Fundamental Issues of Wireless Distributed Computing in SDR Networks

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***Abstract*—Software defined radio (SDR) applications in tactical radio networks involve complex computational processing with stringent hardware and quality-of-service (QoS) constraints. Individual nodes in a network may not meet the high service QoS requirements and may not be able to execute complex tasks by themselves due to resource constraints and limited functionality. In such scenarios, it can be advantageous to execute computational tasks in collaboration with peer nodes by wireless distributed computing (WDC). Such an approach potentially offers several benefits such as efficient resource utilization, robustness and security. However, it is bound to impose an additional communication cost. It is important to understand the scalability and fundamental limitations imposed by the underlying communication system on WDC before pursuing further research on developing architectures, protocols and algorithms for distributed computing in collaborative SDR networks. This paper analyzes the conditions under which WDC is energy efficient as compared to local on-board processing of computational tasks. In addition, the paper discusses the effect of channel errors on the accuracy of the distributed processing.**

I. Introduction

The computational capability of a software defined radio (SDR) can sometimes be harnessed to execute application signal processing software in addition to the communications waveform software. Wireless application services offered by modern networks such as SDR networks, tactical radio networks, and wireless sensor networks may require high computing power in order to process complex computational tasks. In addition, stringent quality-of-service (QoS) and security requirements are also critical for modern radio communication. Since it may be hard for a single radio to fulfill the requirements, mainly due to resource (computing and power resources) constraints or limited functionality, multiple resource-constrained radios can form a wireless distributed computing (WDC) network and collaborate on executing complex signal processing tasks in a distributed manner.

WDC can potentially offer several benefits to SDR networks, such as improved power [1] and energy efficiency, ability to perform complex tasks by utilizing the leveraged computing power of several SDR nodes, robustness, and security. WDC also enables opportunistic usage of idle computing resources that would otherwise remain unused for processing a variety of signal processing applications such as position location and image processing. However, the cost of communication between the distributed processes on several radio nodes negates the benefits achieved by distributing the computational workload.

Although traditional wired distributed computing has been well researched for several years [2], it cannot be directly applied to implement WDC due to the uncertainty introduced by the wireless channel. Therefore, completely novel techniques and/or architectures are needed to implement WDC. This work is now possible because of the availability of key technologies needed to enable this new paradigm, such as fault tolerant computing, distributed computing, SDR, and cognitive radio (CR) technology. SDR provides radio flexibility and reconfigurability in order to meet computing and communication QoS requirements and resource constraints, as illustrated for the case of channel coding in [3]. CR technology enables a host of advanced capabilities that provide more stable wireless links and customization as needed by WDC.

The fundamental issues concerning WDC include, but are not limited to, tradeoffs between local and distributed processing of a signal processing application, errors experienced by computation on erroneous data corrupted by the wireless link that connects the WDC processes on the peer nodes, and cross layer resource allocation. Allocation of power, computing and communication resources involves balancing the computational workload among the peer nodes that optimizes cost functions such as network energy consumption, energy consumption per node and time to complete execution of computing application. In SDRs, where the system power consumption is influenced by both the computational as well as communication hardware power consumption, it is important for WDC mechanisms to take into consideration the tradeoff between the two power consumption components. This paper addresses some of these fundamental issues. Specifically, first it analyzes the conditions under which it is energy efficient to distribute the computational workload among several radio nodes instead of executing it on-board locally on a single node. Second, the fundamental limitation imposed by the underlying communication system on the SDR's computing power is discussed. Third, the cross layer relation between physical layer parameters such as bit-error-rate (BER) and application parameters such as computational accuracy is analyzed.

The remaining portion of the paper is organized as follows. Section II presents the energy consumption models for the computation and communication aspects of an SDR. The energy consumption benefits and tradeoffs of WDC are theoretically analyzed along with simulation results in Section III. The effects of channel errors on computation accuracy is analyzed in Section IV. The conclusions are presented in Section V.

II. System Model of SDR-Based WDC Environment

The WDC environment primarily consists of N_{nodes} SDR nodes with computational capabilities and radio links that connect them. The WDC environment can be modeled in terms of the three main subsystems of an SDR node, namely communication, computation, and power subsystem. This section presents a high level energy consumption model of the WDC system in terms of computation and communication subsystem models that have been previously presented in [3].

