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Resource Allocator for Non Real-Time Traffic in Wireless Networks Using Fuzzy Logic

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Abstract. Providing efficient access to a large user population with variant service requirements in wireless communications networks poses a very challenging problem. Resource allocation in the wireless domain should take into account bandwidth limitations and fading effects inherent to wireless channels, while accommodating for resource constraints encountered in wireline networks. In this paper, a fuzzy resource allocator is proposed in order to facilitate the efficient allocation of network resources in the wireless domain. The network preferentially allocates its resources to real-time (RT) traffic sources. Using effective transmission rate statistics of non real-time (NRT) trafficd sources as a measure of fading channel conditions, the fuzzy allocator optimally allocates the remaining resources to NRT traffic. Simulations show that the fuzzy allocator can reduce delay and incurs fewer retransmissions for NRT traffic. An overall improvement in wireless channel utilization is demonstrated.

Keywords: wireless channel, resource allocation, fuzzy logic, channel utilization.

1. Introduction

Future wireless communications networks are expected to interwork with wireline broadband networks in order to support multimedia services for mobile users anywhere at anytime. Different media types, with varying quality of service (QoS) requirements, may access these networks. These media types may be broadly categorized into real-time (RT) traffic, such as voice and video, which is usually delay sensitive, and non real-time (NRT) traffic, such as still images and text, which is typically loss sensitive. In order to efficiently use network resources, and satisfy QoS requirements, proper resource allocation is necessary. However, the limited radio frequency spectrum and fading conditions inherent to wireless channels pose resource allocation problems which are more complex than those encountered in the wireline domain. This is because signals traveling between transmitters and receivers through a wireless medium undergo attenuation due to transmitter-receiver separation, and the physical environment posed by the propagation path [2]. Transmission rate control in a wireline network depends on network congestion only. In the wireless domain, transmission rate control becomes a function of both network congestion and fading conditions experienced by a transmitted signal.

Traditionally, resource allocation involves using a set of measured parameters to predict the required resources for an upcoming transmission period. The parameters are assumed to have little or no uncertainties [1]. For instance, the wireless channel can be considered to have two states: degraded and non-degraded, with a precisely defined threshold between these states. A measured pilot signal by a mobile host (MH) from a base station (BS) falling within close proximity to the precisely defined threshold is taken as evidential support of the channel being in only one of the two states. Resources are then allocated according to one of the two channel states. The category of logic in which a channel state either does or does not belong to a degradation state is known as crisp logic. However, the rate with which the channel may fade can vary significantly. This poses some difficulty in predicting the optimal user transmission rate based on recent fading channel measurements. Fading effects can decrease a user's effective transmission rate, implying an increase in the need for retransmissions by a loss sensitive NRT traffic source. NRT traffic sources distributed around a BS will have different effective transmission rates due to the various levels of attenuation experienced. Sources with high effective rates may transmit more information while sources with lower effective rates may transmit less. Using this as the premise by which rules for resource allocation are determined, the resource allocator is able to facilitate optimal utilization of channel resources for NRT traffic sources. The resource allocator also takes into account multiple channel states.

The simplification of resource allocation, provisioning of improved service to NRT traffic sources, and resulting improvement in wireless channel utilization has practical significance. In this paper, a fuzzy resource allocator is developed to meet these objectives. The fuzzy allocator accepts the possibility of measurement uncertainty and includes this uncertainty consideration in its definition of fuzzy variables. Thus it allows a gradual transition between the multiplicity of possible channel states. The fuzzy allocator also optimally assigns available channel resources to NRT traffic sources according to their effective transmission rate statistics, which enables more efficient utilization of channel resources. Simulations have demonstrated that the fuzzy allocator can improve NRT traffic delay and resource utilization efficiency in comparison to other resource allocation mechanisms.

The remainder of this paper is organized as follows. Section 2 describes the proposed fuzzy resource allocator model. Section 3 is devoted to the design of the fuzzy resource allocator. Simulation results and their implications are presented in Section 4. Concluding remarks are given in Section 5.

2. System Model

Figure 1 shows the system model of the proposed fuzzy resource allocator. In the model, the base station is the control center which performs the policing function (by leaky buckets) for traffic accessing the integrated wireless/wireline network. Wireless traffic, consisting of both RT and NRT traffic, accesses channel resources using narrowband time division multiple access (TDMA). Through the allocation of network resources, RT traffic is given priority access, thus ensuring that such traffic meets the requirement of minimal delay.

Channel condition information for NRT traffic sources is obtained by observing received signal strengths. Depending on the received signal strength for each source, a channel condition indicator, $rate_{eff}$, may be obtained. Using a measure of the percentage of resources allocated for RT traffic, $\%RT$, along with $rate_{eff}$ as inputs to the fuzzy allocator, output parameters m_l and r_l for leaky bucket control of NRT source l are generated, where $l = 1, 2, \ldots, N$.

Let a defined TDMA time frame be divided into S time-slots. The portion of available slots allocated to RT traffic is given by:

$$RT_{slots} = \lceil S \times \%RT \rceil \,. \tag{1}$$

The slot availability for NRT traffic sources is given by $NRT_{slots} = S - RT_{slots}$. To meet minimum QoS requirements, a minimum allocation of time-slots is made for each NRT traffic

