ANALYZING THE EFFECT OF POWER CONTROL ALGORITHMS ON THE RECEIVER'S COMPUTING RESOURCE CONSUMPTION

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ABSTRACT

Traditional Software-Defined Radios are limited in their ability to share the computational infrastructure between different channel flows of different demands. Future terminals should move to a shared resource model to further improve resource utilization and link availability. For this purpose, an accurate characterization and prediction of the consumed resources by a new user entering the cell is important. At the receiver side, iterative channel decoding algorithms, which exhibit the highest contribution of processing time and energy consumption, consume resources as a function of the signal quality. Therefore, power control has an impact on the computing resources of the receiver. This paper presents a model to characterize the available computing resources of a receiver. This model may be useful for utility-based power control algorithms.

1. INTRODUCTION

From the first Software-Defined Radios [1] introduced in the late 1990s until today, terminals are being designed for a close set of applications. They are also limited in their ability to share the computational infrastructure between different channel flows. Future devices should therefore move to a shared resource model to further improve the computing resource utilization and link availability. Computing resource managers are capable to decide if a new user can be allocated as a function of the available computing resources. For this purpose, an accurate characterization and prediction of the computing resources that are required for serving a new user that enters the cell or moves from one scenario to another is important. The increasing spectral efficiency of modern radio access technologies is obtained at the price of higher computational demands. From the network perspective, base stations computational resources can be shared by several radio operators paying for the infrastructure in a pay-per-use fashion. This concept is very popular in general purpose computing—Cloud computing [2]. In conjunction with platform-independent and component-based designs may lead to higher resource utilization enabling low-cost infrastructure deployment and operation.

At the user terminal, computing resource management is needed when over-the-air upgrades are enabled. Current SDR systems only admit firmware upgrades from the same hardware vendor. The provider keeps record of all manufactured terminals and their capabilities. The user can download only those upgrades that are suitable for his particular device. We, though, envisage a scenario where users may upgrade their terminals with a new radio access technology from other vendors. The sufficiency of computational resources for the actual channel conditions must be asserted by the resource manager.

In terms of resource sharing, there are orders of magnitude more flows in the network side than in the user side. Therefore, resource sharing is only interesting in the network. Moreover, the power consumption on the terminal is dominated by the transmission rather than the reception. However, the objective of this study is to provide a framework for link budged calculations for both receiver sides. Whereas the network side will try to minimize or control the computational utilization, the terminal only needs to ensure the sufficiency of resources.

Channel decoding requires an important amount of processing time. On the other hand, iterative decoders, such as low-density parity check (LDPC) and Turbo Decoders, are capable of adjusting the consumed infrastructure resources (proportional to the number of iterations) as a function of received signal quality. This quality is a function of the adopted power control policy. Then, the transmitted power by each user not only determines the interference level at the receiver, but also the amount of demanded computational resources.

Several authors have analyzed early stopping criteria for iterative decoders (LDPC, Turbo Decoder, etc.) [3][4]. They provide measurements on the average iterations as a function of the signal-to-noise ratio. However, we are not aware of any model that predicts the average number of iterations with only a few parameters. We believe that this is the first step to introduce this type of knowledge to radio resource management or power control algorithms.

The following section introduces the cost function approach for the link parameter selection. Section 3 presents the computational costs model. Section 4 provides some real measurements to demonstrate the suitability of our model, whereas Section 5 discusses its usefulness for power control algorithms. Section 6 concludes the paper.

2. LINK PARAMETER SELECTION: A COST FUNCTION APPROACH

Information can be transmitted over a wireless channel with different link level parameters, including transmission power, spectral efficiency, bandwidth, and coding technique. Different parameters introduce different problems for the transmitter, receiver and network. Therefore, the cost associated to the transmission of a bit depends on these properties and not on the data. In modern flexible networks, these parameters are negotiated between the transmitter and the receiver. Hence, the problem of link parameter decision becomes a problem of cost optimization.

