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Dynamic Resource Management of Cognitive Radio Networks Via Fuzzy Logic Technique

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Abstract

The spectrum is a scarce resource and must utilize efficiently, the cognitive radio is a prospective solution for underutilized spectrum. Introduction of flexibility and intelligence in the wireless devices and applications have introduced the concept of Cognitive Radio. This objective has inspired various research activities on going which included the decision making aspects. In this work, a decision making process in cognitive radio is analyzed using fuzzy logic system, in which Dynamic Resource Management of Cognitive Radio Networks is effectively done. The fuzzy logic tool is very helpful for complex or uncertain process where it is difficult to develop mathematical model. Cognitive radio (CR) is a promising technology to solve the challenging spectrum allocation problem. So that, we have selected three descriptive factors for choosing the aggregation weight in dynamic resource management such as Node's control, Node's Link state amount and Node's Link state time. The efficiency of the decision making process in cognitive radios is analyzed. Based on linguistic knowledge 5 rules are set up. The output of the fuzzy logic system gives the probability of the decision based on the three descriptive factors. Recognizing that fuzzy logic inference can better handle uncertainty, fuzziness, and incomplete information in node convergence report, Fuzzy Convergence is developed as a novel approach to aggregate wireless node control with affordable message overload. We show how fuzzy logic system can be used for decision making operation in cognitive radio.

1. Introduction

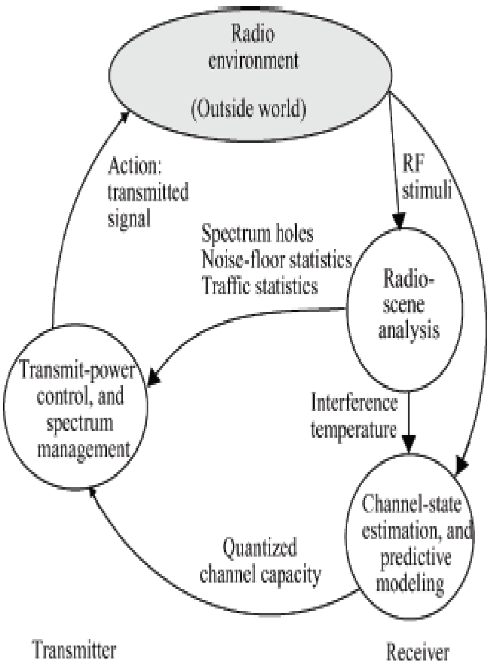
Spectrum scarcity is one of the biggest challenges that the modern world is facing. The efficient use of available licensed spectrum is becoming more and more critical with increasing demand and usage of the radio spectrum. Different researches show that the usage is not uniform throughout the licensed spectrum rather it is heavy in certain parts of the spectrum and has portions that are utilized inefficiently. Some researchers even claim that more than 70% of the licensed frequency band is not in use, most of the time. So, there is much room for work yet in the unutilized parts or the inefficiently utilized parts of the spectrum, to overcome the spectrum scarcity problem.

Different researches are in progress and ways are being found to efficiently utilize the available licensed spectrum. One of the ways is the use of "Cognitive Radio", according to this; the already licensed spectrum can be used more efficiently by introducing artificial intelligence, the decision making to be specific, in the radio. This enables the radio to learn from its environment, considering certain parameters. Based on this knowledge the radio can actively exploit the possible empty frequencies in the licensed band of the spectrum that can then be assigned to other processes in such a way that they don't cause any interference to the frequency band that is already in use.

This makes the efficient usage of the available licensed spectrum possible. The users that are allocated the licensed frequency bands of the spectrum are the primary users and the users that are allocated the empty frequencies within the licensed frequency band, according to their requested QoS specifications, are known as the secondary users or the cognitive users. They are called as the secondary users as they utilize the unused spectrum resources only, on non-interfering basis, with the primary users.

This paper will focus on the implementation of different spectrum allocation techniques for these secondary users, based on Fuzzy logic Algorithms and an evaluation of the performance of these techniques using Matlab coding. This work will focus on the decision-making process mainly, with an assumption that the radio environment has already been sensed and the QoS requirements for the application have been specified either by the sensed radio environment or by the secondary user itself [4].

