UPLINK TRANSMIT POWER CONTROL IN A CODE DIVISION MULTIPLE ACCESS NETWORK: A FUZZY MODELING APPROACH

Keneth O. Osigwe
Deparment of Applied Signal Processing
Blekinge Institute of Technology, Sweden

Evans C. Ashigwuike
Deparment of Electrical and Electronics Engineering
University of Abuja, Abuja, Nigeria
E-mail: *ecashigwuike@ymail.com*

Victor S. U. Uzoechi
Deparment of Applied Signal Processing
Blekinge Institute of Technology, Sweden

ABSTRACT

Transmit power has always placed a significant constraint on the performance of wireless radio systems. The transmit power control problem can be characterized as that of maintaining adequate power in each transmitted waveform so as to increase the expectation that the minimum required SIR at the receiver will at least be reached. Several power control algorithms have been proposed, of which the class of distributed and autonomous transmit power control algorithms have been shown in literature to perform quite satisfactorily when compared to centralized schemes due to the moderate complexity that is achievable; and the vast control and signalling overhead that is saved. This work explores the application of fuzzy control to the subject of modelling uplink transmit power control in code division multiple access system. A possible implementation scenario of an SIR-based fully distributed constrained transmit power control algorithm in a multiservice network by applying fuzzy proportional-plus-integral control with a two-input (error and error change) and one-output (transmit power adjustment command) fuzzy rule base and inference engine is proposed.

Keywords: *CDMA, transmit power control, fuzzy control*

INTRODUCTION

Over the years, wireless communication has been synonymous to radio communication even though other forms of wireless communication (like optical communication) have been developed. Since Marconi transmitted his first radio signal and made a subsequent commercial success out of it (Jens and Seong-Lyun, 2001), radio communication has evolved over the years from broadcast through point-to-point systems and then to mobile systems with very large coverage areas and currently to densely-compacted cellular mobile systems. Each of these systems still finds its use today but has equally undergone immense changes due to better understanding of radio transmission mechanisms and also availability of advanced hardware technologies. The radio propagation mechanism has equally been varied as well. This includes line of sight and non-line of sight propagation, atmospheric propagation etc.

From its beginning, transmit power has always placed a significant constraint on the performance of wireless radio systems. In the primordial and as well as the first generation radio systems, transmit power is primarily used as means to achieve larger coverage area and transmitters are separated by considerable distances (some tens of kilometres) apart. In these systems, the receiver is usually passive and therefore the received signal should reach it with adequate power to be detected and correctly demodulated (Jens and Seong-Lyun, 2001). Today, while receiver performance has vastly improved, transmit power remains an important resource that impacts on radio network performance especially in third generation systems.

The economics of today's wireless radio network pushes to achieve an optimum on the twin and seemingly opposing constraints of greater coverage and more capacity. The cellular paradigm which is now the de facto physical structure for wireless networks makes it possible to achieve both coverage and capacity without severely trading off one for the other. Amongst other resources that must be managed in a cellular system, transmit power stands out since it is by it that cell boundaries - in the first place - are actually delimited. This report explores the subject of transmit power control and hopes to model one such control algorithm using fuzzy logic and fuzzy control as a tool for analysis. Stated more formally, the objective of this work is to investigate proportional-plus-integral fuzzy modeling of a fully distributed and autonomous SIR-based constrained transmit power control algorithm on the reverse link. A possible companion simulation scenario arising from the study of this subject is equally presented and proposed for implementation as a future work. Further on, two more requirements of the controller are proposed. The first being that the controller should be able to adapt its update signal based on the measurements of its input signal and the second is that the controller supports differentiated quality of service (QoS) for at least two classes of continuous transmission services.

Uplink transmit power control is a scarce and strategic radio resource that must be managed in such a way as to ensure that coverage and capacity are jointly adequately maximized in especially spread spectrum systems. Transmit power control has been modeled as an optimization problem and power control command has been of the bang-bang fixed step control type. This study aim is to investigate radio resource management in general and more specifically about transmit power control on the reverse link. It sets out to explore the possibility of applying fuzzy control and develop a system model that may be implemented in an actual simulation to discover the suitability or not of applying fuzzy control to this very important subject.

PROBLEMS OF RADIO RESOURCE MANAGEMENT (RRM) IN THE CELLULAR MOBILE RADIO ENVIRONMENT

The singularly primary radio resource is the frequency spectrum. The frequency spectrum is shared by several radio systems (sometimes occupying proximate positions) and therefore could potentially mutually interfere in undesirable ways where such systems exist in close proximity (Jens and Seong-Lyun, 2001). The personal communication system supports arbitrarily large numbers of users within its service area and under this scenario the radio resource management situation is even further aggravated since the number of users, usually, exceedingly surpasses the nominal number of frequency spectrum channels available to the system. In multi-user systems access to the spectrum has been regulated by carefully partitioning it further into smaller non-interfering bandwidths as in frequency-division multiple-access (FDMA) or by adequately separating and controlling the timing of access as in time division multiple access (TDMA) or by allowing simultaneous access to same chunk of spectrum but differentiating users by spreading codes as in CDMA.