A. Computation Subsystem

Important parameters of the computation subsystem include the computation's energy consumption E_{cp}, power consumption P_{cp}, and latency T_{cp}. For our analytical convenience, we model a complex signal processing task in terms of abstract computational units (CUs). A computational task constitutes N_{CU} discrete CUs. Each CU consumes P_{cp} watts of power, N_{cycles} processor clock cycles and E_{CU} joules of energy. The total time to process all the CUs in the computational task is denoted by T_{cp}, where the processing time per CU is denoted by T_{CU}. Thus, the energy consumed in processing a computational task is given by

$$E_{cp} = E_{CU}\ N_{CU} = P_{cp}\ T_{CU}\ N_{CU}. \quad (1)$$

When a computation subsystem processes one CU it accepts N_{bits}^{in} bits at the input and generates N_{bits}^{out} bits at the output such that $N_{bits}^{out} = \gamma\ N_{bits}^{in}$, where γ is a positive scaling factor. For example, in a complex task comprising of N_{CU} FFT operations, each FFT operation can be considered as one CU with $\gamma = 1$.

B. Communication Subsystem

The communication subsystem is characterized by the communication power consumption P_{cm}, communication latency T_{cm}, and energy consumption E_{cm}. The total transmission time T_{cm} is a function of the number of bits transmitted and the radio transmission time per bit T_{bit} (which is a function of modulation constellation size and network delays). P_{cm} can constitute either the transmitter power consumption P_{tx}, receiver power consumption P_{rx} or both depending on the radio's functionality.

1) Transmitter Energy Consumption: The transmitter energy consumption is given by

$$E_{tx} = P_{trs}\, T_{trs} + T_{tx}\left[P_{amp} + P_{txelec} + P_{DAC} + P_{spt}\right], \quad \text{where } T_{tx} = \frac{N_{txout}}{R_{txout}} = \frac{(N_B/R_c)}{k\ R_s}. \quad (2)$$

T_{trs} and T_{tx} are the transient time and the total transmission time (i.e. time to transmit all the channel encoded data bits) respectively. P_{trs} is the transient power consumption of the radio just after it is switched-on and before it is operational [4]. P_{DAC} is the power consumed by the digital-to-analog converter (DAC). P_{amp} is the power consumed by the power amplifier (PA) in order to produce an output power of P_t with a linear PA inefficiency η and β is a constant amplifier inefficiency term [4]. P_{txelec} is the total power consumed by the active radio hardware components such as the mixer, transmit filter and local oscillator, as given by: $P_{txelect} = P_{mixer} + P_{LO} + P_{filter}^{t}$. P_{spt} denotes the power consumed in executing the transmitter's waveform and associated signal processing tasks such as transmitter beamforming. The total number of bits transmitted is given by $N_{txout} = N_B/R_c$, where N_B is the total number of data bits from the source and R_c represents the channel coding rate. The net radio transmission bit rate is given by $R_{txout} = k\,R_s$, where $k = log_2 M$ is the number of bits mapped into a symbol at the modulator, M is the modulation index, and R_s is the radio transmission symbol rate expressed in symbols per second.

The PA output power P_t (i.e. the antenna input power), which is determined using the Frii's free space path loss model and log-normal shadowing model [5] , is given by

$$P_{t,dBm} = P_{rmin,dBm} - 10\, log_{10}\left[\frac{G_t G_r \lambda^2}{(4\pi d_o)^2}\right] + LM_{dB} - Q^{-1}(p) \times \sigma_{s,dB} + 10\, n\, log_{10}\left(\frac{D}{d_o}\right), \quad (3)$$

where the minimum required received signal power (receiver sensitivity) $P_{rmin} = SNR_{min} \times N$. In Equation 3, $\sigma_{s,dB}$ represents the shadow fading standard deviation, n is the path loss exponent, $1 - p$ is the channel outage probability, G_t and G_r are the transmitter and receiver antenna gains, λ is the signal wavelength, d_o is the near-field reference distance and D is the distance between the transmitter and receiver. The link margin LM_{dB} accounts for the miscellaneous losses in the system that are not explicitly modeled in Equation 3, such as small scale fading. The minimum required receive signal-to-noise ratio SNR_{min} is a function of the required BER, transmit and receiver waveform model (modulation, channel coding and signal processing), and the channel conditions. The mean receiver noise power N is computed as $N = k_B \times T_o \times B \times NF$, where $k_B = 1.3806 \times 10^{-23}$ J/K is the boltzman's constant, $T_o = 300$ K is the ambient temperature, B is the receiver bandwidth in Hz, and NF is the receiver noise figure. Note that the subscript dB indicates that the parameter is expressed in decibels.

