mamdani inference is appropriate. Our example will consider two leading indicators of graduate student performance: grade-point average (GPA) and Graduate Record Examinations**©** (GRE) scores. The number and shape of membership functions are additional design consideration. In this example, each antecedent has three membership functions:

where P is poor, F is fair, and E is excellent. These membership functions can be seen in Figs. 1 and 2.

A graph of a function

Description automatically generatedFig. 1. GPA Antecedent Membership Functions

A graph of a function

Description automatically generated with medium confidenceFig. 2. GRE Antecedent Membership Functions

Each membership function described in the figures above is evaluated for the corresponding input, resulting in the degree to which to an input belongs to the corresponding fuzzy set. Consider a student with a GPA of 1.8 and a GRE score of 650. GPA belongs completely to the poor set meaning that when the three functions are activated. . GRE belongs equally to the poor and fair sets . The resulting fuzzy set memberships will be used in rule evaluation.

Rule evaluation maps the membership of each input to a scaling factor for each consequent membership function. In general, two primary approaches are used to construct a rule table. First, a subject matter expert can use their expertise to codify rules about the behavior of the system. Second, an optimization method can be applied to find a set of rules that minimize a cost function describing the difference between the output of the system and truth training data.

When the rule table can be constructed based on expertise, this provides an explanation facility that documents why the system arrived at an output. This is a significant benefit of Fuzzy Inference Systems compared to other artificial intelligence methods. Fuzzy Inference Systems, like other artificial intelligence systems, can model nonlinear relationships. explanation facility can be applied in tuning and applications.

An experienced professor constructs the following rule table predicting the performance of future graduate students. The professor considers the set membership of the input and determines rules that map inputs to output membership functions using min-max fuzzy logic: a system in which a logical “and” indicates the minimum value should be chosen and a logical “or” indicates that the maximum value should be chosen. In this example, each case is considered conjunctively. Each rule cell’s value is the minimum of its corresponding input membership grade. For each consequent membership function type in the rule table, the maximum of the cells of the same type is the final weight. Thus, in our case, . Poor GRE and Poor GPA implies Poor Graduate student and so on for all cases.

A table with black and white text

Description automatically generatedFig. 3. Graduate Student Quality Prediction Table Rule Activation

Defuzzification uses the outputs of the rule table to scale each consequent membership function by the weights obtained from activating our rule table to obtain a final crisp output. One of the most significant benefits of a fuzzy inference system is that the system can be easily reduced to a look-up table. Instead of having to perform statistical calculations for each device on a network, the inputs can be evaluated by a look-up table with a time complexity of .

Returning to our example the final output will be a graduate student ranking between 0 and 10 where greater values correspond to a better graduate student. To map between our rule table and the output range the following consequence membership functions are used

where P is poor, A is average, G is good, and E is excellent. These membership functions can be seen in Fig. 2 and 3.

A graph of a function

Description automatically generatedFig. 4. Consequent Membership Functions

A line graph with numbers and lines

Description automatically generatedFig. 5 Consequent membership functions scaled by rule table weights.

Consequent membership functions, shown in Fig. 5, are scaled by the weights in the rule table. In our scaling example the following scaling factors were used, The result of this scaling is shown in Figure 6. Defuzzification is applied to the sum of the scaled membership functions at each point.

Many defuzzification methods exist and have application-specific trade-offs. The center of mass of the weighted membership functions, in general, is given by

where the summation is over all of the consequent membership functions, , and their corresponding weights, . If the area of the membership function is

and center of mass

Then the defuzzification can be written as

A hand pointing at a triangle

Description automatically generatedFig. 6. The center of mass of the sum of the weighted membership functions

Applying this defuzzification method to our example returns the final crisp output 7.3.

As FIS are able to control the latent space to reduce the required information transmitted to perform calculation, model nonlinear systems, provide an explanation facility for system outputs, implement a time complexity of , they are well suited for to assess aggregate interference. This is considered in detail in the Mamdani FIS Design section.