Whichever access scheme adopted (usually a mix of any of these), presents a set of RRM challenges. In Jens (1999, 1997), Jens and Seong-Lyun (2001), it is recognized that the particular wireless radio network infrastructure design and deployment impacts on what RRM strategy to adopt. Given a certain infrastructure configuration, therefore, any RRM paradigm strives to maximize the instantaneous number of users that can be simultaneously served by the system at a prescribed quality of service. Quality of service, which is usually defined to suit the nature of a class of service, can be given as blocking probability - that is an attempt to access service is denied; or probability of forced termination - that is the system could no longer support the already active service and therefore drops it; or by average delay of messages and response time etc. Usually there is corresponding relation between QoS specification and the SIR needed to meet it.

Following Jens and Seong-Lyun (2001), the radio resource management scenario is now put in context. Let the set of available base stations be denoted as $B = \{1, 2, \ldots , B\}$, set of available channels per base station for establishing a link be denoted as $C = \{1, 2, \ldots, C\}$ and the set of mobiles be denoted as $M = \{1, 2, \ldots, M\}$. The radio resource management problem concerns therefore how to efficiently and effectively assign waveforms c_k from a base station b_k to a mobile station m_i wishing to become active. Usually efficiency and effectiveness is realized in practice by minimizing the transmit power that may be required to produce a given minimum threshold SIR at the receiver. The fact that a channel assignment is successful is denoted by set $M^k = \{m_i^k\}$; where $k = 0$ indicates an assignment failure for a mobile i. Apart from channels being physically available, it may not be a candidate for assignment after all, if by doing so it would increase co-channel interference or that the pathloss on that channel is severe (as a result of selective fading).

Due to multipath and motion within the mobile environment, fading mechanisms can be as a result of time delay spread or Doppler spread. Time delay spread, on the one hand, would cause flat fading when the coherence bandwidth of the channel is greater than the bandwidth of the transmitted signal. In this case the channel exhibits a constant-gain, linear-phase characteristic. On the other hand, when the coherence bandwidth of the channel is narrower than that of the transmitted signal, frequency selective fading results and the received signal is distorted. Doppler spread, on the other hand, causes slow fading and fast fading respectively. When the frequency spread due to Doppler shift is much less than the transmitted signal bandwidth, the effect of Doppler spread is not significant and slow fading results. A signal experiences fast fading when its bandwidth is less than the resulting Doppler spread. Coherence time is the time domain dual of Doppler spread (inverse of Doppler shift) and it is a measure of the time interval between which two received multipath signals could have a significant correlation in amplitude (Theodore, 2002). The channel effect is mathematically formulated (William, 1986). Assuming that one unit of power is transmitted; then the received power is given as:

$$r(t) = l(t)r_0(t) \tag{1}$$

where $l(t)$ is the channel effects due to shadow fading as a function of time, and $r_0(t)$ is due to Rayleigh fading as a function of time. $l(t)$ and $r_0(t)$ are normally random stochastic processes evolving in time. If one further takes into account the distance dependent propagation loss and d being the radial distance between the base station and the mobile; then (1) can be re-written as;

$$r(t) = d^{-\alpha}\, l(t)r_0(t); \qquad 2 \le \alpha \le 5 \tag{2}$$

The combined effect of the channel on the transmitted signal is called pathloss and it can be used to characterize the channel. If the channel characteristic is denoted as $h(t)$ and the transmitted power as $p_t(t)$ then (2) could be rewritten as;

$$r(t) = \mathrm{p_t(t)h(t)} \tag{3}$$

Where $h(t)$ now replaces the term on the right hand side of (2).

If equation 3 is re-written as $r_j = p_{t,i}G_{ij}$, where G_{ij} is the instantaneous pathloss of the physical channel between receiver j and transmitter i then the G_{ij} can be collected in a channel gain matrix of $B \times M$. B in this case identifies a certain waveform associated with a transmitter of a certain base station. The size of the channel gain matrix and the values of the entries are subject to random variations as terminals become active or leave the system, and as well as they move within the system. This dynamic in turn affects the interference pattern within the system.

$$\mathrm{G} = \begin{pmatrix} G_{11} & G_{12} & \dots & G_{1M} \\ G_{21} & G_{22} & \dots & G_{2M} \\ \vdots & \vdots & \vdots & \vdots \\ G_{B1} & G_{B2} & \dots & G_{BM} \end{pmatrix} \tag{4}$$

Due to this variation, a solution to this system of link gain equations with the objective of maximizing the requisite link gains while minimizing the interference caused as a result is impossible in practical real time implementations. Alternatively, Jens and Seong-Lyun (2001) posit the snapshot analysis where the link gains are assumed highly correlated for a reasonable period of time enough for any resource management algorithm to make decisions have been the sub-optimal alternative to solving this problem. The object of a radio resource management algorithm seeks then to allocate waveforms to as many mobiles as possible in such a way as to optimize capacity of the network while minimizing the effects of interference (co-channel & adjacent channel). A corollary to this is that the energy of the transmitted waveform can be controlled appropriately as well to achieve desired effects. Interference control within the system becomes now about the choice of waveform and then with what energy to transmit it. The snapshot matrix may however, be so bogus as to be impractical to compute under real time situations – for instance, the particular matrix could be ill-conditioned, or its elements too large as to require intense computing power. As a result, therefore, several heuristics have been devised for practical implementation.