2. Cognitive radio cycle



The three cognitive tasks:

- Radio-scene analysis, which encompasses the following: estimation of interference temperature of the radio environment; detection of spectrum holes.
- Channel identification, which encompasses the following: estimation of channel-state information (CSI); prediction of channel capacity for use by the transmitter
- Transmit-power control and dynamic spectrum management. Tasks 1) and 2) are carried out in the receiver, and task 3) is carried out in the transmitter.

From this brief discussion, it is apparent that the cognitive module in the transmitter must work in a harmonious manner with the cognitive modules in the receiver. In order to maintain this harmony between the cognitive radio's transmitter and receiver at all times, we need a feedback channel connecting the receiver to the transmitter. Through the feedback channel, the receiver is enabled to convey information on the performance of the forward link to the transmitter.

The cognitive radio is, therefore, by necessity, an example of a feedback communication system. One other comment is in order. A broadly defined cognitive radio technology accommodates a scale of differing degrees of cognition. At one end of the scale, the user may simply pick a spectrum hole and build its cognitive cycle around that hole. At the other end of the scale, the user may employ multiple implementation technologies to build its cognitive cycle around a wideband spectrum hole or set of narrowband spectrum holes to provide the best expected performance in terms of spectrum management and transmit-power control, and do so in the most highly secure manner possible.

In the following subsections we provide an overview of the three main steps for the cognitive cycle: i.e., spectrum sensing, spectrum analysis, and spectrum decision.

Spectrum sensing

A cognitive radio identifies from the information available in the spectrum, the empty frequencies and the portions of the spectrum that are in use, by sensing the spectrum.

Spectrum analysis

Once identified the empty frequencies, their characteristic are determined, in order to make the allocation of the best possible frequency band among them, to the secondary user, according to the QoS requested by it. This includes the determination of the data rate, the transmission mode, and the bandwidth of the transmission.

The Cognitive Radio can then change its parameters according to the spectrum analysis carried out in the above manner to allocate it to the secondary user.

Spectrum decision

On the basis of the above spectrum analysis, the decision for the allocation of the best possible frequency band to be assigned to the secondary user is taken. This spectrum decision lies among the identified empty frequencies in the spectrum sensing process. Once the operating spectrum frequency band is determined, the communication can be performed over this spectrum frequency band. However, there is still the dynamic spectrum access part to be considered for scheduling purpose, as the radio environment changes over time and space, the cognitive radio should keep track of the changes of the radio environment, at real time. If the current spectrum band in use becomes unavailable, the spectrum mobility function is performed, it must vacate the spectrum for the primary user, and move to a better virtually unlicensed frequency band, maintaining the ongoing communications along with a fair scheduling among the users and spectrum sharing by them, in such a manner that no interference is observed among them. Any environmental change during the transmission such as primary user appearance, user movement, or traffic variation can trigger this adjustment [2].

3. Fuzzy logic architecture

The principle structure of FLC mainly consists of as shown in fig.

1. Fuzzification module
2. Knowledge base
3. Inference engine.
4. Defuzzification module.

1) Fuzzification module

The fuzzification module (FM) performs the following functions

Normalization

Performs a scale transformation (i.e. an input normalization) which maps the physical values of current process state variables into a normalized universe of discourse (normalized domain) When a non–normalized domain is used then there is no need of scale transformation.

Fuzzification

Performs so called fuzzification which converts a point-wise (crisp), current process state variable into a fuzzy set, in order to make it compatible with the fuzzy set representation of the process state variable in the rule-antecedent. Fuzzification when inference is individual rules base firing.

2) Knowledge base

The knowledge base of FLC consists of a database and rule base.

Data base

The basic function of database is to provide the necessary information for the proper functioning of fuzzification module, the rule base and the defuzzification module. This information includes.

- Fuzzy sets (membership functions) representing the meaning of the linguistic values of process state and control o/p variables
- Physical domains and their normalized counterparts together with the normalization and denormalization factors
- Information concerning quantization factors for discretized domain

Rule base

The basic function of an rule-base is to represent in a structured way the control policy of an experienced process operator and / or control engineer in the form of a productions rule such as

if (process state) then (control output)

The if part of such a rule is called the rule-antecedent and is a description of a process state in terms of a logical combination of atomic fuzzy propositions. The then part of the rule is called the rule-consequent and is again a description of the control output in terms of logical combinations of fuzzy propositions. These propositions state the linguistic values, which the control output variables take whenever the current process state matches (at least to a certain degree) the process state description in the rule-antecedent.

