CAPITAL UNIVERSITY OF SCIENCE AND TECHNOLOGY, ISLAMABAD

# Validation of PDASP for Quasi-Stationary MIMO Channel Estimation Through Processing-Inefficient Low-Cost Communication Platforms

by

Ishtiaq Ahmad

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in the

Faculty of Engineering
Department of Electrical Engineering

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TO MY PARENTS AND BELOVED FAMILY

CAPITAL UNIVERSITY OF SCIENCE & TECHNOLOGY
ISLAMABAD

## CERTIFICATE OF APPROVAL

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MEE-153008

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# *Abstract*

In this thesis, a validation of Parallel Distributed Adaptive Signal Processing (PDASP) technique with the deployment of low complexity MIMO channel estimation algorithm is presented. The proposed PDASP architecture is implemented on the processing-inefficient low-cost wireless sensor nodes to validate PDASP architecture in terms of processing time, computational complexity and data transmission delay. Furthermore, processing time, computational complexity and communication delay of PDASP architecture with low complexity MIMO channel estimation algorithm are compared with sequentially-operated MIMO channel estimator for $2 \times 2$, $3 \times 3$, and $4 \times 4$ MIMO communication systems. It is realized that the sequentially-operated MIMO channel estimator is unable to work for $3 \times 3$ and $4 \times 4$ MIMO communication system on single unit; while, these MIMO structures can efficiently be run on PDASP architecture with reduced processing time and memory utilization.

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# Abbreviations

| | |
|---|---|
| MSE | Mean Square Error |
| FIR | Finite Impulse Response |
| IIR | Infinite Impulse Response |
| LMS | Least Mean Square |
| NLMS | Normalized Least Mean Squares |
| VSS-LMS | variable Step Size LMS |
| RLS | Recursive Least Square |
| ISI | Inter-Symbol Interference |
| MIMO | Multiple input and Multiple output |
| WSNs | Wireless Sensor Networks |
| PDASP | Parallely Distributed Adaptive Signal Processing |
| MAFF | Modified Adaptive Forgetting Factor |
| DDRLS | Decision Directed RLS |
| SAF | Sub-band Adaptive Filter |
| DANSE | Distributed Adaptive Node-specific Signal Estimation |
| DRLS | Distributed RLS |
| IID | Independent and Identically Distributed |
| AWGN | Additive White Gaussian Noise |
| ISM Band | Industrial Scientific and Medical radio band |
| FPGA | Field-Programmable Gate Array |
| DSP | Digital Signal Processor |
| ASIC | Application-Specific Integrated Circuit |
| NRF | Nordic Radio Frequency |

# Chapter 1

# Introduction

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## 1.1 Overview

The last two decades have witnessed remarkable research in the field of adaptive filtering for the improvement of their complexity and convergence performance. However, these high definition signal processing techniques are still incapable to be run on a energy constrained and computationally inefficient sensor node due to its small memory and lesser processing capability. Moreover, in MIMO communications, the computational complexity of these high definition signal processing techniques depends on multi-path components and MIMO spatial stream which makes the complexity very high. The Wireless Sensor Nodes (WSNs) have central importance in the field of distributed network which are capable to run high definition adaptive algorithm cooperatively and provides a significant impact on the reduction of computational complexity as well as of processing time.

## 1.2 Wireless Sensor Networks (WSNs)

From the last decade, wireless sensor networks (WSNs) are considered to be the emerging field of research. WSNs offer several benefits as compared to wired networks (e.g., simple deployment, low equipment cost, dearth of cabling, high mobility, self organization and fault-tolerance). Development in the field of wireless communications and semiconductor material make it possible to promote wireless sensor networks (WSNs) for real time implementation problems. WSNs are bunches of small, low power, and low cost nodes which work cooperatively and share the information to central node. A wireless sensor network consists of a few to several hundred nodes depending upon the desired application. Therefore, WSNS has an efficient utilization of sensing, computing, receiving and transmitting data in rigid environments. Normally, these low powered small sensing nodes are equipped with four main components namely; CPU, Sensing unit, battery and radio transceiver that are used for local data processing, capturing of environmental parameters, provide energy and enables wireless communication capability, respectively [1]. Moreover, WSNs are capable of duplex transmission of data from nodes to central location and from central location to nodes. Primarily, the WSNs was used for military applications like, surveillance in battlefield. Now a days, WSNs are used in many commercial and industrial areas, such as process monitoring, environmental monitoring, target tracking, health monitoring and industrial applications. However, in some surveillance applications, these sensor nodes are miniatures. The cost of wireless sensor nodes may vary from a few to many hundred of dollars, depending upon the individual node complexity. One of the benefits of WSNs is the usage of license free 2.4 GHZ industrial scientific and medical (ISM) band which make the node cost effective. According to the Emerson Process Management, the WSNs reduce the installation cost up to 90% as compere to the installation cost of wired networks.

### 1.2.1 Wireless Sensor Nodes

Wireless sensor nodes or sensor motes are the essential components of the wireless sensor networks. These low power wireless sensor nodes are capable of self organization, sensing, processing and communication among themselves. In particular, wireless sensor node consists of a processing unit, low power transceiver module, sensor unit and power unit. A brief overview about these units is as follow:

**- Processing unit:** In the wireless sensor node, the processing unit process the desired data and controls the performance of the other units in the node, such as, transceiver and sensor unit. The most common processors are ATMEGA-16, ATMEGA-128, ASICS, FPGA and DSPs that may be used in any specific node.

**- Transceiver:** Usually the transceiver used by the wireless sensor node is operated on 2.4GHZ ISM band and has the capability of transmit, receive, idle (still) and sleep modes. Moreover, some nodes may use the laser or infrared transceiver in case of line of sight communication as well.

**- Sensor unit:** In the sensor unit, different type of sensors such as temperature sensor, light sensor, humidity sensor and pressure sensor, etc are used to measure the environmental parameters. These sensors are known as passive sensors. However, for monitoring the parameters of environment, the active sensors like radar can also be used in the wireless sensor nodes.

**- Power unit:** Power unit is responsible of providing energy to other units of wireless sensor node. Batteries and capacitor are used in power units for continuous supply of energy, that may used for processing, capturing and communication of data. As batteries and their recharging mechanism is expensive and not feasible in remote areas. Therefore, different dynamic power measurement techniques are used to operate the network for longer duration of time [2].

### 1.2.2 Processing Capability of Wireless Sensor Node

The performance gauge of wireless sensor node depends on the Central Processing Unit (CPU), communication range of transceiver and energy availability. Typically a wireless sensor node provides less processing capability and communication performance due to limited energy resource. In this regard, various nodes are used distributively to run the complex adaptive algorithm. Therefore, the cost of a single sensor node depends on the performance measure starting from a few dollars to hundred of dollars. Most commonly used low cost wireless sensor nodes are ZigBee and ArduinoBT etc.

## 1.3 Inter-Symbol Interference (ISI)

In wireless communication, when one symbol interferes with the subsequent symbol then it may cause distortion in the desired signal. This unwanted phenomenon is known as inter-symbol interference (ISI). Usually, band limited channel and multipaths causes ISI and it is difficult for the decision device to detect the accurate information about the signal at the receiver output. Let us consider a transmitted signal which consists of various symbols, namely; $S_0$, $S_1$, $S_2$, $S_3$, $S_4$, $S_5$, $S_6$ and each having $T$ symbol duration which is clearly envisioned in Fig.1.1 (a).