The columns of the G matrix may indicate the sum of received signal power when $i = j$ and the interference power as a result interfering signals from other transmitters in the system, i.e., $i \neq j$. In a multi-access system like what is considered here, the received signal energy at a mobile or base station can be expressed as;

$$r(t) = \sum_{i=0}^{m-1} a_i h_i(t) u_i(t) + \sum_{j=1}^{k} z_j(t) + n_0 \qquad (5)$$

$s_i(t)$ is the transmitted signal energy and is given as $s_i(t) = a_i u_i(t)$ where $a_i = \pm 1$ (for binary signaling); $u_i(t)$ is the signal waveform; $z_j(t)$ is the interference sources from outside the system and n_0 is the AWGN; and finally $h_i(t)$ retains same meaning as in equations 2 through 3 and is the resultant channel effect (pathloss or channel gain) on the transmitted signal due severally to distance dependent power decay as it propagates toward the receiver, slow fading and multipath. Upon detection by a matched linear receiver however, the signal $s_0(t)$ is the desirable signal and all other components of (5) is regarded as interference. That is;

$$r(t) = a_0 h_0(t) u_0(t) + \sum_{i=1}^{m-1} a_i h_i(t) u_i(t) + \sum_{j=1}^{k} z_j(t) + n_0 \qquad (6)$$

Assuming that external interference power from outside the system can be neglected; and that it is required for a link between transmitter j and receiver i, that the minimum expected SIR be γ_{ij} (target SIR value), then the SIR (Γ) can be expressed as;

$$\Gamma_{ij} = \frac{a_0 h_0(t) u_0(t)}{\sum_{i=1}^{m-1} a_i h_i(t) u_i(t) + n_0} \geq \gamma_{ij} \qquad (7)$$

The transmit power control problem therefore, can be characterized as that of maintaining adequate power in each transmitted waveform so as to increase the expectation that the minimum required SIR at the receiver will at least be reached. This has been shown not to be a trivial endeavor due to the variability of the physical channel with time as well as the interference and other practical constraints on "infinitely" increasing transmit power.

TRANSMIT POWER CONTROL

Power control has been proposed as a primary and effective means for resource allocation and interference management especially in spread spectrum systems. Transmit power has the effect of maximizing the capacity of the network by minimizing the transmit power required to achieve a given SIR. It is equally necessary to ensure acceptable CIR in interference limited cellular systems. Finally uncontrolled power can have adverse effect on capacity and coverage due to interference. Capacity concerns itself with how much traffic can be admitted or handed off, and coverage concerns the reach of base stations and mobile as a function of received signal power. Generally, battery life in terminals is elongated and risk of health hazards due to unrestrained emission of electromagnetic power is greatly attenuated when transmit power is managed properly.

The Transmit Power Control (TPC) problem can be cast in the standard framework of the closed loop feedback control process as pointed out in Chuen (1990), Mabuchi (1993); Dimitar and Ronald (1993). Feedback control is usually more stable and converges faster since it copes better in the presence of disturbances (in this case channel variation) than to open loop systems. Usually, however, in practical systems, both open loop and closed loop power controls have been implemented (Jens, 1997; Kosko, 1992). While open loop power control tackles pathloss and shadow fading by maintaining a local mean received power, closed loop power control has been deployed to offset the effects of fast fading and other time varying channel characteristics, and to reduce the rate of mobile battery power depletion. The implementation of open loop power control in IS-95 for instance, involves transmitting a pilot signal on the downlink and then a mobile terminal upon receiving it estimates the path gain in the downlink direction by measuring the strength of the received pilot (Kosko, 1992).

Normally, the closed loop power control is implemented in cascade comprising of an outer control loop that estimates and continually sets the target SIR required to produce certain BER as the radio environment varies and a faster inner control loop that eventually assigns transmitter power to track the target SIR in the presence of disturbances which can include noise, channel distortions due to shadowing and multipath fading, estimation errors, and possibly control loop delays. The outer control loop typically measures the link quality - a combination of frame and bit error rate depending on the service - in order to set the target SIR. Selecting a minimum possible target contributes to increasing capacity of the system. Figure 1 shows a closed loop feedback power control schematic portraying the inner and outer control loops. The part of the diagram marked out with dashed lines was adapted in Dimitar and Ronald (1993) to depict the inner loop control process.