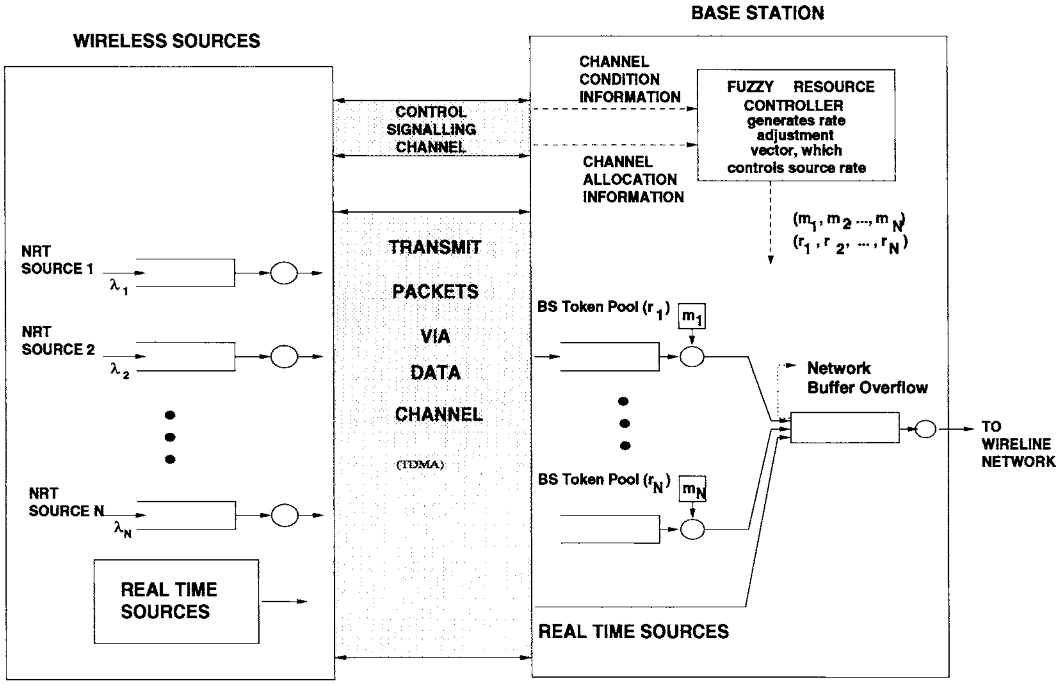

Figure 1. System model of the fuzzy resource allocator.

source. Allocation above this minimum occurs if there are time-slots remaining. The token pool size, m_l, determines NRT slot allocation. Sources experiencing better channel conditions are allocated more time-slots than the allocated minimum. The lth NRT traffic source transmits using repetition coding, with each packet being repeated rep_l times where rep_l is inversely proportional to token generation rate, r_l. High repetition rates, rep_l, are prescribed for sources experiencing poor channel conditions, whereas lower rep_l are prescribed for sources experiencing better chanel conditions. By repeating a packet rep_l times, the likelihood of at least one of the rep_l packets containing an acceptable power level for a given bit position increases. Thus by using repetition coding, the fuzzy token generation rate output vector ensures increased efficiency in the transmission of NRT traffic.

The allocation information is broadcasted to all users in a reservation frame using the control signalling channel. It is assumed that the control signalling channel uses robust coding which ensures readability upon reception at the source end [6]. It is also assumed that there is sufficient buffer space available at the NRT traffic source end, to ensure that packets are not lost due to buffer overflow.

NRT traffic sources are characterized as bursty *ON-OFF* sources. In the *ON* state, the burst length is modeled by a geometric distribution with parameter $\frac{1}{mbl}$, where *mbl* gives the mean burst length for the source when it is in the *ON* phase. It is assumed that the burst or *ON* phase has constant duration, Δt time units. NRT traffic load is defined as a percentage ρ_d of the possible load. With N NRT traffic sources, the mean batch arrival rate for the lth source is given by:

$$\lambda_l = \frac{\rho_d(\%)}{N \times mbl}. \tag{2}$$

The effect of varying NRT traffic load is observed by increasing ρ_d and recalculating λ_i. The mean inter-arrival time, *mia*, is calculated by:

$$mia = \frac{1}{\lambda_l} \tag{3}$$

as described in [5].

Path loss and shadowing effects at a transmitter-receiver separation of d are modelled by:

$$PL(d) = \overline{PL}(d_0) + 10\kappa \log\left[\frac{d}{d_0}\right] + X_\sigma \tag{4}$$

where d_0 is a close-in reference distance obtained through measurements, $\overline{PL}(d_0)$ is the average path loss at the close-in reference distance, κ is the path loss exponent, and X_σ is a zero-mean Gaussian distributed random variable, with standard deviation σ representative of log-normal shadowing [2]. A source transmits a bit as a waveform of a particular power, P_{tr}. Upon arrival at the base station, the waveform has power, P_{rx}, where P_{rx} is given by:

$$P_{rx} = P_{tr} - PL(d) \tag{5}$$

and P_{rx}, P_{tr} and $PL(d)$ are all in dB (m).

3. Fuzzy resource allocator

In fuzzy logic, an element $\{a\}$ can have a degree of membership in a fuzzy set X, where $U \to [0, 1]$ is the universe of discourse, $a \in U$, and $\mu_x(a)$ is a membership function. A membership function associated with a fuzzy set maps an input value to an appropriate membership value. This mapping is known as fuzzification. The universe of discourse U is spanned by $\{X_i\}$ where $i \in \{1, \ldots, n\}$ and X_i are fuzzy sets. X_i may or may not overlap with X_j, where $j \in \{1, \ldots, n\}$, and n represents the number of fuzzy sets spanning U. The definition of fuzzy sets and fuzzy logic, as opposed to *crisp* logic, allows for the gradual transition between states akin to the natural progression of channel degradation.

The principal difference between fuzzy logic and crisp logic arises from the different rules governing membership. Fuzzy logic permits both partial membership and overlapping membership in non-exclusive fuzzy sets, whereas crisp logic does not permit the notion of partial membership. In crisp logic, membership must be exclusive to one set. The benefit of membership functions used in fuzzy logic stems from the ease with which linguistic variables, which may be described in terms of their level of membership in more than one state, can be mapped to fuzzy variables. By considering the dual-state (or multiple-state) membership of variables, a control decision may be made which reflects a more comprehensive understanding of the system state.

When a crisp value is resolved into a mapping of memberships in fuzzy sets, it is said to be fuzzified. This is the first step in implementing a fuzzy controller, as shown in Figure 2.