The similar copies of transmitted signal in which one is delayed by $\tau_0$ and the other is delayed by $\tau_1$ due to one and two multi-path components are shown in Fig.1.1 (b and c), respectively. It can be seen that relative delay $\tau_0 - \tau_1$ between the two delayed version symbols is greater than the symbol duration which may causes the overlapping of two signals which are pointed by the arrows in the Fig. 1.1 (b and c). This overlapping may be constructive or destructive form of interference and this problem can be overcome by getting the knowledge about the propagation environment through the use of adaptive filtering technique.

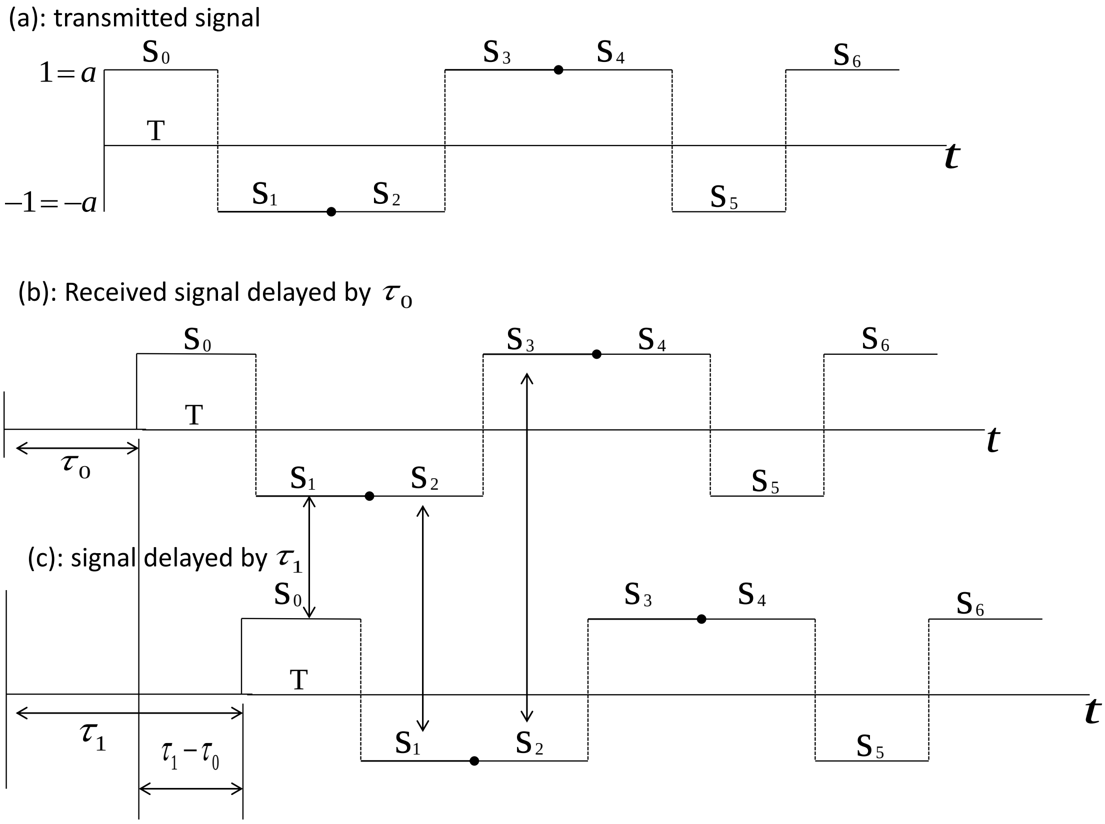


FIGURE 1.1: Inter symbol interference (a). Transmited signal (b). Received signal delayed by $\tau_0$ (c). Received signal delayed by $\tau_1$

## 1.4 MIMO Systems And MIMO Channel Estimation

Multiple input and Multiple output (MIMO) refers to multiple transmitting and multiple receiving antennas, respectively. In MIMO communication systems, the capacity is enhanced significantly without increasing the operational bandwidth of communication channel between transmitter and receiver. However, the increase in capacity is totally based on the assumption that the communication channel between transmitter and the receiver is precisely known. In particular, the wireless channel is highly complex; due to the frequency and time selectivity the wireless channel Turn out to be unpredictable. These are the major limitations which restrict the use of large-scale MIMO communication system in real time environment. Therefore, appropriate channel estimation has central importance in providing critical impact on overall performance of MIMO communication systems. Usually, before of every data transmission, known sequence of training bits are sent. Therefore, by manipulating the known sequence, various adaptive signal filtering technique are capable to estimate the channel state information (CSI) at the receiver side.

## 1.5 Adaptive Filtering

### 1.5.1 Linear Filter

The term filter normally refers to any device that processes a combination of particles/elements given to its input according to a characterized set of rules to produce a corresponding set of particles/elements at its output. However, in signals and systems, filter is usually used to remove the redundant signal components from a specific band of frequencies (e.g low pass filters) or to generate good estimate of the desired signal at its output by reshaping the input signal [3]. The output of linear filter is the linear function of its input signal. However, the output of non-linear filter is not a linear function of its input signal; therefore, powerful mathematics is involved in non-linear signal analysis. Hence, these non-linear systems may be ruled out for real time implementation over low-cost platforms.

### 1.5.2 Adaptive Filter

Adaptive filters are used to extract something desirable from the contaminated signal by varying filter parameters. The values of these parameters can be adjusted or optimized using an adaptive algorithm. The adaptation or adjustment of filter coefficients is the primary process of any adaptive filtering technique. Likewise, adaptive filters are also used to cancel or minimize the undesired components such as, noise and interference from the input signal. Digital filters can be classified on the basis of impulse response duration or of their structural design. The two basic types of adaptive filters are the Infinite Impulse Response (IIR) filter and the Finite Impulse Response (FIR) filter [3–5]. The impulse response of IIR filter is theoretically infinite and denoted as recursive filter on the basis of structural design. On the other hand FIR filter has finite impulse response and no feedback path in the form of previous output is required. Therefore, the output of FIR filter is only dependent on the function of the input signal. Such kind of filters where the output of the system is only dependent on the function of input signal are called non-recursive digital filters. In nutshell, FIR filter is preferred over IIR filter due to some advantages mentioned below