2) Receiver Energy Consumption: The total receiver energy consumption is given by

$$E_{rx} = P_{trs}\, T_{trs} + T_{rx}\left[P_{rxelec} + P_{ADC}\right] + E_{spr}. \quad (4)$$

$P_{rxelect}$ is the total power consumed by the active receiver radio hardware components such as the low noise amplifier, mixer, receive filter and local oscillator, as given by: $P_{rxelect} = P_{LNA} + P_{mixer} + P_{LO} + P_{filter}^{r}$. P_{ADC} is the power consumed by the analog-to-digital convertor (ADC) and

P_{spr} is the receiver signal processing (such as decoding) power consumption. Note that we have assumed the reception time $T_{rx} \approx T_{tx}$.

3) WDC System Model: When the computational task is executed on a single node at a clocking rate of f_{cps}, the total energy consumed in order to process N_{CU} CUs on a single node constrained by the available energy supply E_{supply}, is given by

$$\begin{aligned} E_s = P_{cp}(f_{cps}) \times T_{CUs} \times N_{CU} \leq E_{supply} \quad (5) \\ \text{where } 0 < f_{cps} \leq f_{cpmax}, \\ \text{and } T_{CUs} = N_{cycles}/f_{cps}. \end{aligned}$$

f_{cpmax} is the maximum processor clocking rate. T_{CUs} is the time taken to process one CU in a single node when the processing is performed at a clock rate of f_{cps}.

When performing the same task in a distributed manner on a WDC network, each node consumes energy for communication processes in addition to the computation processes. We make some assumptions in order to model the energy consumption. We consider a homogeneous WDC environment comprising of identical nodes operating with the same system parameters (fixed transmission range irrespective of the actual distances between the nodes) under identical channel conditions. The total computational workload is uniformly allocated to all the nodes. In each node, the communication processes (such as transmission, reception, and channel estimation) and computation processes (such as algorithm execution and memory access) occur concurrently in order to meet certain net latency requirements and to avoid buffering of large amount of data that flows between the computation and communication subsystems. With these assumptions, the energy consumption of each node in the WDC system to computationally process N_{CU1} CUs and transmit or receive the data bits corresponding to N_{CU2} CUs is given by

$$\begin{aligned} E_{node} &= P_{cp}\, T_{CUd}\, N_{CU1} + E_{cm1} \\ &\quad + P_{cm2}\, T_{bit}\, N_{bits}\, N_{CU2} \leq E_{supply}, \quad (6) \\ \text{where } T_{CUd} &= N_{cycles}/f_{cpd}. \end{aligned}$$

T_{CUd} is the execution time of a CU when the node operates at f_{cpd}. N_{CU1} and N_{CU2} are defined based on the workload allocation strategy employed (see Section III-C). E_{cm1} is the energy consumption for miscellaneous processes such as transient processes (irrespective of whether the node is in transmit or receive mode) and is given by $E_{cm1} = P_{trs}\, T_{trs}$. P_{cm2} is the power consumption during transmission or reception of channel bits. The number of bits transmitted or received per CU N_{bits} is defined as $N_{bits} = N_{bits}^{in}\ 1/R_c$ when raw data is communicated and $N_{bits} = N_{bits}^{out}\ 1/R_c$ when processed data is communicated. If the node is required to operate for a long duration with a finite energy supply, then the power consumption for both computation and communication has to be minimized, as evident from Equation 6.

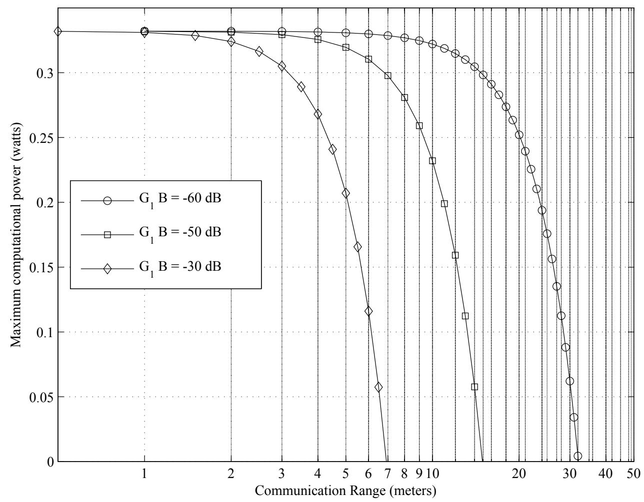

Fig. 1. SDR fundamental limitation and tradeoff between maximum available computation power and communication range for various channel and radio losses assuming G_2 = 0.33 W and SNR_{min} = 10 dB.