Fuzzy logic is implemented through the use of fuzzy rules. A fuzzy rule is defined by the relationship between an observation and an action, and takes the form:

$$\text{if } \{x_i \text{ is } X_i,\ \text{(and, or, not) } x_j \text{ is } X_j, \ldots\},\ \text{then } y_k \text{ is } Y_k$$

where x_i is a measured value; $\{x_i$ is $X_i\}$ denotes the degree of membership of x_i in X_i; y_k is the output value; $\{y_k$ is $Y_k\}$ denotes the degree of membership of y_k in Y_k; k is the number of fuzzy outputs.

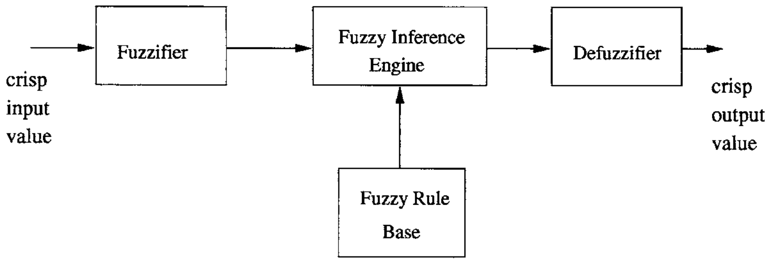

Figure 2. A fuzzy controller model.

A fuzzy rule can also be given a respective weight $w_r \in [0, 1]$ where $r \in \{1, \ldots,$ number of rules$\}$.

The first part of the rule is called the antecedent, and examines the observations and their coupling; the latter part of the rule is called the consequent, and defines the action to be taken [3]. The antecedent and consequent may be multipartite, in which case they are resolved using the *min* operation, *max* operation and *inverse* operation to implement AND, OR and NOT Boolean operators, respectively. The fuzzy sets, X_i and Y_k, represent linguistic variables, thus a fuzzy rule can easily model axioms derived from expert knowledge. A collection of fuzzy rules, $\{R_1, \ldots, R_n\}$, formed from the fuzzy sets, describe the desired observation and control action, and together form a fuzzy rule base. Within the rule base, each rule is evaluated separately, and the result is computed. A fuzzy inference engine determines which of these rules $\{R_i\}$, where $i \in \{1, \ldots, n\}$, are matched and subsequently executed.

The fuzzy inference engine and the fuzzy rule base work in tandem. The rule base contains a collection of rules which effectively implement expert control strategies. In order for these expert control strategies to be determined, the rule base may need to be trained. The method by which the rules are executed (or fired) depends on the inference mechanism implemented by the inference engine. According to some (usually intuitive) approach, the inference engine will contain an algorithm regarding the sequence in which the rules should be fired, or indeed whether they should be fired sequentially at all. If the rule base is extensive, sequential firing may become too time-consuming and some parallel method may be employed instead. If the rule base contains n rules, and the antecedent(s) of K of these n rules are matched, the control action to be taken is decided by the inference engine. Each of the K matched rules may or may not contribute to the final control action. The decision as to which rules contribute to the final action, is implemented by weighting the rules. Usually the overall control action will be the aggregate of the partial control actions suggested by each matched rule [4].

The output from the fuzzy inference engine will be a fuzzy value, which needs to be defuzzified in order to produce a crisp value. The defuzzification may be done by the *centroid method* which evaluates the center of the area resulting from the rule base evaluation.

The fuzzy resource allocator shown in Figure 3, is implemented through two fuzzy inference systems: a repetition rate control system, and an NRT slot allocation system. The former implements the control of token generation rates, whereas the latter implements the control of token pool allocations. The output vectors, M and R, are used to implement resource allocation. In the implementation of the repetition rate control system, fuzzification of the $\overline{RATE_{eff}}$ vector is performed by the fuzzifier, using the membership functions for effective rate as shown in Figure 4.

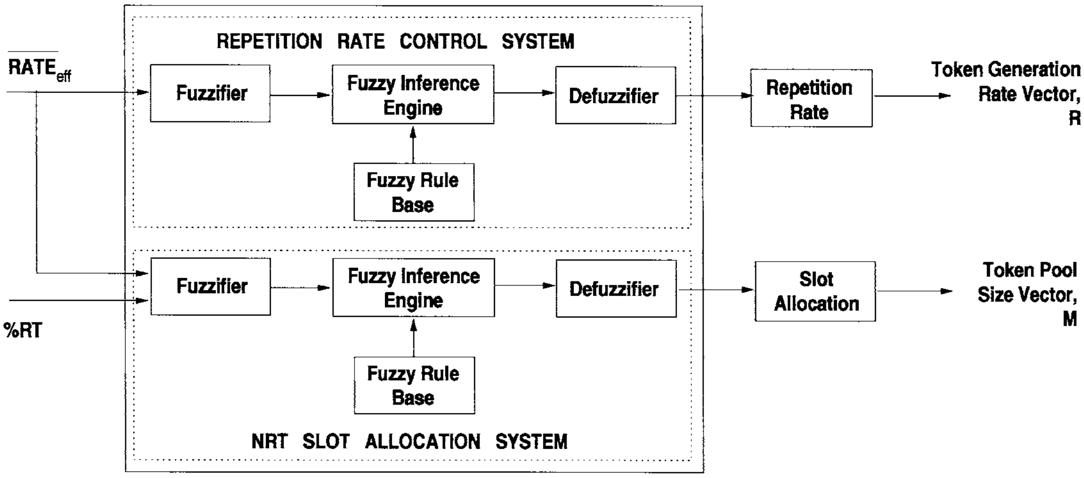

Figure 3. Fuzzy resource allocator.