**i.** The analysis and calculation of the coefficients of FIR filter is more efficient than the IIR filter.

**ii.** FIR filter is unconditionally stable due to the finite input and output.

**iii.** FIR filter has global minimum point than IIR filter.

**iv.** The complexity of FIR filter is much lesser than IIR filter.

### 1.5.3 Mean Square Error (MSE) Criterion

In the field of adaptive filtering, Mean Square Error (MSE) is the prominent performance metric used for the analysis of any adaptive filter. While having the single minimum point, the FIR filter strictly follows the MSE criterion rather than of IIR filter. Consider a discrete time filter with transfer function $H(z)$, to estimate the desired signal $d(n)$ from an input $x(n)$ as depicted in the Fig.1.2. $\hat{x}(n)$ is the filter output and $e(n)$ is the estimation error which is the difference of filter output $\hat{x}(n)$ and the desired signal $d(n)$. $e(n)$ can be expressed as

$$e(n) = d(n) - \hat{x}(n) \tag{1.1}$$

The MSE criterion $\xi$ for the filter shown in Fig.1.2 can be written as

$$\xi = \mathbf{E}[|e(n)|^2] \tag{1.2}$$

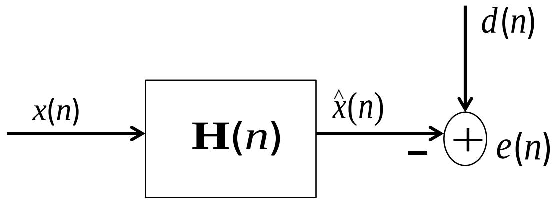


FIGURE 1.2: Typical filtering problem

Where $E[.]$ is the expectation operator and $\xi$ is known as performance function or cost function. For the appropriate selection of cost function, the following points must be taken into account.

**i.** Mathematically, the cost function must be traceable.

**ii.** The cost function should have single minimum or maximum point.

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### 1.5.4 Gradient Based Approach

The theory that comes from stochastic framework is based on Wiener filter [3] and is known as gradient approach. Several gradient-based approaches have been proposed in the existing literature. Among them are Least Mean Square (LMS), Normalized LMS (NLMS) and Variable Step Size (VSLMS) algorithms. A brief overview about each approach is given below.

#### 1.5.4.1 Least Mean Square (LMS) Algorithm

Least Mean Square (LMS) algorithm is the most popular and frequently used algorithm in all over the world [6]. The most important feature of LMS algorithm is linear computational complexity. In the LMS algorithm, the step size parameter and error signal both are used to update the filter coefficients. However, the major drawback of pure LMS algorithm is the fixed step size value; therefore, the fixed step size may cause degradation in the performance of the algorithm when the scaling occurs in the input signal. As smaller step size value results in the form of slow convergence rate and by using larger step size value makes the filter converges fast but as consequence, stability is lost [7].

#### 1.5.4.2 Normalized Least Mean Square (NLMS) Algorithm

In the time varying channel environment, the performance of LMS algorithm with fixed step size is not acceptable. It is very hard to choose the step size parameter in LMS algorithm. Moreover, the inappropriate selection of step size value may causes instability in some cases. Therefore, Normalize LMS (NLMS) algorithm has the preference over LMS algorithm. In NLMS algorithm the normalized step size parameter is used which depends upon the variation of the input signal power. However, the NLMS algorithm still provides slow convergence rate if the input signal is redundant [8, 9].

#### 1.5.4.3 Variable Step Size (VSLMS) Algorithm

In variable Step Size LMS (VSLMS) algorithm, two step size parameters are used to tackle the time varying channel conditions. The computational cost of VSLMS also grows linearly as like in LMS algorithm. However, the major drawback of this algorithm is the misadjustment of filter weights which may occur when the step size value is not set appropriately on the basis of high time variations provided by the channel; therefore, the filter lose its stability.

### 1.5.5 Least Square Based Approach

The Least Square based filtering approach provides faster convergence rate than the gradient based algorithms. However, it results in poor numerical stability and high computational cost [3]. Furthermore, in Least Square approach the filter coefficients can be updated in iterative manner which may ensure valuable amount of saving memory by using forgetting factor parameter. The most important types of Recursive Least Square (RLS) algorithm are standard RLS algorithm and Modified RLS algorithm. A brief overview about each algorithm is given below.

#### 1.5.5.1 Standard RLS Algorithm

In standard RLS algorithm, constant forgetting factor and Kalman gain are used minimize the least square cost function. In this algorithm more weight is assigned to the recent values of the estimation error and tends to forget about the past samples. For lesser memory utilization, the value of forgetting factor is set to be less than unity. Therefore, the RLS algorithm provides fast convergence and good tracking capability in time varying channel environment. RLS algorithm is the special case of Kalman filter and derived through the famous matrix inversion lemma [3] which results in increase of computational complexity.

#### 1.5.5.2 Modified RLS Algorithm

The performance of conventional RLS algorithm depends on the positive constant forgetting factor parameter. In time varying channel conditions, the smaller value of forgetting factor in RLS algorithm provides degraded performance in term of instability. In [10, 11], modified form of RLS algorithm is introduced for time varying channel conditions to overcome the instability and high sensitivity issues. The modified algorithms shows the improved convergence performance than the standard RLS algorithm at the cost of increased computational complexity.

## 1.6 Research Objective

The main objective of this thesis is to validate the performance of Parallel Distributed Adaptive Signal Processing (PDASP) architecture. In this regard, the low complexity MIMO channel estimation algorithm is deployed on low-cost processing-inefficient wireless sensor nodes to substantiate the validation of PDASP in terms of decreased processing time, less computational complexity and low memory utilization.

## 1.7 Literature Review

Advancement in modern technologies and concept of smart cities have brought critical impact on high data rate in the sense of increasing demand of internet availability. Applications like target tracking, video on demand, environmental monitoring and online banking require flawless internet connectivity as well. To meet the increasing data rate demand, Multiple Input and Multiple Output (MIMO) system is important tool to use communication link efficiently. MIMO systems provide high data rate without increasing the operational bandwidth or the power of transmitting signals. However, high data rate and capacity improvement still remains a dream to meet the growing demand of wireless services. To address the aforementioned challenges, various estimation techniques have been proposed in the literature like, space time coding [12–14] and directional antennas [15]. Such technique are used to minimize the channel fading statistics in wireless communication. Therefore, to meet the increasing data rate demands the research community focuses on the finding of better estimation techniques. The limitations in MIMO channel estimation and their effects have been broadly discussed in [16–19]. However, channel estimation algorithm still needs to be examined comprehensively.

In [20], the expression of the estimation algorithm for stationary and quasi-stationary environment is derived by using maximum likelihood MIMO channel estimator. However, the algorithm shows unstable behaviour for the quasi- stationary environment. Furthermore, the structure of the maximum likelihood MIMO channel estimator algorithm is improved in [21] for better tracking performance. However, the improved algorithm needs prior knowledge of channel conditions which is the main drawback of this algorithm. Moreover, the RLS algorithm that is a special case of Kalman filter mostly used for channel estimation and channel equalization. The RLS algorithm provides good tracking performance by assuming the minimum underlying noise in the stationary environment. Therefore, in [22, 23] the performance of RLS algorithm for non-stationary environment using fixed forgetting factor parameter is discussed. It can be observed that the algorithm shows adverse impact by using fixed forgetting factor and provides slow convergence as well as larger memory utilization. In [24], Modified Adaptive Forgetting Factor (MAFF) RLS is introduced in order to decrease the computational complexity of RLS algorithm. However, the modified RLS algorithm shows severe degraded tracking performance due to the iterative change in forgetting factor parameter. Likewise, Decision Directed RLS (DDRLS) for MIMO channel tracking is presented in [25] by claiming lesser complexity for MIMO channel tracking related to Kalman filter. However, due to the increase computational complexity than RLS algorithm is not feasible for implementation to estimate the channel coefficients. Moreover, the modified RLS algorithm is introduced in [26] which provides enhanced tracking performance with respect to the standard RLS algorithm. However, the major drawbacks as compared to conventional RLS algorithm are the increased processing time and computational complexity. In [27], Least Mean Square (LMS) solution is presented for MIMO channel estimation, however, the LMS algorithm provides slow convergence performance as compared to Least Square based algorithm. In [28], a comparative analysis of Sub-band Adaptive Filter (SAF) structures with multi rate filters bank is introduced. The SAF technique exhibits reduced computational cost through the use of LMS adaptive algorithm. However, due to phase and amplitude distortion, these systems may be ruled out to be implemented on real time systems.