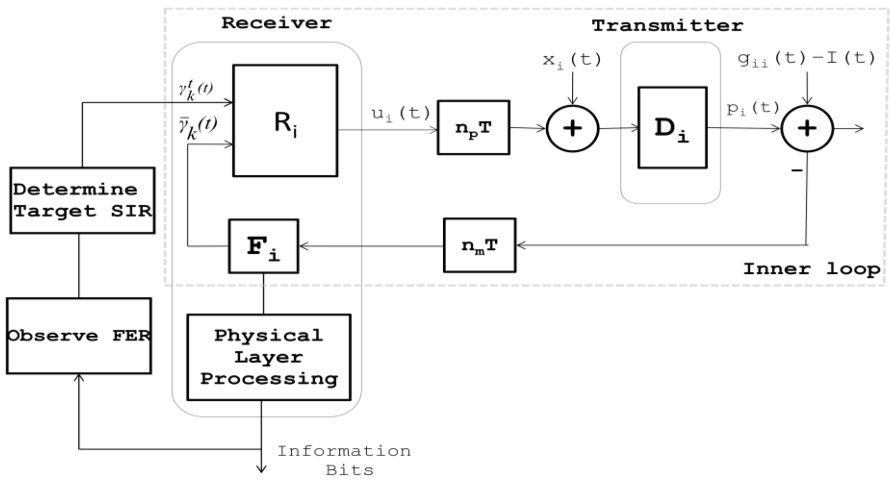

Figure 1: Closed loop power control schematic for SIR-Based Transmit Power Control showing inner and outer Control Loop process

Fuzzy Control

In George and Bo Yuan (1995), a five step design process of a fuzzy controller has been identified and quite elaborately discussed. Figure 2 depicts the components of a fuzzy controller.

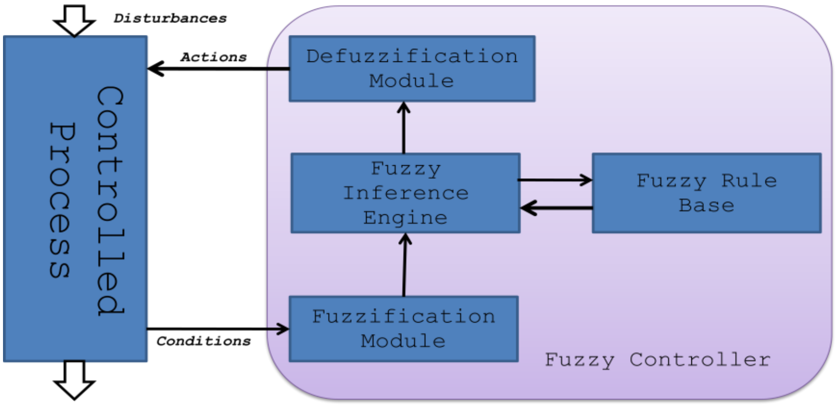

Figure 2: The components of a fuzzy controller processes

Following below is a survey of this work highlighting what should be done in each of the five steps. In each step is discussed specific implementation details relating to this present work. However, Chuen (1990) did no less extensive and comprehensive work in the exposition of the fuzzy logic control methodologies.

Step 1 – Select linguistic states

- Identify relevant input and output variables of the controller as well as their respective ranges of values of interest – that is the universe of discourse.
- Select meaningful linguistic states for each variable
- Choose appropriate fuzzy sets (usually fuzzy numbers) based on the linguistic states. This is termed fuzzy quantization. Some considerations in choosing the fuzzy sets would include whether the shape of the fuzzy set should be symmetric and spread equally about a mean.

Step 2 – Fuzzify input

Introduce a fuzzification (membership) function for each input variable. Such functions would be of the form: f_e: $[x_1, x_2] \rightarrow R$; that is fuzzification function f_e applied on variable e. e being a relevant input variable from the controlled process into the fuzzy controller; x_1 and x_2 being the span of the universe of discourse and R is the resulting fuzzy numbers that eventually enters into the inference process (see step 4 below). A choice however can be made to either fuzzify the input variables into the fuzzy controller or to use the values directly as presented. In the latter case the fuzzification function can be conceptualized to return the same value as the input variable into it.

There are principally direct and indirect methods of constructing membership functions based on expert judgment. In either direct or indirect method, one or multiple expert opinions may be consulted and taken into consideration in building membership functions. Combining these further gives four broad methods of constructing membership functions namely; direct methods with one expert, direct methods with multiple experts, indirect method with one expert, indirect method with multiple experts. When more than one expert is consulted, their opinions upon being translated into suitable membership functions can be uniformly averaged, or averaged according to prior weight ascribed to each expert or, or aggregated in some other meaningful and practical ways. In direct methods, the experts answer explicit questions relating to the problem while in indirect methods, the same questions are presented indirectly and this has the effect of reducing experts' biases on certain aspects of the problem domain.