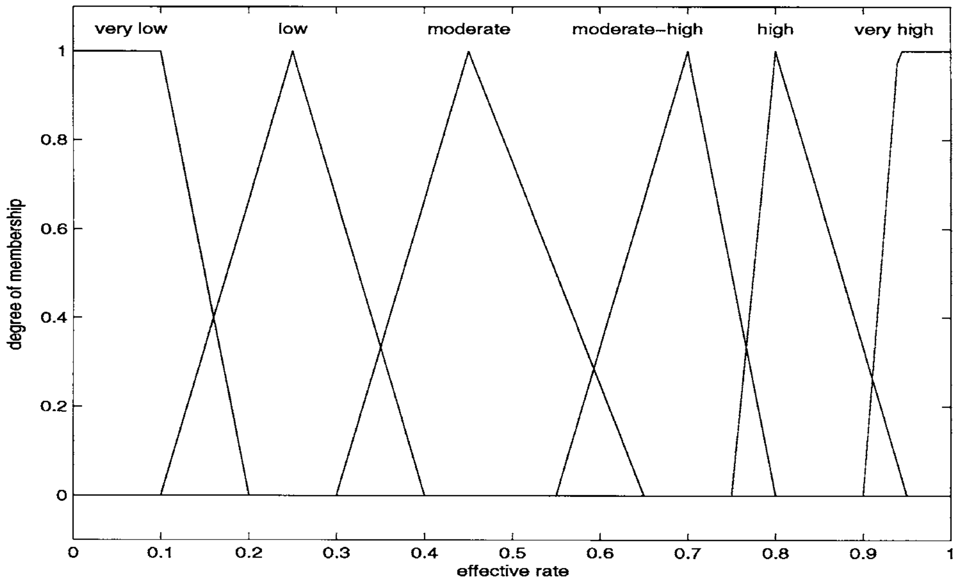

Figure 4. Effective rate input space.

The rules existing in the fuzzy rule base, displayed in Table 1, are evaluated by the fuzzy inference engine. The weight assigned to each rule varies between 0 and 1, and is indicative of the level of confidence an expert places on the importance of the rule describing the target system [9]. For the sake of simplicity, an intuitive approach was used to assign weights to the rules described in this paper. It is important to note that weights may also be determined by using a training data set of desired input-output pairs. The intuitive approach used in assigning weights can be better understood by examining the following examples: The rule "if *effective rate* is *very low*, then *repetition rate* is *very high*" is straight forward since a low *effective rate* is indicative of highly-degraded channel conditions, and under such conditions, the number of times a packet must be repeated is very high. Because the rule is straight foward, or intuitive, it is given a weight of 1. On the other hand, the rule "if *effective rate* is *moderate*, then *repetition*

Table 1. Fuzzy rule base.

Effective rate	Repetition rate	Weight
Very low	Very high	1.00
Low	High	1.00
Moderate	Moderate	1.00
Moderate	High	0.30
Moderate-high	Low	0.50
Moderate-high	Moderate-low	1.00
High	Low	1.00
Very high	Low	0.75
Very high	Very low	1.00

rate is *high*" is less straight forward, and is therefore given an arbitrary lower weight of 0.3. It is not intuitive to give a source, which is experiencing a moderate effective rate (or some degree of channel degradation), a high repetition rate, as such a source would likely suffice with a moderate repetition rate. For a source experiencing a moderate effective rate, the rule "if *effective rate* is *moderate*, then *repetition rate* is *moderate*" would appear to be more appropriate, and would therefore be given a weight of 1.

The rule evaluation result is defuzzified using the output membership functions for repetition rate, as depicted in Figure 5, and the output vector R is obtained. The membership functions used by the fuzzy inference system are determined through the use of expert intuition and a training data set of desired input-output pairs. The training data set is obtained through the simulation of packets being transmitted over a wireless channel with varying degrees of degradation due to transmitter-receiver separation. Through training, the optimum repetition rate, defined as the rate at which a packet experiences minimum delay and minimum number of packet retransmissions, is determined for a given value of effective rate.

The NRT slot allocation is implemented by a fuzzy system with bipartite inputs, which are fuzzified according to the membership functions for *RT usage* or *%RT*, and $\overline{RATE_{eff}}$, as depicted in Figures 6 and 7.

The membership functions for $\overline{RATE_{eff}}$ shown are based on intuition, and the use of training data was not necessary to obtain these functions.

The NRT slot allocation system takes into consideration all ranges of possible RT usage of resources, within the set {*very low, low, moderate, high, very high*}. For each of the five possible categories of RT usage, all possible effective rate categories in {*very low, low, moderate, high, very high*} are considered. Thus the fuzzy resource allocator accounts for all possible resource availability and channel degradation conditions, or all possible combinations of the pair (*RT usage, effective rate*).

Table 2 displays the rules found in the fuzzy rule base for the NRT slot allocation system. Rules describing the most extreme cases of RT usage and effective rate are given the highest weighting, because in these cases, the desired control action is most obvious. This can be demonstrated by examining the first rule in Table 2:

"If *RT usage* is very low and *effective rate* is very high, then *share_of_slots* is very high".

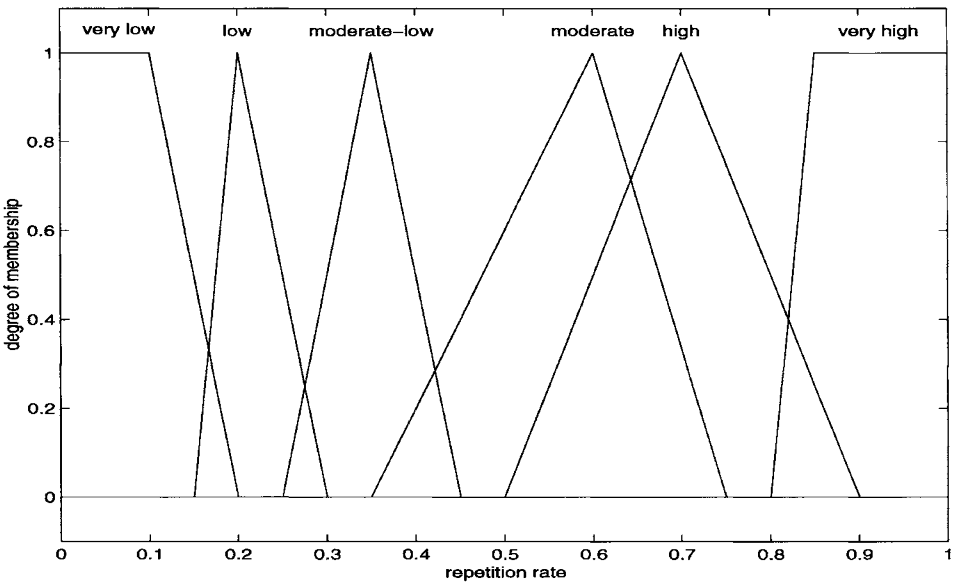

Figure 5. Repetition rate.