III. Benefits of WDC over Local Processing

This section presents a tradeoff that exists between computation and communication parameters in a SDR that is fundamental to the design and analysis of WDC in SDR networks. Next, a WDC performance metric that quantifies the energy benefits of WDC is defined followed by a simulation study of the same.

A. Limits on Computational Capability

A fundamental limitation of the computational capability of each node in a WDC system arises as a result of the power (or energy) constraint expressed in Equation 6. The maximum power available to computational processes that are executed concurrent with the transmission process in a node, is given by

$$\begin{aligned} P_{cp}(f_{cp}) &\leq P_{supply} - (G_1\, SNR_{min}\, D^n) - G_2 \quad (7) \\ \text{where } G_1 &= \frac{\eta\, k_B\, T_o\, NF\, (\sigma_s)^{-Q^{-1}(p)}\, (4\pi)^2}{G_t\, G_r\, \lambda^2\, d_o^{n-2}}\, LM, \\ \text{and } G_2 &= P_{DAC} + P_{spt} + P_{trs} + \beta + P_{txelec}. \end{aligned}$$

The expressions for G_1 and G_2 have been derived in [3]. Figure 1 exhibits the non-linear tradeoff between the communication range and the maximum power available for computational purposes. The maximum power available for computation purposes is lesser for more harsh channels. Figure 1 has been plotted with the assumption that there is sufficient power supply available to operate the processor in a SDR node at the maximum clock frequency.

The tradeoff between computational capability and communication power consumption in the presence of a power supply constraint, although a trivial one, serves as a foundation for WDC system design aspects such as dynamic resource allocation. In the presence of a dynamic channel, when power control is exercised the dynamic variation in the amount of power available for computation purposes can be modeled as a stochastic process.

B. WDC Energy Savings Metric

Consider a scenario where a node (designated as the master node) receives a request for processing a complex signal processing application. The master node has to make a decision of whether to process the computational tasks locally or in a distributed manner by shedding its workload to the peer nodes (designated as slave nodes). This decision can be made based on evaluating the proposed WDC performance metric which indicates the energy consumption savings achieved by executing a computational task in a distributed manner in comparison to local on-board processing of the same task. The energy savings achieved by the master node in a homogeneous WDC environment is defined as

$$\begin{aligned} E^{node}_{savings} &= E_s - E_{node} = P_{cp}(f_{cps})\, T_{CUs}\, N_{CU} \\ &- P_{cp}(f_{cpd})\, T_{CUd}\, N_{CU1} - E_{cm1} \\ &- P_{cm2}(D, SNR_{min})\, T_{bit}\, N_{bits}\, N_{CU2}. \end{aligned} \quad (8)$$

Equation 8 indicates that the savings in computational energy consumption achieved by distributing the workload is negated by the overhead imposed by the communication of data between the nodes in WDC network. The savings depend on the channel conditions, the underlying radio platform and the network topology. A negative value of energy savings indicates that it is energy efficient to perform the task on-board locally as compared to distributed processing. The savings can be expressed as a percentage as given by $E^{node}_{saving}/E_s \times 100$.

C. Simulation Results

In our simulation to compute the energy saving, we have assumed that the master node uniformly distributes the total workload (i.e. N_{CU} CUs) among all the nodes in the network including itself, such that $N_{CU1} = N_{CU}/N_{nodes}$. The total number of CUs allocated to the $N_{nodes} - 1$ slave nodes for processing is given by $N_{CU2} = N_{CU} - N_{CU1}$. The master node processes its share of tasks (i.e. N_{CU1} CUs) and transmits $N_{bits} \times N_{CU2}$ bits of data to the slave nodes. Upon processing their respective share of the total workload, each slave node transmits the results back to the master node. It is assumed that the communication with the master node is time-division multiplexed. All the nodes consume the same amount of computational energy E_{CU}. It is also assumed that the nodes enter a sleep state (low energy state) after completing the allocated tasks.