Step 3 – Formulate inference rules

Subsequently the knowledge pertaining to the given control problem is formulated in terms of a set of fuzzy inference rules. Two ways to formulate an inference rule would be upon consulting the opinion of a human expert in that field or from empirical data through a learning process with the help of, for instance, neural networks.

The general form of the rule is: *if X then Y*, where X is a set of input variables resulting from the fuzzification process and then Y the set of outputs resulting from the inferences. Typically, the combinations or aggregation of inputs that result in an inference could be unwieldy in size but it has been shown that a certain subset, in practice usually small in number, of all possible fuzzy inference rules is more often than not sufficient to obtain acceptable performance of fuzzy controllers. Pruning down to this subset could be achieved by exploiting appropriate statistical data regarding the significance of each rule under known design assumptions.

Step 4 – Determine the fuzzy implication

The inference engine combines the input variables of a fuzzy controller with relevant fuzzy inference rules to make inferences regarding the output variable. For instance, in the case of un-fuzzified inputs;

$$If \quad \langle e,\ \dot{e}\rangle \ \ is \ \ A\times B,\ \ then \ \ k \ \ is \ \ C, \tag{8}$$

Where,

$$[A,\ B](x,\ y) \ = \ \min[A(x),\ \ B(y)] \tag{9}$$

and k is the set of control actions (upon defuzzification) determined as a result of reaching the set of inference C. Or if the input measurements to the fuzzy controller are fuzzified then

$$\langle e_0,\ \dot{e}_0\rangle \ = \ f_e(x_0)\times\ f_e(y_0) \tag{10}$$

e may be taken as error as a result of the difference between the target parameter and the actual measured value and $\dot{e}$ the rate of change of this error.

Step 5 – Defuzzify output

This step is the defuzzification stage where the set of inferences reached in the inference engine is converted into a crisp set of real values in order to issue appropriate and intelligible control commands to the controlled process. Several defuzzification methods have been proposed. The centre-of-area (COA) method, selects a defuzzification value by dividing the area under the membership function into two equal sub areas. The COA is sometimes also referred to as the centre of gravity or the centroid method. The Mean-of-maxima (MOM) method on the other hand selects a crisp value that corresponds to the maximum value of the membership function. It is averaged when there is more than a crisp value with maximum membership degrees. In the centre-of-maxima (COM) method an average is taken of the smallest and largest possible defuzzified crisp value. There is yet another method called the fuzzy mean, (FM) (Renhong and Rakesh, 1991).

As much as choosing meaningful membership functions pertaining to the specific problem increases the practical usefulness of fuzzy systems, the defuzzification as the last stage of a fuzzy control system is of no less importance since the crisp values obtained from it should equally be meaningful if the controlled system would perform within expectation. In Renhong and Rakesh (1991), a reasonable but not necessary requirement for defuzzification is proposed to the effect that the obtained crisp value should occur at the maximum of the membership function. It then goes ahead to show that the respective COA, MOM and FM defuzzification methods result in same value when applied to a particular fuzzy interval with symmetric membership functions. Furthermore, Mabuchi (1993) considers how a most proper crisp value might be determined from a given fuzzy set or interval value with respect to an established criterion. In this paper, the concept of sensitivity analysis is introduced. The crisp value is selected based on a sensitivity criterion that measures the discrepancy between a would-be most appropriate defuzzified value and the unknown "true" value of defuzzification. The crisp value eventually selected should be such as to minimize the sensitivity in the possible worst case. Ronald and Dimitar (1993) proposed and formulated defuzzification as essentially as a problem of converting the fuzzy set into a sort of probability distribution and then proceeding to calculate an expected value. Finally in Dimitar and Ronald (1992), a defuzzification approach based on level sets (i.e. α-cuts) is put forward and applied on the COA and MOM method. It equally recognizes that defuzzification could be made adaptive by varying the α-levels to yield different defuzzification values and learning can be facilitated thereby.

PROPOSED SIMULATION SCENARIO: SYSTEM MODEL

As stated previously; the objective of this work is to investigate proportional-plus-integral fuzzy modeling of a fully distributed and autonomous SIR-based constrained transmit power control algorithm on the reverse link. For the proposed simulation scenario, the distributed constrained power control algorithm of equation 3.9 is recommended to form the crux of an implementation.

The proposed fuzzy controller is a two-input, one-output rule base and inference regulator system. The Mamdani inference system is the chosen fuzzy inference with inputs as error (e) and change in error (Δe). Error is the difference between the SIR set point and the actual received SIR at any instant at the receiver, error change is the difference between two consecutive errors, that is, the current error minus the previous error and finally the output of the inference is the incremental transmit power command (Δp). The units of the inputs and output are in decibel (dB). These three parameters are the respective universes of discourse with ranges of value as follows: $E = \{e: -18dB \le e \le 18dB\}$, $\Delta E = \{\Delta e: -12dB \le \Delta e \le 12dB\}$ and lastly $\Delta P = \{\Delta p: -6dB \le \Delta p \le 6dB\}$. For each of these universe of discourse, seven fuzzy sets have been defined as follows; large negative (LN), medium negative (MN), small negative (SN), Zero (ZE), small positive (SP), medium positive (MP), Large positive (LP). At steady state, the system is expected to converge to the set point in this case target SIR by the width of the ZE linguistic qualifier. For finer control, therefore, the region of support of the fuzzy set may be re-calibrated when the values of error and change in error inputs remain around the ZE variable.