Moreover, distributed network based architecture provides improved performance for many communication applications such as environmental monitoring, channel estimation and source tracking [29–32]. On a distributed adaptive signal processing estimation platform, the processing is distributed over the network where the network nodes are allowed to exchange information among themselves in such a way that the parameter estimation converges in much lesser time [32, 33]. In [33–38], diffusion techniques are used to find the unknown filter coefficients. In these techniques, the parameters of adaptive algorithm are distributed over the adaptive network to work on a desired goal. However, the major drawback is increased communication burden which makes a critical impact on the execution time of the adaptive algorithm. For example, in $M$ nodes diffusion network, the communication load is written by $M \times N$ times, where $N$ shows the dimension of diffused vector. Therefore, the $M \times N$ load implies a crucial impact on the communication burden of the adaptive network. Moreover, several approaches are presented in the literature where the significant effort has been made to reduce the communication burden provided by the diffusion techniques in the distributed network [39–45]. However, all the given techniques still provide insignificant role in the sense of reduced execution time of the algorithm. In [46], a Distributed Adaptive Node-specific Signal Estimation (DANSE) technique is introduced by using wireless sensor network. The idea behind the DANSE technique is to estimate the channel weight vector by following non-adaptive Wiener Hopf equation rather than the use of adaptive filtering algorithm, like LMS and RLS algorithm. This makes DANSE incapable to run any adaptive filtering algorithm on the distributed platform which is the major drawback of this technique. In [47], a low complexity MIMO channel estimation is introduced. The low complexity algorithm provides $O(M^2)$ lesser multiplication cost than RLS algorithm which is still remains unexplored to be implemented on low cost wireless sensor nodes. Moreover, in [48], a PDASP architecture is introduced. The PDASP architecture runs the RLS algorithm in parallel fashion by using the low cost wireless sensor nodes which exhibit $O(2M^2)$ multiplication and $O(M^2)$ addition complexity. Furthermore, for low doppler rate, the processing time of PDASP is 82.29% and 95.83% lesser than that of sequential MIMO RLS and Kalman algorithms respectively.

## 1.8 Problem Statement And Research Methodology

As discussed above, PDASP architecture provides much lesser complexity and processing time than sequentially operated adaptive algorithm on single unit. However, it has not been validated through implementation. This motivates us to setup a test bed in order to validate the performance of PDASP in terms of computational cost, processing time and communication burden.
In this thesis, a validation of parallel distributed adaptive signal processing (PDASP) [48] architecture is presented with the implementation of low complexity MIMO channel estimation algorithm [47]. To run the PDASP architecture distributively, low cost Arduino platforms with different memory utilities are used to validate the performance of distributed architecture in terms of processing time, computational cost, memory utilization and communication delay using different MIMO antenna systems with sequentially operated low complexity MIMO channel estimator algorithm. The measurements are obtained on different MIMO systems by considering direct and multi-path components. It is realized that the single unit is unable to run sequentially operated $3 \times 3$ and $4 \times 4$ MIMO systems. However, deploying the PDASP architecture on low cost sensor nodes effectively run these systems with the improvement of processing time, computational complexity and memory utilization. Moreover, it is observed that the communication delay depends on the number of antennas. The communication burden may increase with the increase of MIMO antennas or multi-path components between the transmitter and receiver.

## 1.9 Thesis Contributions

The summarized research contributions of this thesis are given below

**(i)** The validation of Parallel Distributed Adaptive Signal Processing (PDASP) through computationally constrained low cost communication platform is introduced.

**(ii)** The balancing procedure for the information interchange over PDASP architecture is presented.

**(iii)** The PDASP architecture effectively runs 3×3 and 4×4 MIMO communication systems with direct and multipath components.

## 1.10 Thesis Organization

In Chapter 2 the system model is presented. The system model consists of channel model and receiver model for MIMO communication system. Chapter 3 describes the implementation and test bed setup for PDASP architecture. Furthermore, the communication load balancing procedure is also introduced for effective information interchange among the distributed nodes. In Chapter 4 the measurement results are presented by considering $2 \times 2$, $3 \times 3$ and $4 \times 4$ MIMO communication systems with or without multipaths and finally, Chapter 5 draws the conclusion.

# Chapter 2

# System Model

## 2.1 Channel Model

An $N \times N$ MIMO communication system equipped with $N$ transmitting and receiving antennas is shown in Fig. 2.1. The $mth$ received signal $y_k^{(m)}$ at time index $k$ can be written as.

$$y_k^{(m)} = \sum_{n=1}^{N} w_k^{(m,n)} x_k^{(m,n)} + \beta_k^{(n)} \qquad (m = 1, 2, 3, \ldots N) \tag{2.1}$$

where the superscript "$m, n$" shows the $nth$ transmitting and $mth$ receiving antennas, $w_k$ is the channel attenuation coefficient between transmitter and receiver, $x_k$ is the input signal and $\beta_k$ is Additive White Gaussian Noise (AWGN) which is added at the receiver side. During the block fading transmission environment the autocorrelation function of channel coefficients can be expressed as

$$E\{w_k^{(m,n)}[w_k^{(m,n)}]\} \cong J_o(2\pi f_D^{(m,n)} T|k - i|) \tag{2.2}$$

Where $E\{.\}$ is the expectation operation, $J_o(.)$ is the zeroth order first kind Bessel function $f_D$ is the doppler frequency and $T$ is symbol duration. According to the uncorrelated scattering model [49], the auto regressive model of length $l$ by