The system parameters used in the simulation are listed in Table I. The channel parameters have been chosen to simulate a moderately harsh wireless channel. The power consumption parameters of the radio hardware components have been cited from [4], [6]–[9]. These values have been measured for narrow band systems that can transmit over a bandwidth of the order of 30 KHz at an operating frequency of 2.4 GHz. The values of G_1 and G_2 have been computed from these parameters as $G_1\, B = 2.0182 \times 10^{-10}\ W/m^3$ and G_2 = 0.33 W. SNR_{min} has been set assuming BPSK modulation in fading channels with no coding in order to achieve a BER of 10^{-3}. Arbitrary values have been assumed for the remaining parameters as follows: $T_{bit} = 1/(32\ kbps)$ such that $T_{tx} = \frac{N_{bits}\, N_{CU2}}{32\ kbps}$, N_{bits} = 512 data points $\times$ 32 bits per data point. P_{cm2} is the sum of the transmit and receive power consumption at the master node.

TABLE I
SIMULATION PARAMETERS.

Parameter	Value	Parameter	Value
n	3	SNR_{min}	10 dB
η	5	P_{txelec}	82.8 mW
NF	10 dB	β	174 mW
p	99 %	P_{trs}	58.7 mW
G_t, G_r	2 dBi	P_{DAC}	15.4 mW
f	450 MHz	P_{stat}	0.25 mW
σ_s	8 dB	LM	15 dB
d_o	10 m	B	30 KHz
P_{rxelec}	102.8 mW	P_{ADC}	4.6 mW
E_{spr}	0.2 joules	T_{trs}	470 μ secs

The scaling of energy savings with the complexity of the computational task (expressed in terms of E_{CU}) is shown in Figure 2. For all computational workloads, a computational task with a high energy consumption of $E_{CU} > 0.35$ joules benefits from WDC under the given channel conditions. A non-trivial observation can also be made that energy savings do not scale linearly with the workload. This is because, under a uniform load balancing scheme, higher workloads result in delegation of an increasing percentage of the total workload to the slave nodes. This, in turn, results in higher savings in computational energy consumption, but at the cost of an increasing communication overhead for the master node. It is also observed that the savings do not scale linearly with the energy complexity of the task.

The energy savings in the master node varies with D and N_{nodes} as shown in Figure 3. The savings increase with an increase in the number of collaborative nodes due to decreased computational workload per node. However, for large N_{nodes}, the energy savings does not increase significantly due to increase in the number of bits transmitted out to the slave nodes and received back from them. The master node has to transmit more data and compute on less data thereby expending higher transmission energy. The decrease of energy savings with distance is attributed to the increasing transmitter power consumption at the master node. In this scenario, it may not be energy efficient to delegate tasks to slave nodes that are located beyond a radius of 500 m away from the master node.

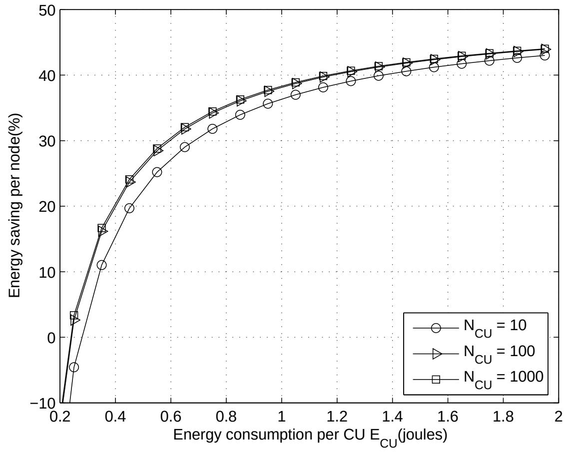

Fig. 2. WDC fundamental limitation and tradeoff between energy saving and computational energy consumption per CU (E_{CU}) for different computational workloads (N_{CU}) assuming $N_{nodes} = 2$ and D = 200 m.