Figure 3 below shows the graphical representation of trapezoidal membership functions for these fuzzy sets defined within the universes of error, change in error and incremental transmit power command respectively. Trapezoidal-shaped membership functions have been in widespread use in real time, fuzzy target-tracking control systems (Kosko, 1992). It has been equally shown that the ratio of the length of the bases of the trapezoidal membership function should be about 50 percent to achieve best tracking performance. This claim is worth exploring in an implementation of this system model and possibly comparing the performance of the trapezoidal membership functions with the ratios of the lengths of the bases other than 50 percent. More so, the performance of the triangular membership function can be investigated and compared with that of the trapezoidal shapes.

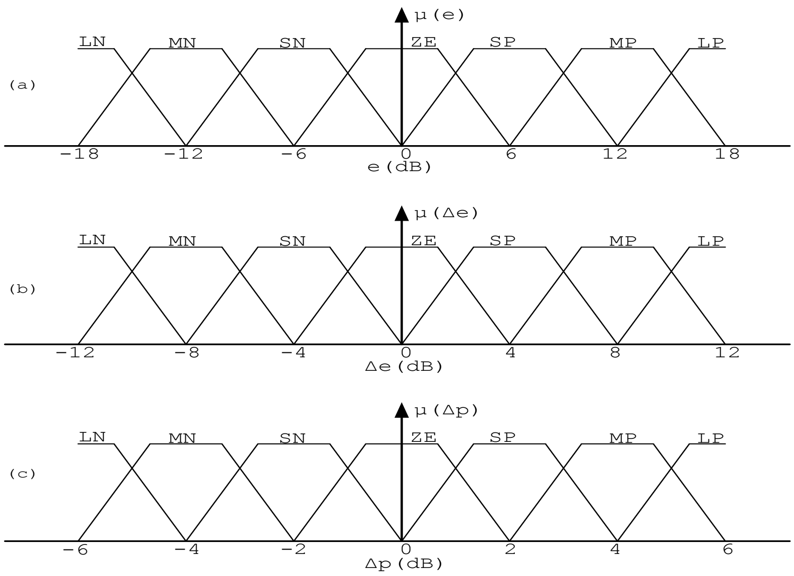

Figure 3: Graphical representation of the trapezoidal membership function for the fuzzy set values showing (a) the error (b) change in error (c) incremental power

The performance of the fuzzy controller on the one hand, can be estimated respectively in terms of rise time, power shoot, and how fast it converges to the target SIR when compared to an ordinary SIR-based system that simply increments power by the value of the change in error. This basis for comparison is supposedly more reasonable than the commonly used fixed-step control benchmark especially when it is realized that generally the performance of an information feedback control have always been known to be better than that of the decision feedback control. On the other hand, the performance of this fuzzy controller can also be measured in terms of the conditional outage probability (Pr), which according to Prasad, Jansen and Kegel

(1993) is usually recognized as the main criterion for the traffic capacity and communication quality of CDMA systems since capacity is defined as the maximum number of users per cell for which the outage probability is less than a specified value.

$$pr = \iint_{(x,y)\in R_c} \Pr\{\Gamma < \gamma\} f(x, y)\,dxdy \qquad (11)$$

where Γ is the measured SIR, γ is the target SIR and $f(x, y)$ is an expression for the probability density function for Cartesian positions coordinates (x, y) of the desired mobile unit as well as the interfering mobile units. R_c represents the service area of the mobile network of interest. Using the conditional outage probability measure of performance, trapezoidal-shaped and triangular-shaped membership functions are generally compared. For the trapezoidal shapes, the impact of using various ratios of the length of the bases is equally compared. Better performance therefore may be interpreted as greater number of active users that simultaneously achieves at least the target SIR. Finally the root mean square tracking error forms another valid and informative basis for comparing the respective shapes.

In deriving the fuzzy rule base, Po-Rong and Bor- Chin (1996) considered the curve of a typical envelope of a fading process which consists of two primitive curves of downward deep fades and those generated by second-order systems. By so doing, two sets of rules were developed. The first set of rules applies in the step response portion of the curve of the second-order system and the second set of rules applies to combat downward deep fades. Tables 1 and 2 present these rules.