## Spectral Brokering

Similar in principle to the automated frequency coordination (AFC) system at 6 GHz and SAS in the 3.5 GHz band, the cooperative brokering system coordinates spectrum use between active and passive users by considering spectral, spatial, and temporal resource use in its network and implementing constraints on potentially interfering devices. The brokering system functions by accepting operating requests from multiple radiometers and 5G systems, then undertakes a multi-stage culling process to determine interference potential between any pair of requests. If a device is identified as a potential interferer, a spatial-spectral mask is calculated considering the prioritization of passive devices and is communicated to all users. The 5G transmitter’s controller then has the opportunity to optimize beam pattern and reconfigurable power-amplifier (PA) matching networks to maximize resource use within the constraints provided by the broker.

The operating requests shared by users contain information regarding time of use, frequency and bandwidth, transmission power and receiver tolerance, and geographical location and directionality. With this information the broker begins assessing the most recently submitted request against existing allowances of other devices, covering all combinations of device pairs. In each assessment, five stages of culling take place in which the broker evaluates overlap between parameters.

The first three stages look for time overlap of the requests, whether the devices are within line of sight of each other, and whether the main beam of the transmitter’s antenna pattern intersects the location of the other device. In stage four, free space loss calculations determine whether power of a transmission will exceed the interference tolerance of the receiving device. The final stage performs frequency interference calculations by first looking for direct overlap between requested bands, then for out-of-band (OOB) interference potential.

Each stage of analysis can short-circuit subsequent stages, meaning that, if at any point in the culling process no overlap is determined, then each device in the pair of devices under evaluation will be considered to be free of potential interference from the other, and the broker will proceed to the next pair immediately, bypassing the remaining stages. If none of the five stages of the culling process rule out the potential for interference, the broker will generate a spatial-spectral mask for the interferer that limits transmission power as a function of frequency and direction. If no interference is expected from any individual device, the broker then, making worst-case assumptions, sums the powers of transmissions at each receiver's location to estimate the total levels of interference that may be seen. If the aggregated signal level exceeds the device's interference tolerance, a spatial-spectral mask is provided to the most recent user to submit a request for spectrum with intent of reducing the aggregate interference to acceptable levels.

# Network Model

## Network Topology

To simulate the environment for evaluating interference we consider a homogenous network comprised of a single radiometer among a set of 5G transmitters. Locations of the transmitters are spaced approximately the same distances from one another while the radiometer location varies across the ~1 km2 region encompassing the devices. Fig. 7 shows an example of the network containing three transmitters with a single radiometer placed at the center of the coexistence space.

A diagram of a satellite connection

Description automatically generated with medium confidence

Fig. 7. Device placement in network area of approximately 1 km2

## Modeling Devices

Spectrum consumption models (SCMs) are used to represent devices in our simulations. SCMs are a data structure made up of 11 data elements, each articulating some aspect of spectrum use [17]. SCM types follow an aggregation hierarchy and include transmitter, receiver, system, and set models. In our example, we use only the transmitter and receiver types. Transmitter models capture the RF emissions of a transmitting device by identifying location of the device, operating times, a spectral mask (what power at what frequencies), and directivity. The intent of the transmitter model is to provide bounds on temporal, spatial, and spectral aspects of a device’s emissions. Receiver models define interference thresholds for a receiving device by capturing its location, operating times, an underlay mask (tolerance to what powers at what frequencies), directivity of reception, and susceptance to intermodulation effects. The temporal, spatial, and spectral limits imposed by these models on transmitting devices are intended to account for individual and aggregate interference.

Transmit powers and radiometer tolerance are captured as power spectral densities (PSD). Antenna models are assumed to be isotropic to simplify calculations, thus no antenna gain is captured by the models. The center operating frequency of the radiometer is 23.84 GHz with a channel bandwidth of 200 MHz and the 5G band of interest is the 5G-NR n258 band (24.25 – 27.5 GHz) with a fixed channel bandwidth of 200 MHz. The PSD of out-of-band emissions from transmitters is on the order of ‑50 dBW/200 MHz, well below the allowed emission limit published in [18] but high enough to produce aggregate interference depending on the relative location of the radiometer.