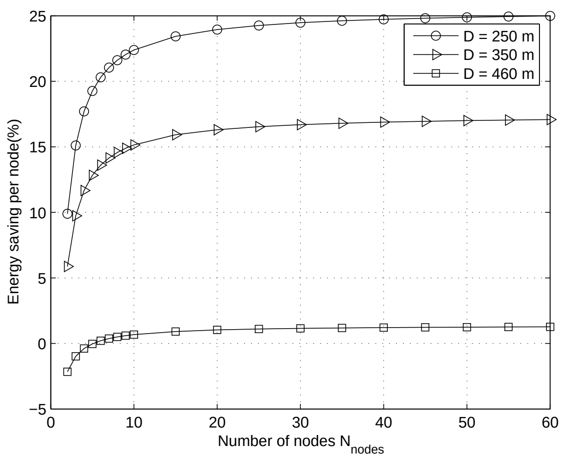

Fig. 3. Scalability of master node energy savings with network size for various communication ranges assuming N_{CU} = 10 and $E_{CU} = 0.35$ joules.

IV. Relating Communication Overhead to Computation Accuracy

While the previous section discusses the scalability of WDC energy efficiency with various radio and computational workload parameters, this section analyzes the impact of the communication link on the accuracy of the computations that will be performed by the nodes in the WDC network. We consider a simple two-node scenario where node 1 captures data and transmits the data x through a noisy wireless channel to node 2. Node 2 is required to compute a function of the data $f(x)$ in order to make some high level application level decisions. Node 2 receives corrupted data and computes the function of this corrupted data. There are two main sources of error to the function input, namely quantization error and channel error. Given an error, denoted by Δx, in the input to a function $f(x+\Delta x)$, the computational error can be represented by Δf. In the case of a linear function, $\Delta f = f(\Delta x)$. In general, the computational error percentage can be defined as

$$F_e = \left| \frac{f(\overline{x}) - f\left(\overline{x} + \overline{\Delta x}\right)}{f(\overline{x})} \right| \times 100, \tag{9}$$

where $\overline{x}$ refers to the vector of function inputs and $\overline{\Delta x}$ represents the errors in the input vector. The relation between the probability of bit-error P_{be} and F_e is derived next.

Let the number of bits in a binary word representing the value of x be $B = \lceil log_2 \, n \rceil$. The probability of word error can be computed in terms of the number of bits flipped, as given by $P_{se} = \sum_{i=1}^{B} {}^{B}C_i \, P_{be}^{i}(1-P_{be})^{B-i}$. Next, the error resulting from flipping of bits is computed. Let $b = (b_0, \, b_1, \ldots, \, b_n)$ represent a binary word, where b_0 represents the MSB (most significant bit) that has a decimal value of 2^{n-1}. The mean word error is given by

$$\Delta x_{mean} = \sum_{i=1}^{B} P_{be}^{i}(1-P_{be})^{B-i} \sum_{j=1}^{{}^{B}C_i} \sum_{k=1}^{i} (-1)^{w} \; 2^{r_k^j}. \tag{10}$$

In equation 10, ${}^{B}C_i$ permutations are possible when i bits are flipped at a time. r_k^j denotes the position of the flipped bit and w = 2 when 0 is flipped to 1 while w = 1 when 1 is flipped to 0.

Flipping of the MSB causes a high error of 2^{n-1} and flipping of only the MSB causes maximum error. Considering only the error component which contributes significantly to the mean error, Δx_{mean} can be approximated as

$$\Delta x_{mean} > P_{be}(1-P_{be})^{B-1} \, 2^{n-1}. \tag{11}$$

For a linear monotonically increasing function in one variable x, the function slope is given by $|\Delta y/\Delta x| = S$, where $|\Delta y| = |f(x) - f(x+\Delta x)|$. Thus, the mean computation error percentage is given by

$$F_e > \frac{S}{f(x)} \, P_{be}(1-P_{be})^{B-1} \, 2^{n-1} \times 100. \tag{12}$$

Equation 12 gives the approximate relationship between the probability of bit error, which is a physical layer metric, to the function error percentage which is a application layer metric. Relating these two metrics allows for cross-layer optimization in setting the SDR parameters such as transmit power, modulation and coding. This relationship is discussed next with the help of a simulation.