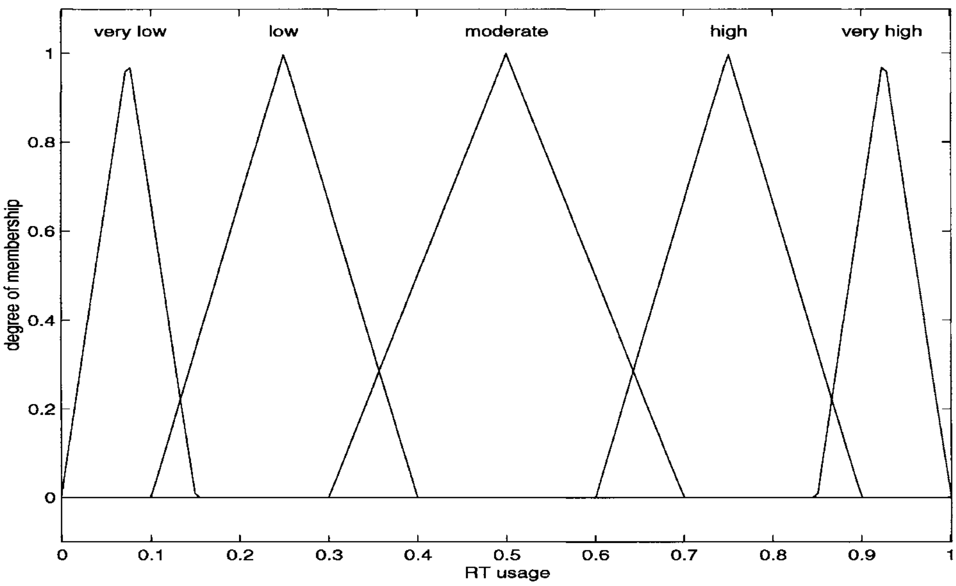

Figure 6. RT usage input space.

Consideration of this rule makes clear its intuitive nature; if *RT usage* is *very low*, there exist more resources which are available to NRT traffic sources, hence more slots may be allocated to NRT traffic sources accessing the wireless channel. However, slot allocation should be done according to the ability of NRT traffic sources to best utilize the available resources. This optimal slot allocation is done by assigning a *very high share_of_slots* to NRT traffic sources with *very high effective rates*, indicating very good channel conditions.

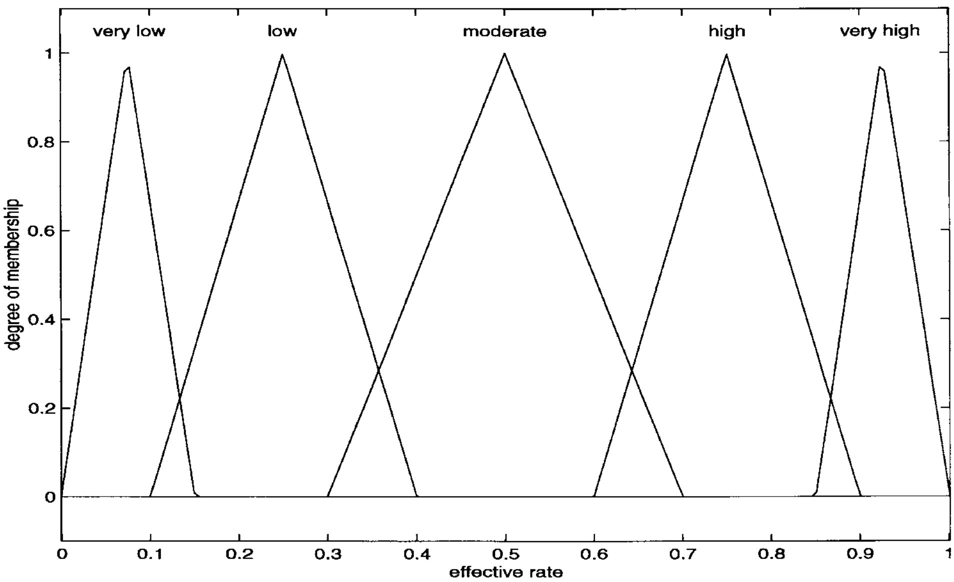

Figure 7. Effective rate input space.

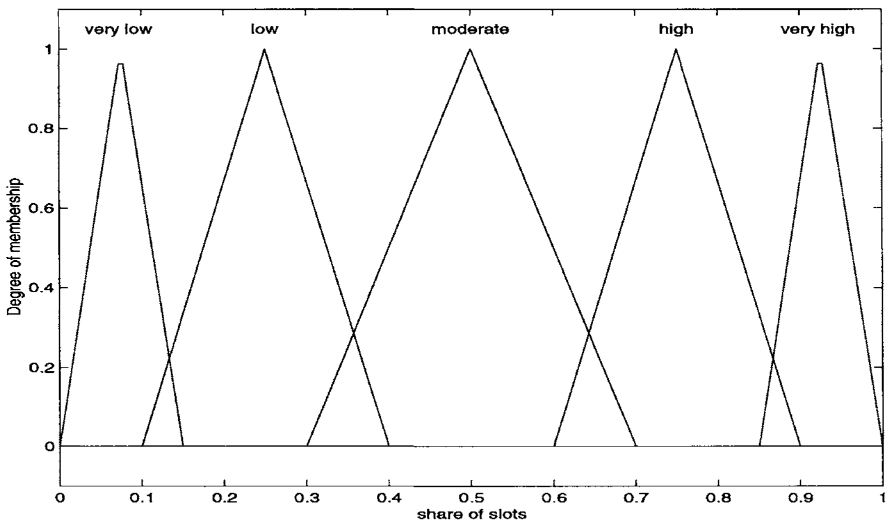

Figure 8. Share of slots allocated.