## Data Generation

The FIS can function immediately upon implementation but benefits from a training period in which the membership functions and rule base are adjusted to infer results more accurately. A training dataset of path loss inputs and truth interference outputs is provided to the FIS. The tuning process is finished once error between the truth and system’s output is minimized to a desired degree. Our goal in this design is not necessarily to provide the most realistic representation of interference, but to show that an FIS can be tuned to function in an arbitrary scenario. Thus, the dataset generated for tuning uses a simple representation of interference.

Because the FIS is designed to operate specifically in the 24 GHz radiometer/5G scenario, an aggregated PSD of ‑166 dBW/200 MHz or greater is assumed to inflict harmful interference [19]. Fuzzy systems, like neural networks, are capable of non-linear classification, thus the input and outputs need not be on the same scale. The measure of interference provided to the system is the ratio of the interfering emission PSD to the radiometer’s tolerance after linearization, values greater than or equal to 1 being classified as interference. As such, information regarding the tolerance of the radiometer and the interference power is conveyed through interference values implicitly.

Training data for the FIS is collected by sweeping the location of the radiometer across the network’s geographical area while capturing the path loss values between it and other devices. At each location, the amount of interference presented to the radiometer by a gNB is calculated from a range of PSDs and the free space path loss between devices. Making worst-case assumptions, the interference contribution from each gNB is summed at the radiometer’s location to estimate the aggregate interference. The final data set captured for use by the FIS consists of a range of PSDs for each gNB emission at each radiometer location, path losses to the radiometer, the individual interference contribution, and the final aggregate interference level.

# Mamdani Fuzzy Inference System Design

Our goal is to translate linguistic variables into a calculable process that will infer the potential interference between a transmitter/receiver pair. The variables chosen to describe the inputs of this design are simply “low”, “medium”, and “high”. Additional variables may be included if less ambiguous data is available, but these are chosen to demonstrate the effectiveness of this approach given broad membership classification. With knowledge of distance, direction between devices, and antenna characteristics, the spectral broker is able to provide the PSD and anticipated path loss of transmissions to the FIS as antecedents. The path loss input is fuzzified but taking its membership grade with the fuzzy sets of low, medium, and high path loss values determined by the propagation environment. The rule base is formed by our chosen linguistic variables and relationship between path loss and interference level. Rules are activated by min-max logic and the results used as weights for the consequent membership functions. As with the antecedent, the consequent set of interference values is comprised low, medium, and high subsets. The final defuzzied value is the center of mass of the weighted and summed consequent membership functions.

## Input Parameters (Antecedents)

Our design considers only power and path loss of transmissions. Functions of low, medium, and high path losses are initially crafted based on expectations of the simulated network in which we are testing the system. Under the assumption of isotropic reception and radiation, free space path loss indicates approximately 120 dB of loss over the 1 km distance across the network. The lower end of this scale is the anticipated path loss over 50 meters while medium losses encompass values in between. Fig. 8 shows the varying membership grades of a given path loss value with the sets of low, medium, and high losses.

A graph of a number of lines

Description automatically generated with medium confidenceFig. 8. Path loss (dB) Membership

## Rule Base

The implications that drive fuzzy inference are captured by a set of rules that describe the relationship between the antecedent and consequent. Rules are crafted based on expert intuition and domain knowledge. Though trivial in this case, the implications of more complicated systems can be captured by a larger rule base. The rule set used in our design is shown below in Table 1.