A. Simulation Example

We consider the case of an FFT computation as an example signal processing application since FFT is a very widely employed signal processing algorithm that is primitive to several complex signal processing applications. The FFT sizes N_{FFT} (or size of the data) and domain of the inputs (represented by n) to the FFT algorithm are varied in the simulation. The input vector $\overline{x} = \{x_1, x_2, \ldots, x_{N_{FFT}}\}$ of size N_{FFT} is generated by randomly choosing the vector elements with uniform probability from an alphabet of $[0, 1, \ldots, n-1]$. The input values are converted to binary words and mapped to BPSK symbols before being transmitted through an AWGN channel with

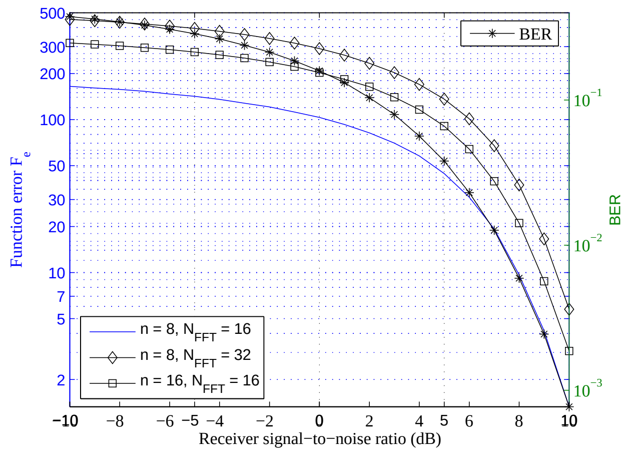

Fig. 4. Relationship between function error and BER for various values of SNRs, n and N_{FFT} for FFT computation scenario.

given signal-to-noise ratio. At the receiver, the BPSK symbols are demodulated to yield estimates of the binary words. The estimated binary words $\hat{\overline{x}}$ are converted to their decimal equivalents and applied as input to an N_{FFT} point FFT. In order to quantify the error performance of the FFT operation, the function error is computed as: $F_e = \sum_{i=1}^{N_{FFT}} |y_i - \hat{y}_i|$, where y_i and $\hat{y}_i$ refer to the i^{th} element in the FFT function output vectors $\overline{y} = FFT\left(\overline{x}\right)$ and $\hat{\overline{y}} = FFT\left(\hat{\overline{x}}\right)$ respectively.

The simulation is repeated for 10000 instances of the FFT input vector and channel noise. The function error rate is computed as an average over the 10000 instances of the simulation. The function error and BER are plotted in Figure 4. The plot shows how the BER is related to the function error for a given channel SNR. Thus, we can analyze the impact of the parameters of the computation application on the required BER which is a QoS metric that needs to be specified by the application. For instance, if the application requires a function error of less than 2, then it needs to request the communication subsystem for a BER of less than 10^{-3}.

V. Conclusions and Future Directions

Wireless distributed computing (WDC) is a novel paradigm which extends the capabilities of an individual SDR node in collaboration with peer nodes in the network. In this manner, a complex signal processing application that may not be executed on a single node due to resource constraints, can be executed in a distributed manner on a network of collaborating SDR nodes. The breakpoint when WDC is energy efficient compared to on-board local processing has been analyzed in this paper with the help of fundamental power consumption models for WDC communication and computation subsystems and a proposed energy savings metric. The paper also analyzes the limitations and associated tradeoffs of distributing the computational tasks in a WDC environment. It has been shown that the energy benefits, scalability and limitations of WDC are significantly influenced by the communication overhead involved in distributing the workload.

WDC is energy efficient when the communication overhead does not dominate over the computational energy consumption. From the discussion presented in this paper, it can be inferred that under certain channel conditions it is economical to process more CUs on-board the master node while delegating less CUs to the slave nodes. Second, a small sized network located within a short range yields better WDC energy efficiency as compared to a large network located over a wide range. The principles discussed in this paper can also be applied in reducing the communication overhead in wireless sensor networks. In a sensor network, each sensor node collects measurements and is required to transmit them to the data fusion center. Sometimes, it may be energy-efficient to process the measurements and minimize the amount of data transmitted. Finally, the paper presents a novel aspect of cross layer design in WDC networks where the application layer specifies the required BER based on the computational accuracy that it expects.

While this paper presents a preliminary study of the fundamental issues of WDC, there are several aspects of the research that are currently being undertaken. Some of them include: (a) Experimental verification of the benefits of WDC and feasibility of WDC on a SDR platform such as GNU radio, (b) Extension of the analysis presented in this paper to determine how different characteristics of the radio can affect the energy efficiency of WDC and (c) Analysis of cross layer design tradeoffs between communication and computation parameters that can impact WDC performance.

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