This optimization approach typically maximizes the system capacity (minimizes interference), user fairness or network revenue. Adaptive modulation and coding (AMC) is a technique for dynamically adjusting the spectral efficiency while maximizing the overall throughput or meeting the user requirements. Another adaptive technique is bit loading and power allocation used in OFDM systems to assign bits and energy to each sub-carrier. Again, the technique is typically used to maximize the system capacity.

This work focuses on the impact that these parameters have on the utilization of computing resources of SDR equipment. Consumed resources can be categorized in: radio, transmitter and receiver resources. Bandwidth, interference and time are the main radio resources consumed during a transmission. The transmitter consumes as a function of the energy required to transform the raw information into symbols (signal processing) and the radiated and dissipated energy (RF amplification). The receiver consumes as a function of the energy required for the estimation of the most likely transmitted bit sequence (signal processing) and the energy consumed in the RF stage.

Let us set aside radio and transmitter resources and address the receiver at the network and terminal sides. Although SDR processors power consumption is much greater than classic digital receivers [5], it is still orders of magnitude lower than transmission power. However, SDR terminals are constrained by the availability of computational resources. In the network side, as more flows from more users are being processed, the power consumed in the SDR processors is of more interest. In general, the power consumed in signal processing is proportional to the time the processor is performing a task. Sometimes this is not strictly true, due to static power consumption. However, modern techniques like dynamic voltage-frequency scaling (DVFS) can reduce processor power consumption if it is underutilized. In the following sections we will center our attention on the processor time as computational resource.

3. RECEIVER'S COMPUTATIONAL COSTS MODEL

Traditional receivers present a computational complexity proportional to the sample rate and the signal complexity. Today's receiver complexities are also a function of the received signal quality and the expected outage quality – the class of iterative receivers includes parallel and serially concatenated convolutional codes, LDPC coding, and joint turbo equalization and detection. More precisely, the number of iterations needed to achieve a certain quality (bit error rate) is a function of the input signal quality (signal-to-noise or interference ratio). Since the complexity per iteration is constant, we can express the receiver computational complexity as an offset plus a variable contribution, which is a function of the number of iterations. Hence the complexity (C) is the time spent by the processor expressed in seconds per information bit (s/bit). It is a function of the signal-to-noise and interference ratio (γ) and the target bit-error rate (P_b):

$$C_{P_b}(\gamma) = C_0 + C_{iter} NOI_{P_b}(\gamma), \qquad (1)$$

The first term of the equation, C_0, is the offset computational cost and it depends on the desired user quality and throughput, that is, code type, code rate, throughtput and modulation. It is either dynamically changed with an AMC technique or assigned as a function of the user service, voice, video, data, and so forth. The second term is the product of the number of decoder iterations (*NOI*) and the cost of processing one iteration, C_{iter} expressed in seconds/bit·iteration. *NOI* depends on the target bit-error rate and the received signal quality, which is a function of transmitted power and the channel attenuation. The desired throughput and quality can be achieved with a wide margin of transmitted power levels. For example, let us suppose a signal coded with a turbo coding scheme. For a given channel conditions, the transmitter can overcome the channel attenuation by transmitting at high power, letting the receiver perform just a few iterations to achieve the desired BER (bit error rate).

Observing the behavior of several iterative decoders, we find that the number of iterations performed in the decoding of a block of data is a random variable whose average is a function inversely proportional to the SNR. The following model characterizes the number of iterations (*NOI*):

$$NOI_{P_b}(\gamma) = N_{\max} - \left(N_{\max} - N_{\min}\right) f_{P_b}(\gamma) + z \, , \quad (2)$$

where $N_{\max}$ and $N_{\min}$ are the maximum and minimum number of iterations respectively, z is a zero-mean random process which depends on the realization (data frame) whose probability density function is analyzed in section 4.2. The function $f_{P_b}(\gamma)$ has to be a decreasing function taking values from 0 to 1. From the experience of observing several decoders performance, we selected a sigmoid-like function since it represents small beginnings that accelerate reaching a point of small increments. It is defined as:

$$f_{P_b}(\gamma) = \left(1 + e^{-\alpha(\gamma - \gamma_0)}\right)^{-1} . \quad (3)$$