The fuzzy inference engine outputs the result of the executed rules to the defuzzifier, where the centroid method is used to determine the crisp value *share_of_slots*. The output membership functions that facilitate this process are shown in Figure 8.

The membership functions depicted in Figures 6–8 are uniform in their shapes because they are obtained from an intuitive understanding of the desired system operation; they are not skewed by training. The membership functions shown in Figure 8 do not give the specific number of slots to be allocated to each user. Instead they indicate the share, or portion of

Table 2. Fuzzy rules for NRT slot allocation in the fuzzy allocator.

RT usage	Effective rate	Share_of_slots	Weight
Very low	Very high	Very high	1.00
Very low	High	High	1.00
Very low	Moderate	Moderate	1.00
Very low	Low	Low	1.00
Very low	Very low	Very low	1.00
Low	Very high	Very high	0.50
Low	High	High	1.00
Low	Moderate	Moderate	1.00
Low	Low	Low	1.00
Low	Very low	Very low	1.00
Moderate	Very high	High	0.50
Moderate	High	Moderate	0.75
Moderate	Moderate	Low	1.00
Moderate	Low	Very low	0.50
Moderate	Very low	Very low	1.00
High	Very high	Moderate	0.50
High	High	Low	0.75
High	Moderate	Low	0.50
High	Low	Very low	1.00
High	Very low	Very low	0.75
Very high	Very high	Low	0.50
Very high	High	Very low	0.75
Very high	Moderate	Very low	0.75
Very high	Low	Very low	1.00
Very high	Very low	Very low	1.00

available slots, that should be allocated. The crisp value for the number of slots allocated for the lth NRT traffic source is given by:

$$NRT_l = \frac{share\_of\_slots_l}{\sum_{l}^{N} share\_of\_slots_l} \times (slots\ available\ for\ NRT\ traffic - N) + 1$$

where N is the number of NRT traffic sources in the system, and the lth NRT traffic source is guaranteed at least one slot. The number of slots available for NRT traffic sources is given by:

$$\lfloor (1 - \%RT) \times number\ of\ slots\ in\ frame \rfloor .$$

The slot allocation to a user is the means by which token pool size is adjusted. As described, token pool size is allocated as a combination of factors. It considers first the portion of the channel available for NRT traffic. From this portion, N slots are first reserved to ensure a minimum packet rate for all users. The remaining portion of the channel, when allocated to

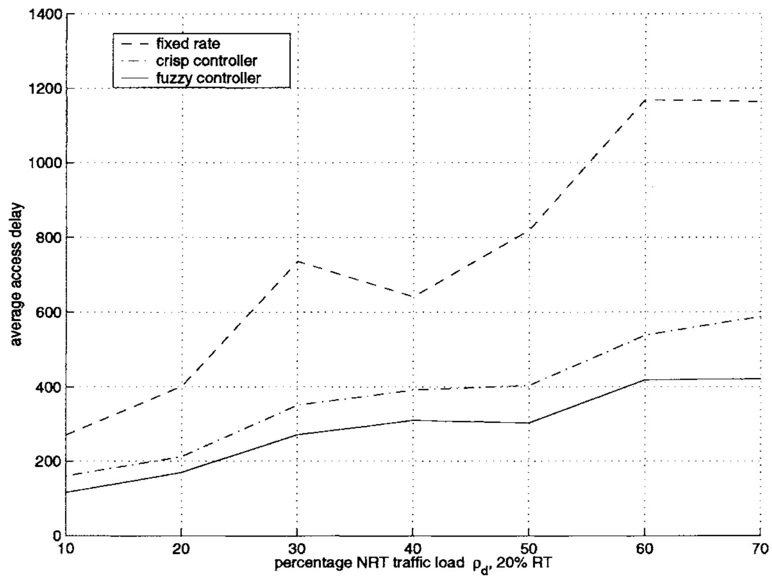

Figure 9. Effect of increasing ρ_d with $\%RT = 20$; $\kappa = 2.7$.

users, will form the excess rate above the minimum packet rate which has been promised to all users. In order to maximize the utilization of this "extra" channel capacity, token pool allocations are made such that the extra channel capacity is allocated to users with better effective rates. Excess channel capacity is allocated by allocating more slots to users with better effective rates. This effectively increases the token pool size for users with good channel access conditions.

4. Simulation Results

Access delay is defined as the delay which a packet experiences in getting from the source end to the network interior. Average access delay is calculated by summing the delay over all packets transmitted, and then dividing by the total number of packets transmitted. Figure 9 shows the effect of increasing NRT traffic load on average access delay. Differences in the performance of the crisp allocator and the fixed rate system, as compared to the fuzzy allocator, are apparent. The fixed rate system does not employ repetition coding to compensate for signal attenuation, and hence its very large access delay is expected. By increasing the path loss exponent, the effects of a greater degree of clutter in the propagation path are explored.