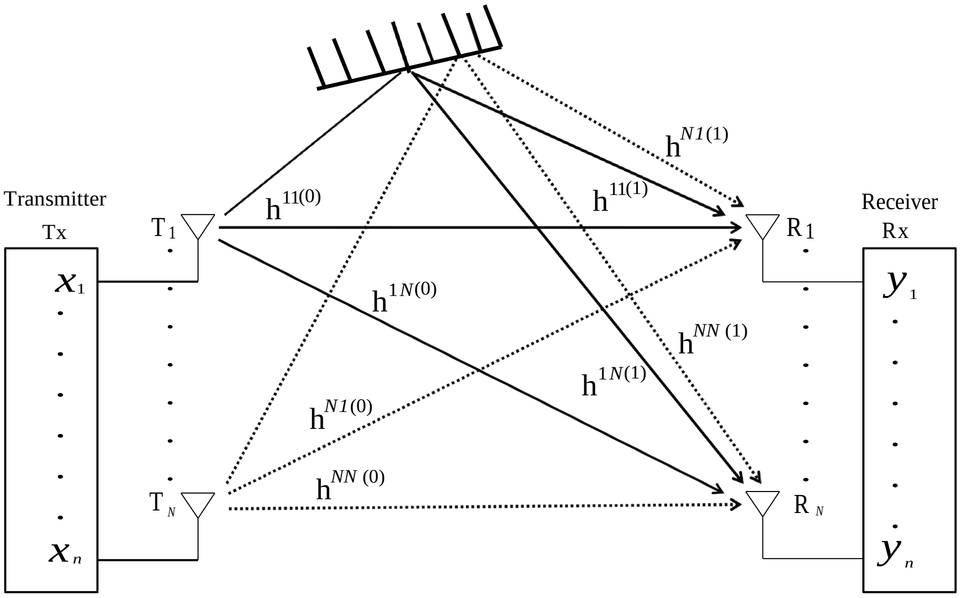


FIGURE 2.1: Frequency-Selective channel model for MIMO communications.

considering the assumption of independent MIMO streams can be written as

$$w_k^{(n,m)} = \sum_{l=1}^{L} \gamma_i^{(m,n)} w_k^{(m,n)} + \vartheta_k^{(n)} \tag{2.3}$$

where $\gamma_i^{(m,n)}$ is the *ith* channel coefficient between *nth* transmitting and *mth* receiving antennas and $\vartheta_k^{(n)}$ is independent and identical distributed (i.i.d) Gaussian process having mean zero and their variance can be expressed as

$$E\{\vartheta_k^{(n)}[\vartheta_k^{(n)}]^*\} = \sigma^2_{w_k^{(m,n)}} \tag{2.4}$$

To achieve the optimal parameter for AR channel model, eq. 2.4 can be solved through Wiener equation [50], we get

$$J_o(2\pi f_D^{(m,n)} T|k-t|) = \sum_{l=1}^{L} J_0(2\pi f_D^{(m,n)} T|k-l-t|)\gamma_i^{(m,n)} \tag{2.5}$$

for $\quad t = k-l, k-l+1, k-l+2, k-l+3, \dots k-1$

The power of each channel coefficient in non-stationary environment using the assumption of unit power channel matrix can be expressed as

$$\sum_{k=1}^{l} E\left[\left|w_k^{(m,n)}\right|^2\right] = 1 \qquad \forall n, m \tag{2.6}$$

The velocity of mobile user and Doppler shift in the carrier frequency cause the time variation in the channel. Therefore, the standard assumption which is feasible in many of the cases can be defined as

$$f_D^{(m,n)} = f_D \qquad \forall n, m \tag{2.7}$$

The channel coefficient $\gamma$ is assumed to be same for all $f_D^{(m,n)}$ [51]. Therefore, due to assumption used in eq. 2.7, we have

$$\gamma = J_o(2\pi f_D T) \tag{2.8}$$

To accommodate the channel variations, the channel matrix $\mathbf{W_k}$ relative to first order Markov process [52], can be written as

$$\mathbf{W}_k = \gamma \mathbf{W}_{k\text{-}1} + \varsigma_k \tag{2.9}$$

where $\varsigma_k$ is $N \times N$ matrix of i.i.d Gaussian processes with variance $\sigma_\varsigma^2$ can be expressed as

$$\sigma_\varsigma^2 = 1 - \gamma^2 \tag{2.10}$$

Rewritting the eq. 2.1 in matrix by using the assumption of parallel interference [53], we have

$$\mathbf{y}_k = \mathbf{W}_k^H \mathbf{x}_k + \beta_k \tag{2.11}$$

where,

$$\mathbf{W}_k = \begin{bmatrix} w_k^{(11)} & w_k^{(12)} & \dots & w_k^{(1N)} \\ w_k^{(21)} & w_k^{(22)} & \dots & w_k^{(2N)} \\ \vdots & \vdots & \dots & \vdots \\ w_k^{(N1)} & w_k^{(N2)} & \dots & w_k^{(NN)} \end{bmatrix}$$

is $N \times N$ channel matrix, $x(n) = [x_k^{(1)}, x_k^{(2)}, x_k^{(3)} \dots x_k^{(N)}]$ is the transmitted signal vector and $\beta_k$ is white noise with variance $\sigma_\beta^2$. Due to multi-path fading provided by the propagation environment, the channel matrix $\mathbf{W}_k$ becomes $\widetilde{\mathbf{W}}_k$ with $N \times N(M)$ dimension. Where $M$ shows the number of multi-path components. The dimension of $\widetilde{\mathbf{W}}_k$ is not only dependent on the number of transmitting and receiving MIMO streams but also depends on the number of multi-paths present between transmit and receive antennas which is clearly shown in Fig.2.1. Now the channel matrix $\widetilde{\mathbf{W}}_k$ having each entry $w_k^{(trl)}$ as $t = 1, 2, 3 \dots N$, $r = 1, 2, 3 \dots N$, $l = 0, 1, 2, 3 \dots M - 1$ can be written as

$$\widetilde{\mathbf{W}}_k = \begin{bmatrix} w_k^{(11(0))} & \dots & w_k^{(11(M-1)} & \dots & w_k^{(21(0))} & \dots & w_k^{(N1(M-1))} \\ w_k^{(12(0))} & \dots & w_k^{(12(M-1)} & \dots & w_k^{(22(0))} & \dots & w_k^{(N2(M-1))} \\ \vdots & \vdots & \vdots & \dots & \vdots & \vdots & \vdots \\ w_k^{(1N(0))} & \dots & w_k^{(1N(M-1)} & \dots & w_k^{(2N(0))} & \dots & w_k^{(NN(M-1))} \end{bmatrix}$$

Similarly, the transmitting signal $\mathbf{x}_k$ becomes $\widetilde{\mathbf{x}}_k = [x_{(k)}^{(1)} \dots x_{k-(M-1)}^{(1)} \dots x_{(k)}^{(2)} \dots x_{k-(M-1)}^{(2)}$ $\dots x_{k-(M-1)}^{(N)}]$ which can also depends on the multi-path components provided by the propagation environment.