3) Inference engine

There are two basic approaches employed in the design of the inference engine of a FLC.

1. Composition based inference (firing)
2. Individual rule based (firing)

Composition based inference

In this case the meanings of each individual rule are aggregated into one fuzzy relation describing the meaning of the overall set of rules. Then inference or firing with these fuzzy relations is performed via the operation composition between the fuzzified crisp input and the fuzzy relation representing the meaning of the overall set of rules.

Individual-rule based inference

In this case, first each single rule is fired.

1] Computing the degree of match between the crisp input and the fuzzy sets describing the meaning of rule-antecedent and

2] "Clipping" the fuzzy set describing the meaning of the rule-consequent to the degree to which the rule-antecedent has been matched by the crisp input.

Finally, the "clipped" values for the control output of each rule are aggregated, thus forming the value of the overall control output [1].

4) Defuzzification module

The functions of the defuzzification module (DM) are

Defuzzification

Converts the set of modified control output values into a single point-wise value.

Demoralization

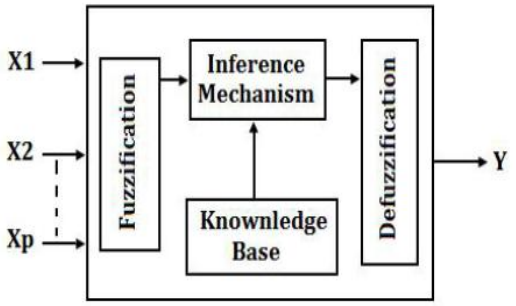
Maps the point-wise value of the control output onto its physical domain. It is not needed if non-normalized domains are used [6].

4. Result and discussion

In cognitive radio network, the decision making of resource management is based on knowledge of the operational environment. The rule based decision making scheme consider various parameters such as Node's control, Node's Link state amount, Node's Link state time and Aggregation weight. The fuzzy approach is discussed in this section, with design steps required to construct fuzzy inference system are mentioned as follows

- Identify the inputs, outputs and status of CR's.
- Partition the universe of discourse or the interval spanned by each variable into a number of fuzzy subsets, assigning each a linguistic label.
- Assign or determine a membership function for each fuzzy subset.
- Assign the fuzzy relationships between the inputs or states fuzzy subsets on the one hand and the outputs fuzzy subsets on the other hand, thus forming the rule-base.
- Choose appropriate scaling factors for the input and output variables in order to normalize the variables.
- Fuzzify the inputs to the decision making scheme.
- Use fuzzy approximate reasoning to infer the output contributed from each rule.
- Aggregate the fuzzy outputs recommended by each rule.
- Apply defuzzification to form a crisp output.

The functional block diagram of a fuzzy inference system used in the proposed approach is as shown in Figure 2, in which crisp inputs are converted to fuzzy inputs by using process of fuzzification. When inputs are applied to the mamdani FIS then inference engine computes the output set corresponding to each rule. The defuzzifier then computes a crisp output from the number of fuzzy If-Then rules.



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A fuzzy system with a p-inputs and single output is described by a collection of *l* linguistic If-Then rules is given

R^l : $IF\ x_1\ is\ A_l^1\ and\ x_2\ is\ A_l^2 \ldots\ldots and\ x_p\ is\ A_l^p\ THEN\ y\ is\ B_l$

where, $A_l^1, A_l^2, \ldots\ldots and\ A_l^p$ are the fuzzy sets representing the *l*th antecedent pairs and B_l is the fuzzy set representing the *l*th consequent. For set of conjunctive rules, the aggregated output for the *l* rules is given by,

$$\mu_y(y) = min\left[\mu_y^1(y), \mu_y^2(y), \ldots \mu_y^l(y)\right] \qquad for\ y\ \epsilon\ Y$$

The weighted average method is the most frequently used technique for defuzzification but usually restricted to symmetrical output membership function and is given by,

$$z^* = \frac{\sum \mu_c(\bar{z}).\bar{z}}{\sum \mu_c(\bar{z})}$$

Where, $\sum$. is the algebraic sum and $\bar{Z}$ is the centriod of each symmetric membership function. Here, we design fuzzy inference system to solve the opportunistic spectrum access problem in CR networks. Expert knowledge for selecting the best suitable SU to access the available band is collected based on three antecedents such as, node's control, state amount and link state time, with one consequent as aggregation weight. Based on the knowledge of linguistic variables, Five If-Then fuzzy rules are used to take the decision for opportunistic spectrum management, which is shown in Table 1.