The parameters α and γ_0 characterize the performance of the receiver. Parameter γ_0 indicates at which SNR threshold the decoder starts converging whereas α relates the convergence increases with the received signal quality The model is general enough to accommodate several decoders' performances by tuning α and γ_0 parameters, as showed in Section 4.1. The function, moreover, is easily derivable:

$$\frac{dNOI(\gamma)}{d\gamma} = \left(N_{\max} - N_{\min}\right) \alpha f_{P_b}(\gamma)\left(1 - f_{P_b}(\gamma)\right) . \quad (4)$$

4. EXPERIMENTAL MEASUREMENTS

This section provides measurements of the computing resource consumption for real cases. First we present the average number of iterations, obtained in simulations, for some iterative receivers (parameters α, γ_0, $N_{\max}$, $N_{\min}$ in (2)). Second, we analyze the statistical nature of the number of iterations (z in (2)) and, finally, we present measurements of the offset parameter C_0 (in equation (1)) in real SDR implementations of UMTS and WiMAX receivers.

4.1. Average Number of Iterations

We measure the average number of iterations to estimate – using nonlinear least squares estimation techniques – the parameters α and γ_0 of our model for several iterative decoders. Simulation data (average number of iterations) is normalized to take values from 0 to 1 before performing the parameter estimation. During this process, the values $N_{\max}$ and $N_{\min}$ are extracted. The experiment also allows us to validate the fitness of our model with real data. The average *NOI* is obtained using an early stopping criteria, which stops the decoding after the estimated BER is below a threshold.

Different stopping criteria are used depending on the family of the decoder: For concatenated convolutional codes, the HLS method estimates the BER as a function of the extrinsic log-likelihood ratios (LLR) [6], whereas the LDPC decoder stops when the received code word is correct (parity check). Different BER targets have been simulated for the same decoder in the HLS case. Table 1 and Table 2 show the results of our simulations. The column ε^2 shows the model estimation error. All simulations have been run over a total of 10 000 bits for each SNR value. Fig. 2 (at the end of the paper) shows graphically the fitness of the simulation results with the theoretical model.

Table 1. Turbo Decoder model parameters

Interl.	Mod.	HLS	$N_{\max}$	$N_{\min}$	α	γ_0	ε^2
UMTS 1000	BPSK	10e-3	7.20	2.0	7.41	1.33	0.9964
		10e-6	12.68	4.0	2.94	1.52	0.9130
	QAM16	10e-3	7.01	2.0	2.09	3.64	0.9992
		10e-6	11.62	3.3	1.33	4.19	0.9762
UMTS 100	BPSK	10e-3	8.26	2.0	2.54	1.57	0.9530
		10e-6	12.46	7.96	4.50	1.41	0.9791
	QAM16	10e-3	7.50	2.18	1.06	3.96	0.9836
		10e-6	11.94	4.26	1.00	4.13	0.9762
WiMAX 8192	BPSK	10e-3	7.84	2.0	6.19	1.39	0.9956
		10e-6	14.44	3.05	3.99	1.57	0.9649

Table 2. LDPC model parameters

Code	Mod	$N_{\max}$	$N_{\min}$	α	γ_0	ε^2
LDPC WIMAX	BPSK	1000	2.1	6.75	0.89	0.9997
LDPC 5000	BPSK	1000	0.15	13.82	1.12	0.9996

4.2. Random Effect on the Number of Iterations

The statistical nature of the *NOI* has three sources: the BER estimation uncertainty, channel fading and the Gaussian behaviour of the LLR values. For the purpose of computing resource management, however, it is desirable to define an upper bound for the resource demands in order not to exceed a certain processing latency. $N_{\max}$ could be used as this upper bound, but it is easy to observe that the system is over dimensioned since for some SNR values many allocated resources will not be used. Moreover, if resources are shared (e.g. the network side), this inefficiency becomes more severe. Therefore, a statistical analysis allows us to reserve an amount of computational resource that will be required during a statistically significant time. Fig. 1 shows the histogram of 10 000 realizations of a WiMAX Turbo Decoder.