## 2.2 Receiver Model

In low complexity MIMO estimation algorithm, all subparts of filter are interdependent on each other which makes the adaptive algorithm to run in sequential manner. Before introducing the parallel structure of low complexity MIMO estimation algorithm, it is necessary to introduce some timing variables that can be

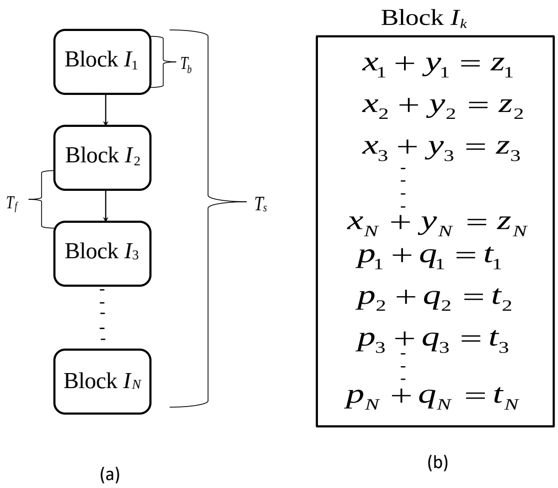


FIGURE 2.2: Sequential working of low complexity MIMO channel estimation (a) sequential working of individual blocks (b) process involved in a single block

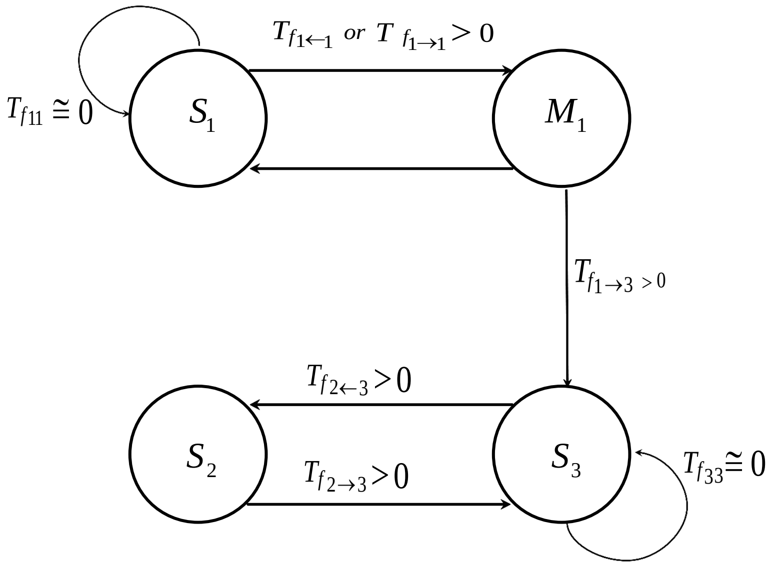


FIGURE 2.3: parallely-operated low complexity MIMO channel estimation

defined as below.

**-Computational Time $T_c$:** It is the time required by a processor for single computation.

**-Block processing time $T_b$:** It is the multiple of $T_c$ consists on a single block of algorithm.

**-Fetch time:** It is the time to take the information from one block to another block.

**-Algorithm step time $T_s$:** It is the time taken by the algorithm for one complete iteration.

The sequential working of low complexity MIMO estimation algorithm is shown in Fig. 2.2, where it can be visualized that all the blocks of algorithm are working sequentially. The fetch time, $T_f$, will be zero if the low complexity MIMO estimation algorithm is operated on a single unit. However, by using PDASP architecture, the fetch time will vary and depends upon the size of data elements that are being transmitted. The block diagram of PDASP is shown in Fig. 2.3. The PDASP architecture consists on one master node $M_1$ and three slave nodes $S_1$, $S_2$, and $S_3$ respectively. The nodes $M_1$ and $S_3$ are interlinked with $S_1$ and $S_2$, respectively, while $M_1$ is also connected to $S_3$. In the PDASP architecture, all the four processing nodes would cooperatively work on the desired process and then interchange the information among the nodes. The computational time of each block is different from other blocks in PDASP architecture. Therefore, the computational time of any specific block is dependent upon the numbers of $T_c$. Furthermore, all the processing nodes in the PDASP architecture are synchronized with each other for being working on a combined goal. In this way, the computationally incapable low cost small platform is made capable to run the complex adaptive algorithm parallely.

In the proposed scenario, the PDASP architecture and MIMO-capable cluster head both are working in parallel with one another. The MIMO capable cluster head that has limited signal processing capability which is only engaged in communication with a far gateway. The PDASP architecture runs the complex adaptive algorithm for MIMO channel estimation and then gives the channel matrix to the MIMO-capable cluster head to estimate the data for next of the communication session. The parallel structure of PDASP architecture and MIMO-capable cluster head is depicted in Fig. 2.4. The communication data frame that is designed for distributed signal processing is shown in Fig. 2.5. It can be seen that the training and information sessions are represented by $C_i$ (i=0,1,2,...) and $B_j$ (j=1,2), respectively. This communication data frame is designed in such a way that at the same time MIMO-capable cluster head and PDASP architecture both are engaged in data and channel estimation, respectively. In this data transmission frame the coherence time $T_c$ includes the twice of training and data sessions. Where the coherence time is the duration of time over which the channel impulse response remain constant. During the section of $B_1$, or $B_2$, the MIMO capable cluster head estimates the data using the prior information of channel matrix which is clearly envisioned in Fig. 2.5. However, during the session of $C_1$ or $C_2$, the training bits are known and available at the PDASP architecture. Therefore, the MIMO cluster head directly gives the received symbols to PDASP architecture, so that the PDASP architecture estimates the channel for next data session.

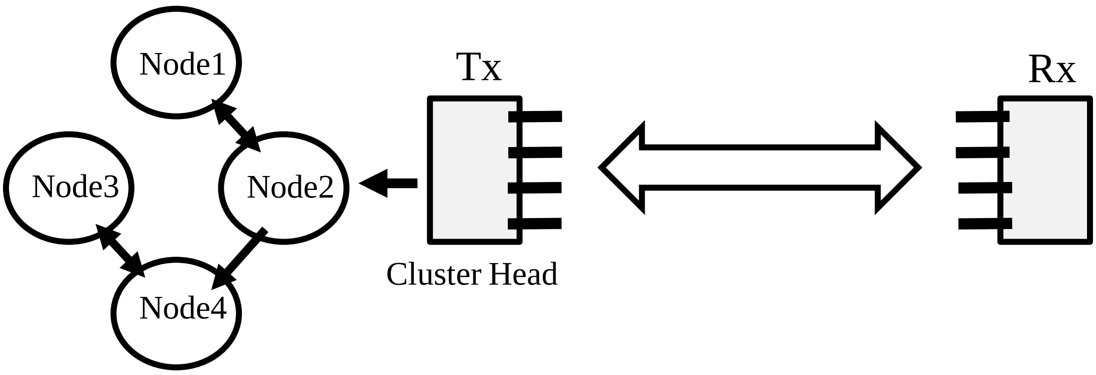


FIGURE 2.4: MIMO-capable cluster head based PDASP communication

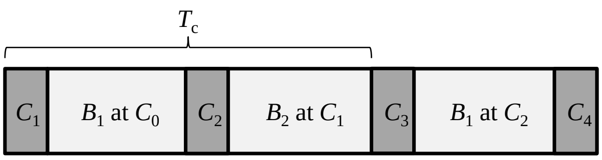


FIGURE 2.5: Block transmission data sequence

## 2.3 General Assumptions

In order to validate the PDASP architecture, the following assumption must be taken into account.

**i.** The quasi stationary block fading channel environment is considered for modeling the channel.

**ii.** The $2 \times 2$, $3 \times 3$ and $4 \times 4$ MIMO communication systems are considered with one multipath ,two multipath and no multi-path components.

# Chapter 3

# Implementation and Testing

In this chapter, the approaches used for the implementation and testing of PDASP architecture are discussed.