1. Fuzzy Inference System Rule Table

|  |  |
| --- | --- |
|  | **Rule** |
| 1 | If (Path loss is Low) then (Interference is High) |
| 2 | If (Path loss is Medium) then (Interference is Medium) |
| 3 | If (Path loss is High) then (Interference is Low) |

## Output Membership Function (Consequent)

As shown in Fig. 9, the adjustments to the consequent membership functions during the tuning process render them inconsistently spaced. This is due to both overfitting the system to a small training dataset and the nature of the truth values. As detailed in the data generation section, the measure of interference used by the system is a ratio of the linear interfering emission PSD to the radiometer’s noise tolerance, meaning values greater than or equal to 1 are classified as interference. The majority of the training data did not exceed the 1:1 ratio. Of the data that did, the value was typically less than 3, this is the reason for the increased breadth of the low membership function relative to the others. The medium and high membership functions settled in their respective locations and shape due to sparse instances of extremely high interference when the radiometer location nearly coincides with the location of a transmitter. Because there is significant overlap between antecedent membership functions, the full range of values on the horizontal axis in Fig. 9 are achievable despite the large space where there appears to be no association with any function.

A graph of a graph

Description automatically generated with medium confidenceFig. 9. Interference Ratio Membership

## Tuning and Optimization

To decrease the size of our search space and enable fast turning the system was tuned disjunctively for power. Our data was broken into smaller data sets that held power constant and nine FISs were tuned independently of each other. This can be done because the power and path loss are independent. The result of this tuning can be seen by comparing Figs. 9-13 to see the path loss and interference ratio membership functions before and after tuning. Tuning was performed in MATLAB using the Global Optimization Toolbox, Fuzzy Logic Toolbox, and the Parallel Computing Toolbox. A genetic algorithm was parallelized and applied to each disjunctive section for a specified number of iterations. After that number of iterations has been completed the error is assessed and if it is within our acceptable error threshold the script moves on to tune the next disjunctive section. If the error is greater than the acceptable error threshold the optimization restarts with another seed.

# Simulation Results

As discussed in earlier sections the results of the tuned fuzzy inference system can be implemented as a look-up table, reducing time complexity to . This control surface predicts the interference ratio for a single transmitter/radiometer pair in the simulated network. The control surface, shown in Fig. 10, is constructed from each disjunctive FIS which was trained on a single PSD. The results closely align with the free space path loss (FSPL) shown in Fig. 11. In general, as the path loss decreases and power increases, the resulting interference increases.

A graph of a graph

Description automatically generated with medium confidence

Fig. 10. FIS Control Surface

A graph showing a curve

Description automatically generated with medium confidence

Fig. 11. FSPL Control Surface

After tuning, the FIS was evaluated at each of the inputs of the three transmitter-receiver pairs in the example network. Each of the predicted interferences was summed assuming full constructive interference and the Mean Absolute Percent Error (MAPR) was found. The aggregate interference MAPR was calculated to be 6.4888%.

Achieving this error was not without tradeoff under the circumstances of our design. The system is overfitted to a small dataset, evident by the shape of the consequent membership functions. Though it would be difficult to generalize this particular design to new data, the outcome still has important implications, namely we have demonstrated that a fuzzy system with a single path loss input can infer the resulting interference between two wireless devices to fair degree of accuracy. This is possible due to the nature of the truth data on which it was tuned. The membership functions were able to be coerced into shapes that map logarithmic inputs to a linear output because of the function approximating abilities of fuzzy systems and the power information contained implicitly in the truth data.

A graph of a graph with bubbles

Description automatically generated with medium confidenceFig. 12. Predicted Aggregate Interference Error

Fig. 14 gives a visual description of MAPE. The line describes a perfect interference ratio prediction. Our model’s predictions are the blue dots around the line. The distance between each dot and the line represents the error. Because of how our training data is collected, there are significantly fewer data points leading to large interference ratio values. In future work, Fuzzy Inference Systems can be applied to training data derived from other spectrum brokering systems.

# Conclusion

An FIS design has been presented which can predict aggregate interference while reducing complexity of the calculations. This approach can be used to enable departure from worst case aggregate interference assessments. In this approach, the ambiguity inherent in modeling propagation environments and spectrum usage is handled by the fuzzy mathematical framework. Simulation results show that, after tuning, the system reaches reasonable agreement with free space path loss estimations. This implies that the FIS may be tuned to match more complicated propagation models and interference scenarios that previously relied heavily on statistical measures. To this end, the authors hope to expand this work by applying FIS to predicting aggregate interference on a real-world network with larger training data set.

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