Table 1: Fuzzy control rule base for the approximated second order system

		Error change						
		LN	MN	SN	ZE	SP	MP	LP
Error	LN				LN			
	MN	LN	LN	LN	MN			
	SN	LN	LN	MN	SN	ZE		MP
	ZE	LN	MN	SN	ZE	SP	MP	LP
	SP	MN		ZE	SP			
	MP				MP			
	LP			LP	LP			

Table 2: Fuzzy control rule base for combating downward deep fades

		Error change						
		LN	MN	SN	ZE	SP	MP	LP
Error	LN	LN	LN	LN	LN	LN	LN	LN
	MN							
	SN							
	ZE							
	SP					MP	MP	MP
	MP					MP	MP	MP
	LP	LP	LP	LP	LP	LP	LP	LP

A 19-cell CDMA cellular structure of equal diameter is assumed each with an omni-directional transmit antenna at the centre. The cell structure as depicted in figure 4 shows a centre cell annotated as cell 0 and two tiers of cells – the first tier is annotated 2 to 7 and the second tier 8 to 19 respectively. The mobile terminals in each cell are uniformly distributed that gain access to and leaves the network independently. While call arrival is assumed to follow a Poisson distribution, the duration of call sessions is taken to be exponentially distributed. It is recognized that the calling and the called terminal might reside in the same cell area or in different cell areas and that due to mobility the cells inhabited by each terminal could change from time to time thereby necessitating a handover. While mobility within the cell of interest is allowed, no handover is contemplated in this problem formulation. The concern here however would be with the case where the mobile terminals remain always within the same cell – in this case cell 0. In fact tier 1 and tier 2 cells are only necessary as interference sources so as to investigate how activities of mobile terminals in those cells affect the centre cell.

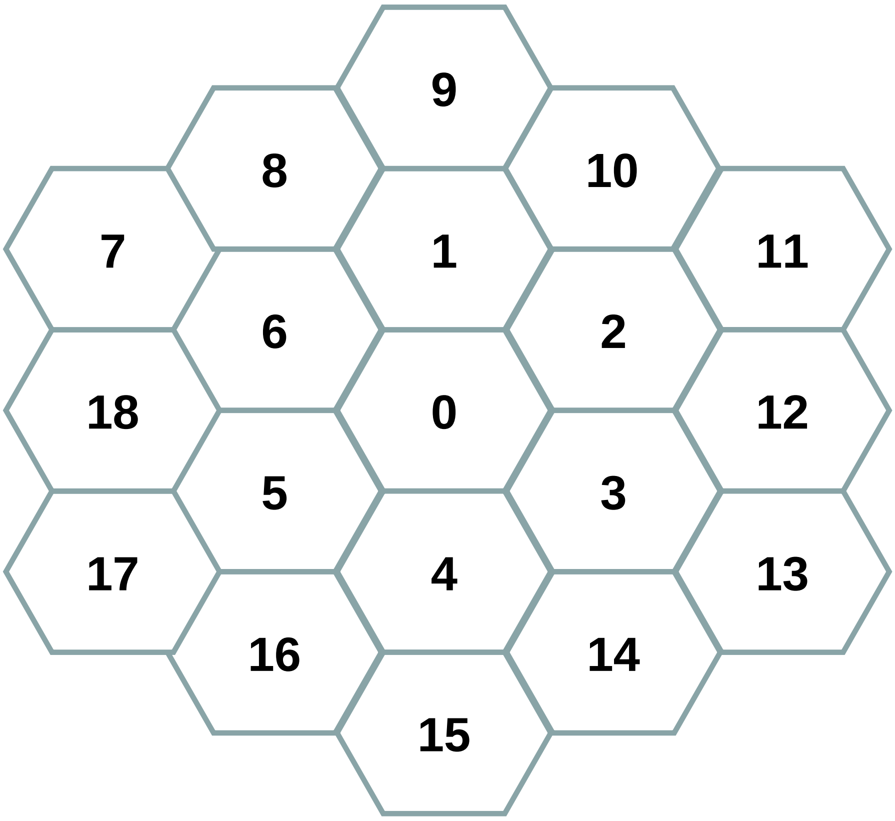

Figure 4: The cellular layout showing the two tiers of cells around cell 0

Assuming interference-dominant mobile cellular environment, the interference model may follow equation 7 but written (that is the denominator of that expression) more explicitly as;

$$I = \sum_{k=1}^{N_0-1} p_k^r(d_k) + \sum_{b=1}^{6}\sum_{k=1}^{N_b^{(1)}} p_{bk}^r(d_{bk}) + \sum_{b=1}^{12}\sum_{k=1}^{N_b^{(2)}} p_{bk}^r(d_{bk}) \qquad (12)$$

where $p_{bk}^r(d_{bk})$ expresses the power received at the desired base station (in this case base station 0 in the figure (4) as a result a k^{th} active mobile inside a b^{th} cell interfering at the desired base station from a distance d_{bk}. d_{bk} is in fact the point in a Cartesian space where a certain mobile is located within a certain base station. $N_b^{(t)}$ is the number of active mobiles in base station b of tier t of the surrounding interfering base stations. When $t = 0$, then $b = 1$ and coincides with the desired base station 0. When $t = 1$; $b = 1, 2, \ldots, 6$; and when $t = 2$; $b = 1, 2, \ldots, 12$ respectively. The first term on the right hand side of (12) is the interference contribution by the $N_0 - 1$ active mobiles within base station 0. Note that in this case, for simplicity, $p_{0k}^r(\cdot) = p_k^r(\cdot)$ and $d_{0k} = d_k$. In like manner, the second and third terms express the contributions from the mobiles and base stations from the first and second tiers respectively. Further on, the channel impairments model follows equation (2) which for convenience is repeated here.