## 3.1 TestBed Setup

In testbed setup, four low cost wireless sensor nodes from the Arduino platform are used to implement the PDASP architecture. The sharing of information among the nodes in PDASP architecture is established by NRF24L01 radio transceiver modules. The distance among the four senor nodes is set approximately $24cm$ with each apart. The balancing communication model is used for information interchange over the PDASP architecture. The features and specifications about the selected arduino nodes and NRF24l01 transceiver module are shown below.

### 3.1.1 Arduino

Arduino is an open source platform comprising of different low cost micro-controllers like, ATmega2560, ATmega8, ATmega168, ATmega328, ATmega1280. Each arduino device has different features like I/O pins, flash memory and on-chip SRAM memory. The Arduino nodes namely; Nano, Uno and Mega are used to substantiate the validation of PDASP architecture. The main specifications of Nano, Uno and Mega are shown below.

#### 3.1.1.1 - Arduino Nano

Arduino Nano is small board based on Atmega168 with on board components such as RAM and Flash etc. The main features of arduino Nano are shown below.

- operating voltage: 5V
- Non-volatile Memory: Flash On-chip 16 KB
- Memory: On-chip SRAM 1KB
- CPU speed: 16MHZ

#### 3.1.1.2 - Arduino Uno

On the other hand, Arduino Uno is comprising of Atmega328P micro-controller. The main specifications of the Arduino Uno are as shown.

- operating voltage: 5V
- Non-volatile Memory: Flash On-chip 32 KB
- Memory: On-chip SRAM 2KB
- CPU speed: 16MHZ

#### 3.1.1.3 - Arduino Mega2560

Likewise, Arduino Mega uses the Atmega2560 microcontroller and it has the following on board specification.

- operating voltage: 5V
- Non-volatile Memory: Flash On-chip 256 KB
- Memory: On-chip SRAM 8KB

- CPU speed: 16MHZ

### 3.1.2 NRF24L01 Transceiver

In PDASP architecture, the communication is possible among four nodes through the NORDIC radio NRF24L01 Trans-multiplexer Modules. The NRF24L01 is operated on 2.4GHz industrial scientific and medical (ISM) band. It is low cost module with significant features like low current consumption, $enhancedshockBurst^{TM}$ and 125 RF channels. The maximum transmission speed of this Module is 2Mbps. Likewise, the maximum output power is 0dbm at 11.3mA. Moreover, the NRF24L01 module is easily interfaced with arduino by using built in libraries.

## 3.2 Communication Load Balancing Procedure

The comparison between the sequential and PDASP architecture is discussed thoroughly in [48]. In this section, the procedure of information interchange over PDASP architecture is presented. The PDASP architecture consists of four processing nodes, namely; $M_1$, $S_1$, $S_2$ and $S_3$ which are clearly envisioned in Fig. 3.1. Among four wireless sensor nodes, $M_1$ behaves as the master node while $S_1$, $S_2$ and $S_3$ are acting as slave nodes. The selection of $M_1$ as master node is on the basis of maximum computational complexity occupied among all nodes in the PDASP architecture. Before running the expensive procedure parallely, $M_1$ sends a beacon message to all the slave nodes to make them ready for working on the desired goal. After that, all the four nodes would ready to work on the desired process. As, the computational cost occupied by node $M_1$ is greater than those of slave nodes in PDASP architecture. Therefore, all the slave nodes wait until the process of the master node $M_1$ is not completed and then all the nodes would share the information among themselves. The communication load balancing procedure for PDASP architecture is shown in Fig. 3.1. In the balancing procedure, first of all

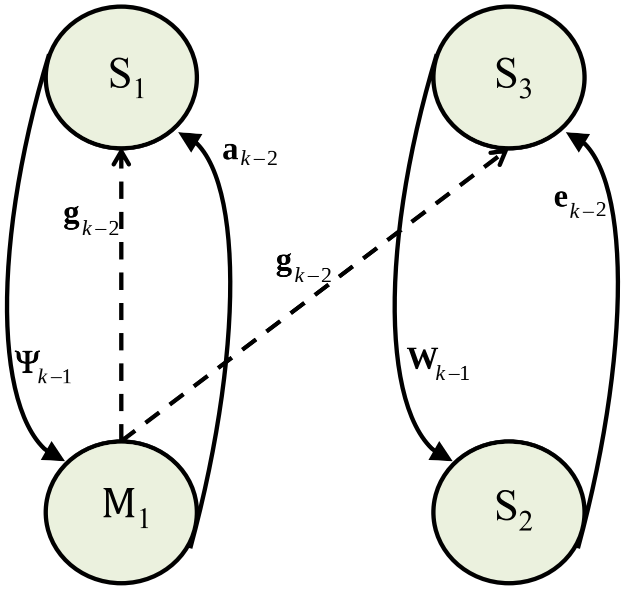


FIGURE 3.1: Balancing procedure for the transmission of data over PDASP architecture

$\mathbf{g}_k$ is transmitted from $M_1$ towards $S_3$ and $S_1$ then $S_1$ and $S_3$ forward the information of $\boldsymbol{\Psi}_k$ and $\mathbf{W}_k$ towards $M_1$ and $S_2$, respectively. Likewise, after getting the information of $\boldsymbol{\Psi}_k$ and $\mathbf{W}_k$, $M_1$ and $S_2$ share the information regarding $\mathbf{a}_k$ and $\mathbf{e}_k$ towards $S_1$ and $S_3$, respectively. Moreover, it is noted that without considering the multipath components the communication burden for the MIMO communication system is totally balanced over the network. However, the communication burden may vary while considering multipath components that will be discussed in the next chapters.

## 3.3 Implementation of PDASP Architecture

The PDASP architecture with its implementation on low cost platforms by running low complexity MIMO channel estimation algorithm is shown in Fig. 3.2. The low complexity MIMO channel estimator provides $N^2$ lesser multiplication complexity than those of RLS and robust variable forgetting factor (RVFF-RLS) adaptive

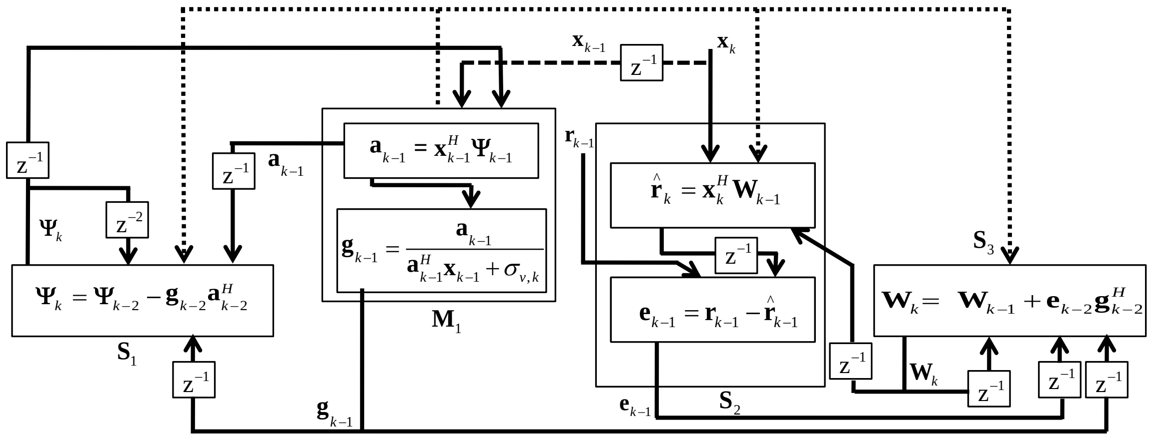


FIGURE 3.2: PDASP architecture for low complexity MIMO channel estimator with non-aligned time indexes