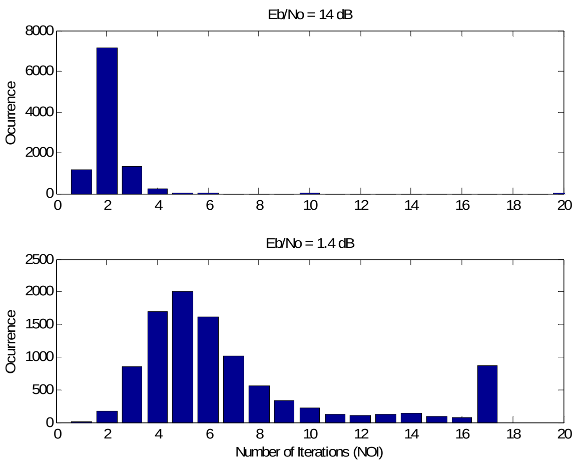

Fig. 1. Histogram of the number of iterations for different SNR values

4.3. Constant Computational Costs

In this section we give experimental measurements for the offset term C_0 of equation (1). The waveforms have been implemented in the ALOE middleware [7], following a component-based design approach and are executed on an Intel Centrino 2.2 GHz processor. This middleware has an integrated tool to measure the execution time of each waveform's component at each invocation.

Table 3 and Table 4 show the measurements of the execution time of the WiMAX and UMTS receivers for different data rates. (Detailed UMTS bit-level measurements are presented in [8]). The complexity is expressed in microseconds per information bit.

Table 3. UMTS bit level receiver computational costs

	64 kbps	144 kbps	384 kbps
C_0 (μs/bit)	0.25	0.28	0.39

Table 4. WiMAX bit and symbol level receiver costs

	BPSK	QPSK	16QAM ½	16QAM ¾	64 QAM ¼	64 QAM ¾
C_0 (μs/bit)	10.3	17.6	25.8	27.6	28.0	44.2

5. POWER CONTROL AND RECEIVER COMPLEXITY

The aim of power control algorithms is to provide an acceptable connection to each user while minimizing the interference to others and, thus, maximizing the channel capacity. Other objectives are reducing the radiation or increasing the terminal's battery life, which is not very significant due to the power amplifier inefficiency. Each user demands a quality of service (QoS) target, which can be expressed as the minimum signal to interference ratio (SIR) or BER. A power control algorithms finds a vector of transmitter powers such that all signals overcome the interference produced by the rest of user's signals [9].

This approach is, however, not optimum for data transmission, characterized to tolerate fewer errors and allowing higher delays and throughput variations. Several authors observed that hard-SIR based algorithms tend to transmit at too high power levels. For the purpose of power control in data communications, a class of algorithms use microeconomics and game theory approaches to find a solution [10]. These algorithms, called Utility Based Power Control (UBPC) algorithms, replace the QoS target by a net utility function. Each terminal expresses its QoS demands with a utility function. A pricing function limits the transmitting power as a function of the number of users in the cell [11]. The terminal optimizes the net utility function and finds its optimal transmission power. In noise-limited channels the cost of a transmitted watt is not a function of the rest of the users' transmissions. In these networks, the optimum point is a tradeoff between the cost of the transmitted energy and the cost of the signal processing complexity at the receiver.