$$r(t) = K\, d^{-\alpha}\, l(t)\, r_0(t); \qquad 2 \le \alpha \le 5 \qquad (13)$$

where K is a constant for any given parameters of the transmitter and receiver. Taking into consideration that $l(t)$ which is due to variation in environmental clutter is a Gaussian distributed random variable (13) can be rewritten as;

$$r(t) = K \cdot d^{-\alpha} \cdot 10^{\xi/10} \cdot r_0(t); \qquad 2 \le \alpha \le 5 \qquad (14\ )$$

ξ is a random is a Gaussian random variable with zero mean and standard deviation, σ. Typical values of 4 and 8dB have been assumed for α and ξ respectively. Together, $r(t) = K d^{-\alpha} 10^{\xi/10}$, is usually referred to as the local mean signal. $r_0(t)$ which is the fast fading component of the pathloss may follow either Rayleigh or Rican fading distribution process that remains correlated until at least one power command cycle is executed. Within this time, the mobile is considered stationary and then could change its position afterwards. Finally, time delay in the loop cycle has not been contemplated in this model or rather has been assumed to be of a unit scale.

CONCLUSION

In Code Division Multiple Access (CDMA) systems, capacity and coverage must necessarily be planned simultaneously to get the most of each. Interestingly, both elements are controlled by transmit power. For instance, on one hand, to have a wider area of coverage, transmit power will need to be upped in both the forward and reverse link directions; while on the other, uncontrolled power transmission especially in the uplink adversely affects the capacity of a CDMA system. The near-far problem is one effect of uncontrolled power that impinges badly upon coverage and capacity. Cell breathing therefore is a dynamic mechanism that adjusts the coverage-capacity relationship in order that at least near optimum capacity is always achieved from time to time, as mobile stations move, in, out and within, cells.

There is actually no hard limit on capacity of a CDMA system - its capability for graceful degradation makes that possible; unlike in channelized FDMA and TDMA systems where there are a known number of frequency channels and time slots available. However, when an expected quality of service becomes a requirement, it is to the extent that uplink transmit power is controlled that makes that possible. Transmit power therefore, is singularly an important radio resource in CDMA system that ought to be managed effectively so as to extract good coverage, optimum capacity and at the same time maintain an expected quality of service. Furthermore, in wideband spread spectrum systems of the 3G networks transmit power offers a singularly unique mechanism by which differentiated QoS can be offered in a multiservice and heterogeneous environment.

Fuzzy set theory represents a grand paradigm shift (George and Yuan, 1995) which yields more expressive information content that helps in discerning more information content for better systems analysis and decision-making (Turksen, 1997). There is no more excluded middle but a fuzzy middle from which information that have otherwise been untapped in bivalent set theory can be harvested; and contradiction is no longer about affirming or negating either extremes of a proposition.

Fuzzy proportional integral derivative (PID) control performs comparatively better that the conventional PID control in terms of shorter rise time to the set point or fast response, minimum overshoot beyond the set point and faster settling time. The point is made in (Lui and Lewis, 1993) that PID controller can provide good results if suitable (fixed) gains are found (and that endeavor is usually not easy to come by) but that do not mitigate in any way though, the conflict of interests between the requirements of fast response and minimum overshoot. With appropriately chosen membership function for the error, fuzzy controller works like a PID with variable gains whose value depends on the error. It is the variable gains that make the closed-loop system respond quickly with almost zero overshoot even though exact knowledge of the system dynamics is not available (Lui and Lewis, 1993).

Deploying fuzzy logic control in managing the uplink transmit power in CDMA systems has the effect of increasing the overall capacity of the system. In Po-Rong and and Bor- Chin (1996a, 1996b), it is reported that for the same number of users the fuzzy PI control achieves considerably lower conditional outage probability with a gradual rate of increase as the number of users increase when compared to 1dB fixed-step control. Recall that the conditional outage probability is a measure of traffic capacity and communication quality in CDMA systems. More so the root mean square tacking error for the fuzzy PI control is equally lower. This is expected since generally the fuzzy PI controller exhibits fast response or rise time, minimum overshoot and shorter settling time which in essence when cast in transmit power control terms would translate that using fuzzy PI control it could be hoped that there might not be excessively an over- or under- assignment of transmit power to mobile stations each time a power command is issued. An implementation of proposed system model would provide insight into the performance of certain shapes of membership functions.

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