Figure 10 shows the performance of the fuzzy allocator being significantly better than that of the non-fuzzy resource control mechanisms. This improved performance becomes most significant for regions in which the path loss exponent is representative of urban areas (that is for path loss exponent κ greater than 2.5). In urban areas, user density is expected to be higher. In order to enable frequency reuse, cell size is usually reduced. The likelihood of problematic interference between users increases as user density increases. In small areas with high user density, increasing a user's signal power should be delayed as long as possible, in order to reduce the extent of signal interference between users. Using a fuzzy allocator, fading effects experienced in highly shadowed areas can be mitigated. This reduces the need for users to

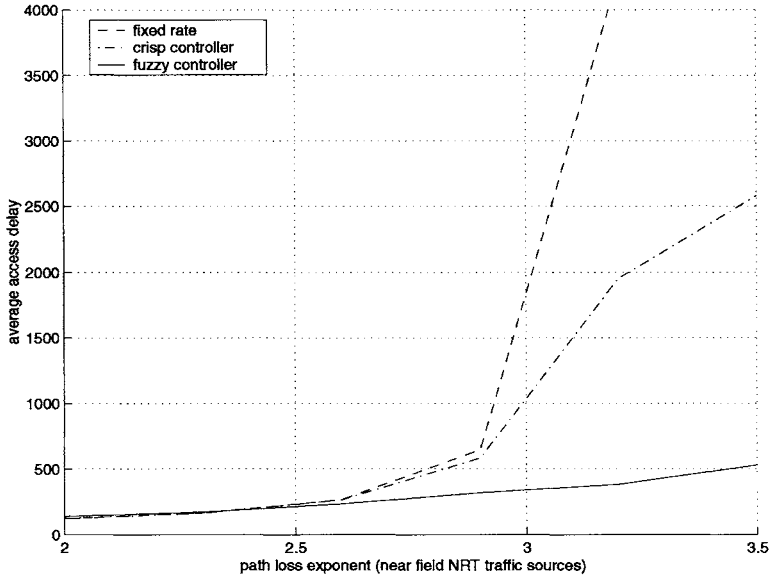

Figure 10. Effect of increasing path loss exponent on average access delay.

employ higher power signals, as with the same power level, a much lower access delay may be achieved.

Packet efficiency is a measure of the number of retransmissions which an NRT traffic source must make in order to have its packet received with sufficient power at the base station end. For simulation purposes, packet efficiency is defined as:

$$\frac{\textit{number of packets received correctly by base station}}{\textit{number of packet transmissions from source}}$$

where the denominator includes retransmissions.

Packet efficiency is examined as the path loss exponent increases, as shown in Figure 11. Packet efficiency is high when the path loss exponent is low. As the path loss exponent increases, packet efficiency decreases. This trend is to be expected because an increasing path loss exponent indicates increasing clutter in the propagation path. The result is more attenuation of signals arriving at the base station, and consequently more packet retransmissions by the source. For a given message stream, the fuzzy allocator with its ability to calculate effective repetition rates, reduces the number of times a user must retransmit packets. These results imply that, should a fuzzy resource allocator be employed, more users could be ensured access to resources, since each user would utilize resources more efficiently.

Channel utilization is a measure of the portion of channel resources which actually get used for NRT traffic transmission. It is defined as the ratio of the number of packets received correctly at the base station when NRT traffic sources are in their ON phase, to the total number of packet spaces (a function of the number of slots) allocated for NRT traffic transmission, and is given by:

$$\frac{\textit{number of packets received correctly by base station}}{\textit{number of packet spaces allocated}}.$$

Figure 12 shows channel utilization with changing *%RT*. The extent to which the channel is utilized by NRT traffic sources is reduced when channel resources available to these users

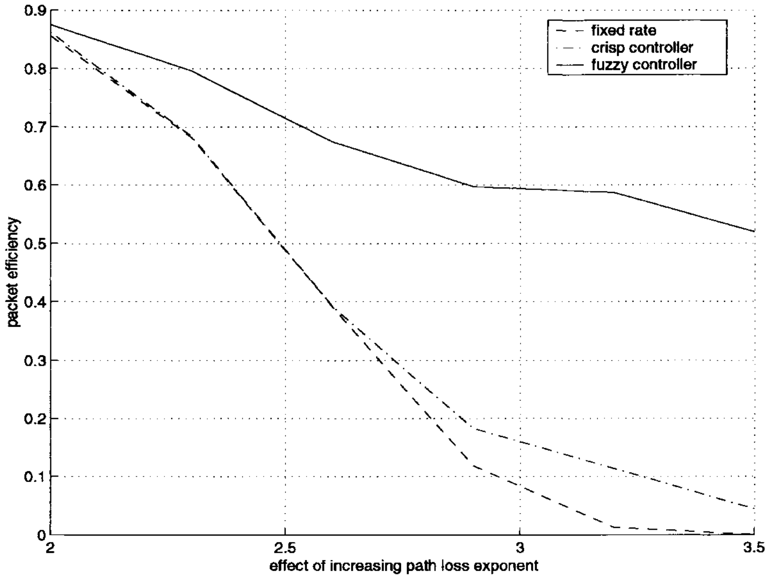

Figure 11. Effect of increasing path loss exponent on packet efficiency.

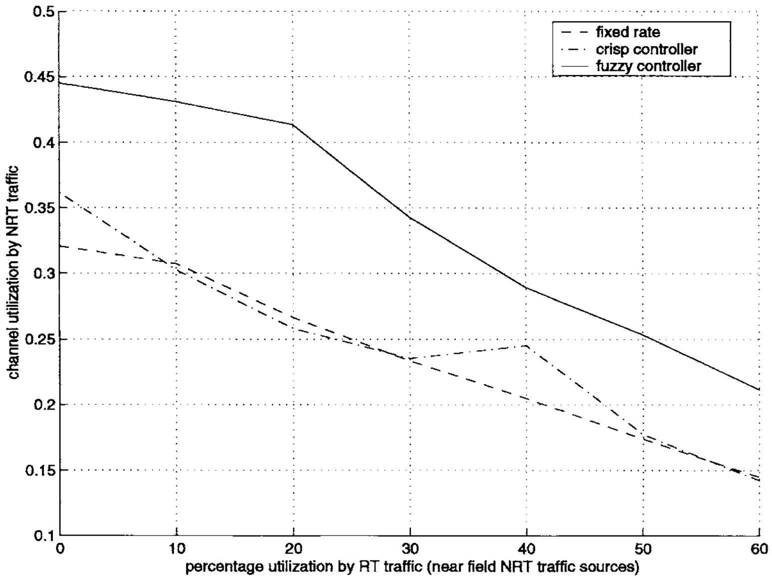

Figure 12. Effect of changing $\%RT$ with $\kappa = 2.7$.

diminish. As $\%RT$ increases, and resources become limited, the fuzzy allocator is able to optimally assign limited resources to those users who are best capable of using these resources. The overall number of allocations in which users are able to successfully transmit their packets is thus increased, and channel utilization increases.