In this work, using rule based fuzzy logic system, we combine the above three descriptors to determine optimal solution to assign spectrum opportunistically. After analyzing the characteristics of link state aggregation data, the Fuzzy Convergence prototype system is built for evaluating node control in link states, and it is developed with the fuzzy logic inference technique. Specifically, the system could handle imprecise or uncertain information collected from the wireless nodes. Adopting link state aggregation characteristics, three important design criteria are suggested: (a) The network bandwidth consumption required to exchange local convergence for hot spots could be extremely high.

Thus, a control plane for link states is capable of considering the unbalanced link states. (b) For lesser impact from small users, a control plane should not apply the same evaluation cycle for all nodes. The super users can be updated more often than the small users. (c) Given a link state number, it makes sense to evaluate the large link states more often than the small users. (c) Given a link state number, it makes sense to evaluate the large link states more often than the small ones.

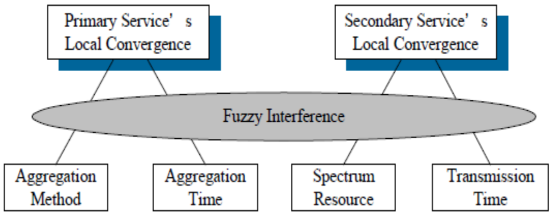

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Figure 3 illustrates system works by performing two major inference steps: local convergence calculation and global control aggregation. It shows the local convergence calculation for link states. In local convergence calculation, nodes perform fuzzy inference on local parameters to get the local convergence.

The fuzzy inference mechanism can catch uncertainties information and is self-adjusting. Adaptively, it can track the variation of local parameters, such as interference power, interference power, bandwidth of a frequency band, path loss index, and so on.

In global control aggregation, the Fuzzy Convergence system aggregates local convergence collected from all nodes to generate a global control for each node. The system adopts fuzzy inference to get the global control aggregation weights. The aggregation weights are identified using three variables: the node's control, the link state aggregation date, and the link states amount.

In a full-scale P2P control plane, the number of fuzzy inference rules should be extended to several hundreds. Also, Table 1 lists some frequently used fuzzy inference rules to Fuzzy Convergence system construction [3].

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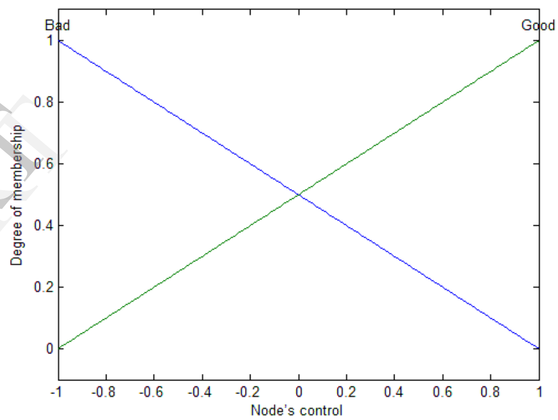
Condition	Rules
The node's control is good and the link state amount is high	The aggregation weight is large
The node's control is good and the link state amount is low	The aggregation weight is medium
The node's control is bad	The aggregation weight is small
the link state amount is very high and the link state time is new	The aggregation weight is large
the link state amount is very low and the link state time is very old	The aggregation weight is small

In fuzzy inference system, three antecedent propositions can be expressed in fuzzy partitions such as Bad, Good for *Input-1*, Low, Very Low, High, and Very High for *Input-2*, Old and New for *Input-3*. The consequence i.e. the aggregation weight is divided in to three levels which are Small, Medium and Large.