Our model can be used as an additional term in the pricing function, hence accounting not only for radio or transmitter costs but also for receiver costs. In [3], for instance, the authors consider a situation where a mobile terminal is lost in the mountains with limited battery. If we desire to send them data, we would set the cost per transmitted watt to the lowest possible value (0) so that a high SNR reaches the receiver. The mobile would then need only a few iterations for decoding the message. On the contrary, the terminal would set its cost per transmitted watt to a very high value to consume as little energy as possible and let the rescue team's terminal perform a high number of iterations. We can say that both terminals exchange computational resources against radio resources [12].

6. CONCLUSIONS

This work presented a framework for including the computational costs in the link parameter selection process. We have presented a model for characterizing computational resources at the receiver as a function of the received signal quality. This model can be easily integrated in utility-based power control algorithms as an additional term of the pricing function.

Future work will extend the model to joint iterative detection and equalization and study the behavior of net utility functions including the receiver computing cost considerations. The transmitter complexity when using spatial diversity techniques will also be characterized. The final target is to provide a general tool for exchanging computational and radio resource utilization, embracing the transmitter, the network and the receiver.

ACKNOWLEDGMENT

Part of this work was carried out while Ismael Gomez was visiting the Communications Engineering Lab (CEL) at the Karlsruhe Institute of Technology. The use of CEL's facilities is gratefully acknowledged.

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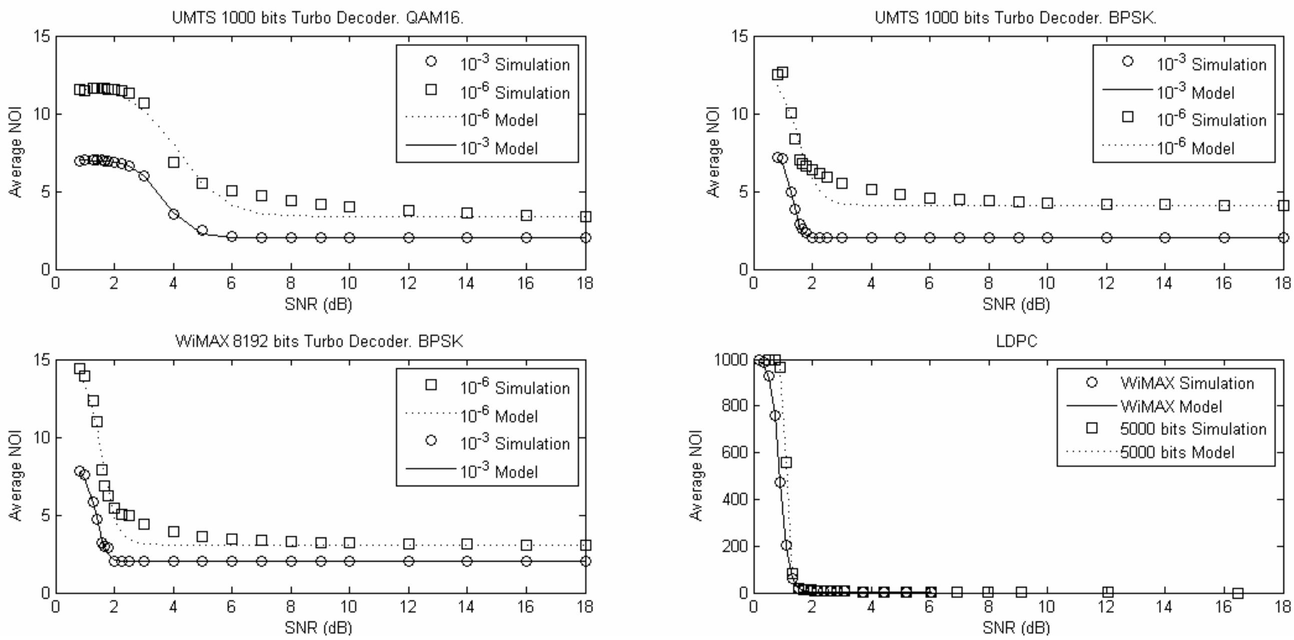

Fig. 2. Model estimations for different decoders