Figure 13 shows that channel utilization deteriorates as the path loss exponent increases. This result is expected, because with a larger extent of clutter in the propagation path, more retransmissions become necessary due to signal attenuation, and resolution of signals, even with channel coding, becomes difficult. In the range of path loss exponent between 2 and 2.3,

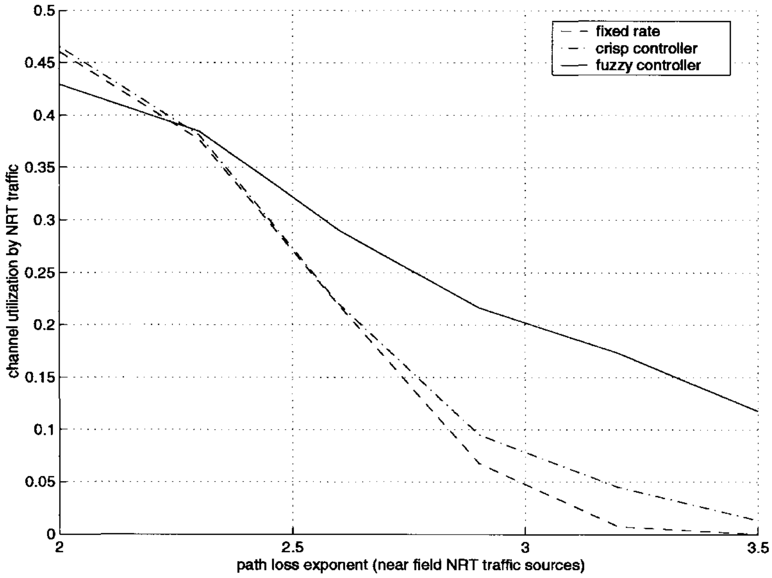

Figure 13. Effect of increasing path loss exponent on channel utilization.

the crisp and fixed rate controllers show better performance than that of the fuzzy controller. This is expected as the lower range of path loss exponent represents a relatively uncluttered propagation path. In such areas, a crisp or fixed decision may be made with a great degree of accuracy. Urban area cellular is represented by path loss exponent values between 2.7 and 3.5, with 3.5 representing a highly shadowed area. With the path loss exponent representing a highly shadowed area, the fuzzy allocator shows performance improvement over non-fuzzy allocators. These results suggest that, with significant signal attenuation, the fuzzy allocator requires fewer retransmissions, and uses channel resources more efficiently.

5. Conclusion

A fuzzy resource allocator was developed to provide optimal resource allocation for NRT sources, given the higher priority resource requirements for RT sources. A crisply coded adaptive resource allocator was used for comparison, along with a fixed resource allocation allocator. The fuzzy allocator was shown to reduce both access delay and retransmissions for NRT traffic. Channel utilization was also improved with the fuzzy resource allocator. The simplicity, low implementation cost [7], and performance benefit, demonstrated suggest that the fuzzy resource allocator would be a viable mechanism for optimal resource allocation.

The benefits of a fuzzy resource allocator, as described in this paper, are not only limited to TDMA systems, but can be extended to third-generation (3G) systems. Through the efficient allocation of time-slots, 3G systems employing code-division multiple access/time-division duplex (CDMA/TDD) have shown to experience improvements in overall system capacity [8]. Further research can be done in order to determine the benefits of employing a fuzzy resource allocator in 3G systems.

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References

1. M. Schwartz, *Broadband Integrated Networks*, Prentice Hall PTR, Upper Saddle River, New Jersey, 1996.
2. T.S. Rappaport, *Wireless Communications: Principles and Practices*, Prentice Hall PTR, Upper Saddle River, New Jersey, 1996.
3. G. Klir and B. Yuan, *Fuzzy Sets and Fuzzy Logic: Theory and Applications*, Prentice Hall PTR, Upper Saddle River, New Jersey, 1995.
4. T.D. Ndousse, "Fuzzy Control of Multi-Rate Traffic in Multimedia Cell-Based Networks", *Telecommunications Systems*, Vol. 8, pp. 79–93, 1997.
5. J.H. Bandara, "A Fuzzy Resource Allocator for Wireless Non-Real-Time Traffic", Masters thesis, University of Waterloo, Canada, August 1999.
6. X. Wu and I. Lambadaris et al., "A Comparative Study of Some Leaky Bucket Network Access Schemes", in *Proceedings of IEEE Globecom '94*, 1994, pp. 1586–1591.
7. V. Catania, G. Ficili, S. Palazzo, and D. Panno, "A Comparative Analysis of Fuzzy Versus Conventional Policing Mechanism for ATM Networks", *IEEE/ACM Transactions on Networking*, Vol. 4, No. 3, pp. 449–459, 1996.
8. W.S. Jeon and D.G. Jeong, "Comparison of Time Slot Allocation Strategies for CDMA/TDD Systems", *IEEE Journal on Selected Areas in Communications*, Vol. 18, No. 7, pp. 1271–1278, 2000.
9. X. Shen and J.W. Mark, "Mobility Information for Resource Management in Wireless ATM Networks", *Computer Networks*, Vol. 31, pp. 1049–1062, 1999.
10. P. Demestichas et al., "Management of Networks and Services in a Diversified Radio Environment", in *Proceedings of IST Mobile Communications Summit 2001*, September 2001.

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