We use triangular membership functions to represents input as well as output parameters of decision making structure. MFs are shown in Figure 4(a) (b) (c) (d), since we have three antecedents and three fuzzy subsets, we need to set up 5 rules for this fuzzy system. Then, we design rules, which will be depending on various operating conditions and human knowledge. According to rules as follows,

R^l : IF Noode's control (x_1) is A_l^1 and Nodes Link state amount x_2 is A_l^2 and Node's Link state time x_3 is A_l^3 THEN Aggregation weight (y) is B_l



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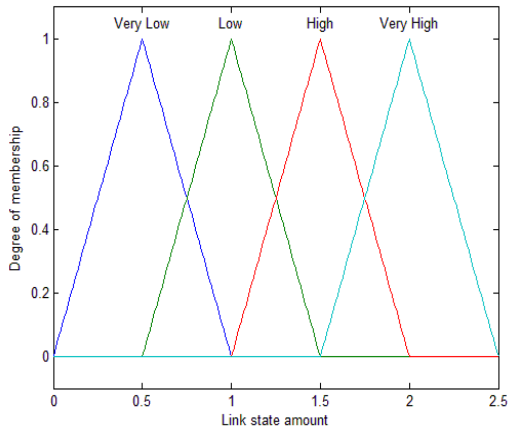

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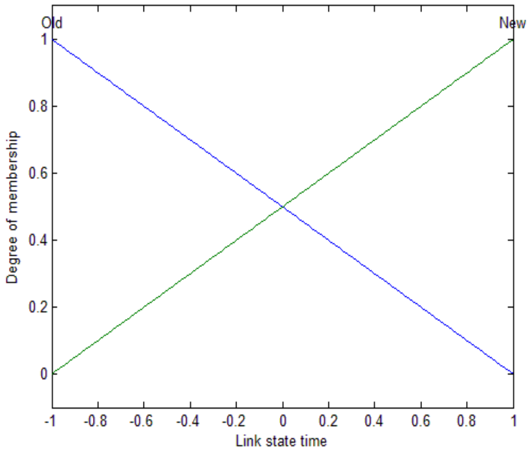

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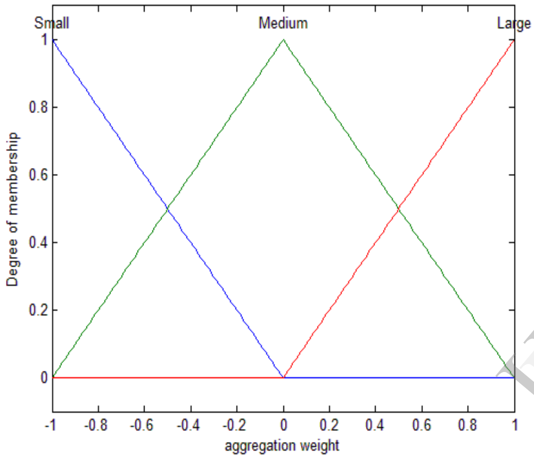

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$$c_{avg}^{l} = \left(\frac{\sum_{i=1}^{5} w_i^l \; c^i}{\sum_{i=1}^{5} w_i^l} \right)$$

The above equation represents output of fuzzy inference engine used in dynamic resource management for cognitive radio network. Table 1 shows the rules corresponding to the parameters used for decision making operation. For every input (x1; x2; x3), the output y of the designed system is computed as

$$y(x_1, x_2, x_3) = \left(\frac{\sum_{i=1}^{5} \mu F_1(x_1)\, \mu F_2(x_2)\, \mu F_3(x_3)\, c_{avg}^{l}}{\sum_{i=1}^{5} \mu F_1(x_1)\, \mu F_2(x_2)\, \mu F_3(x_3)} \right)$$

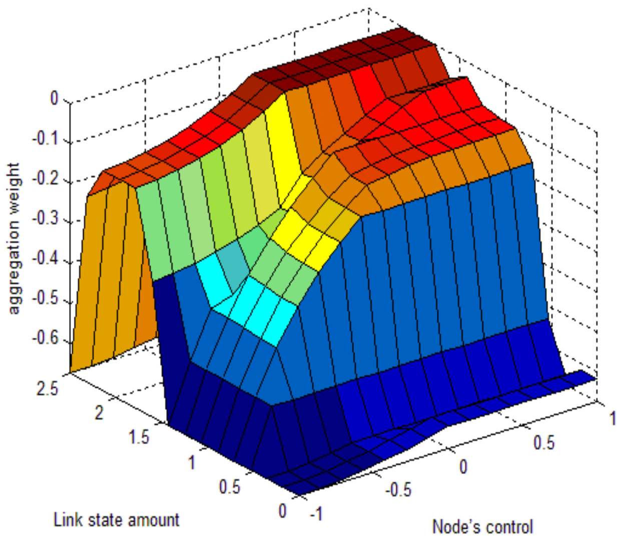
From above equation, we get 4D surface, but it is impossible to plot visually so that we fix one of three variables. The optimized decision making result is obtained with help of fuzzy logic technique.

5. Simulation results

To evaluate the response of fuzzy system in CRs, we randomly generated normalize sequence values of three descriptors as Node's control was a random value in the interval [-1 1] and its Node's Link state amount in [0 2.5] with third parameter as Node's Link state time were normalized to [-1 1]. The output of fuzzy decision making, ie the aggregation weight was selected to access the available spectrum was computed and Figure 5 (a) (b) (c) represents the opportunistic dynamic resource management decision surface for the cognitive user.

Fuzzy Logic provides a different way to approach a control or classification problem. Fuzzy approach requires a sufficient expert knowledge for the formulation of the rule base, the combination of the sets and the defuzzification. The employment of fuzzy logic might be helpful, for very complex processes, when there is no mathematical model for highly non-linear processes or if the processing of expert knowledge is to be performed [5].

The results show that, optimum dynamic resource management in cognitive network. The decision making operation will enable the resource management opportunistically which will in turn improve spectrum utilization. It is important to investigate some solutions to prevent some users from using spectrum ineffectively and solve the mobility management problem in order to keep a high QoS of cognitive radio.



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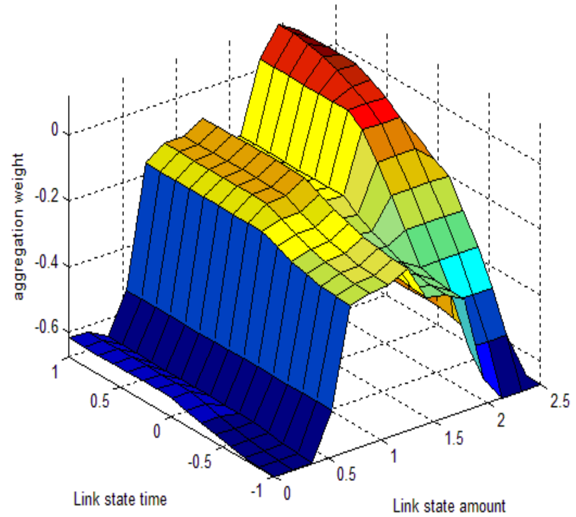

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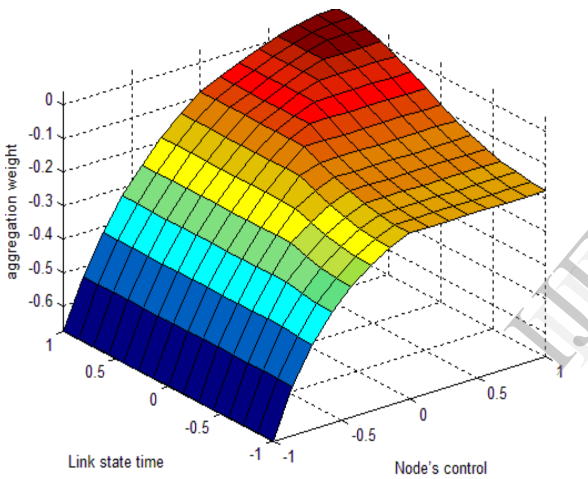

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6. Conclusion

Recognizing that fuzzy logic inference can better handle uncertainty, fuzziness, and incomplete information in node convergence report, Fuzzy Convergence is developed as a novel approach to aggregate wireless node control with affordable message overload. A mamdani fuzzy inference system is based on experiences from a group of network experts, so that an acceptable decision can be obtained. As a result, we represent the opportunistic resource management in terms of decision surface. In this work, the resource management for the future heterogeneous network is illustrated. The analysis indicates that the fuzzy logic interference could be a clearly effective for distributed management in heterogeneous wireless environment. The Fuzzy Convergence is designed as a mechanism to enable efficient spectrum etiquettes, and it enables each node to dynamically decide on an affordable message overhead in terms of local information. Also, with the performance advantages in dense or clustered networks environment.

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