filtering algorithms. By using the PDASP architecture, the low complexity MIMO estimation algorithm runs in parallel fashion with time non-alignment to ensure the measure of low processing time respective to each sensor node in the network. Let, the processing time taken by filter weight matrix $\mathbf{W}_k$ , estimation error $\mathbf{e}_k$, Kalman gain $\mathbf{g}_k$ and error covariance matrix $\mathbf{\Psi}_k$ be $T_{\mathbf{W}}$, $T_{\mathbf{e}}$, $T_{\mathbf{g}}$ and $T_{\mathbf{\Psi}}$, respectively. Therefore, the time taken by the sequential algorithm when it runs in cascaded fashion [48] can be written as

$$T_{\mathbf{\Psi}} + T_{\mathbf{g}} + T_{\mathbf{e}} + T_{\mathbf{W}} = T_{\text{tot}}. \tag{3.1}$$

The processing time taken by the master node $M_1$ is greater than those of slave nodes. Therefore the equivalent time of each slave node relative to the master node $M1$, can be defined as

$$\begin{aligned} \mid T_{\mathbf{g}} - T_{\mathbf{\Psi}} \mid &= \Delta T_{\mathbf{\Psi}} \\ \mid T_{\mathbf{g}-T_{\mathbf{e}}} \mid &= \Delta T_{\mathbf{e}} \\ \mid T_{\mathbf{g}-T_{\mathbf{W}}} \mid &= \Delta T_{\mathbf{W}} \end{aligned} \tag{3.2}$$

Therefore, equivalence processing time $T_{eq}$ can be expressed as

$$T_{\mathbf{g}} = T_{\mathbf{\Psi}} + \Delta T_{\mathbf{\Psi}} = T_{\mathbf{e}} + \Delta T_{\mathbf{e}} = T_{\mathbf{W}} + \Delta T_{\mathbf{W}} = T_{eq} \tag{3.3}$$

TABLE 3.1: Working procedure of PDASP without multipath components for MIMO communication system

| | |
|---|---|
| Initilize: $\mathbf{W}_{k-1}, \mathbf{a}_{k-2}, \hat{\mathbf{r}}_{k-1}, \mathbf{\Psi}_{k-1}, \mathbf{\Psi}_{k-2}, \mathbf{e}_{k-2}, \mathbf{g}_{k-2}$ | |
| parallel procedure for $M_1$, $S_1$, $S_2$ and $S_3$ | |
| for k=0:N | |
| Process node $S_2$ | |
| at time $t_1$: | $\hat{\mathbf{r}}_k^T = \mathbf{x}_k^T \mathbf{W}_{k-1}$ |
| at time $t_1$: | $\mathbf{e}_{k-1} = \mathbf{r}_{k-1} - \hat{\mathbf{r}}_{k-1}$ |
| at time $t_1$: | wait $\Delta T_{\mathbf{e}}$ |
| Process node $M_1$ | |
| at time $t_1$: | $\mathbf{a}_{k-1} = \mathbf{x}_{k-1}^T \mathbf{\Psi}_{k-1}$ |
| at time $t_1$: | $\mathbf{g}_{k-1} = \dfrac{\mathbf{a}_{k-1}}{\mathbf{a}_{k-1}^T \mathbf{x}_{k-1} + \sigma_{v,k}}$ |
| Process node $S_1$ | |
| at time $t_1$: | $\mathbf{\Psi}_k = \mathbf{\Psi}_{k-2} - \mathbf{g}_{k-2} \mathbf{a}_{k-2}^T$ |
| at time $t_1$: | wait $\Delta T_{\mathbf{\Psi}}$ |
| Process node $S_3$ | |
| at time $t_1$: | $\mathbf{W}_k = \mathbf{W}_{k-1} + \mathbf{e}_{k-2} \mathbf{g}_{k-2}^T$ |
| at time $t_1$: | wait $\Delta T_{\mathbf{W}}$ |
| at time $t_2$: | Transmit $\mathbf{g}_{k-1}$ from $M_1$ to $S_3$ and $S_2$ |
| at time $t_3$: | Transmit $\mathbf{e}_{k-1}$ from $S_2$ to $S_3$, $\mathbf{a}_{k-1}$ from $M_1$ to $S_1$ |
| at time $t_4$: | Transmit $\mathbf{\Psi}_{k-1}$ from $S_1$ to $M_1$, $\mathbf{W}_k$ from $S_3$ to $S_2$ |
| end for | |

The strict and sufficient condition in terms of low processing time can be written as

$$T_{eq} + T_{f,\mathbf{\Psi}} + T_{f,\mathbf{g}} + T_{f,\mathbf{e}} + T_{f,\mathbf{W}} \ll T_{tot} \tag{3.4}$$

where $T_{f,\mathbf{\Psi}}, T_{f,\mathbf{g}}, T_{f,\mathbf{e}}$ and $T_{f,\mathbf{W}}$ are the fetch times regarding the transmission of data over the PDASP architecture. The working procedure of PDASP using low complexity MIMO channel estimation algorithm is shown in Table. 3.1, where all the nodes would capable to share the information among themselves after getting the time equivalent to maximum processing time of master node.

## 3.4 Sequential Implementation and Memory Limitation

In sequential algorithm, all the subparts are integrally running on single unit. While executing the sequential algorithm on single unit, the memory limitation comparisons on $2 \times 2$, $3 \times 3$ and $4 \times 4$ MIMO communication system with one, two and no multi-path components are shown in Table. 3.2. It has been observed that as the number of MIMO antennas and multi-path components increase the low memory devices like NANO and UNO are unable to run the low complexity MIMO channel estimation algorithm on single unit.

TABLE 3.2: Memory limitation comparison on different sequential MIMO systems with direct and multipath components using sequential implementation

| Aurdino Platform | Multipath Components | $2 \times 2$ MIMO | $3 \times 3$ MIMO | $4 \times 4$ MIMO |
|---|---|---|---|---|
| NANO | No Multipath | Working | Working | Working |
| UNO | No Multipath | Working | Working | Working |
| MEGA | No Multipath | working | Working | Working |
| NANO | One Multipath | Working | Memory Error | Memory Error |
| UNO | One Multipath | Working | Working | Memory Error |
| MEGA | One Multipath | Working | Working | Working |
| NANO | Two Multipaths | Memory Error | Memory Error | Memory Error |
| UNO | Two Multipaths | Working | Memory Error | Memory Error |
| MEGA | Two Multipaths | Working | Working | Working |

TABLE 3.3: Memory improvement for different MIMO systems with direct and multipath components using PDASP architecture

| Aurdino Platform | Multipath Components | $2 \times 2$ MIMO | $3 \times 3$ MIMO | $4 \times 4$ MIMO |
|---|---|---|---|---|
| NANO | No Multipath | Working | Working | Working |
| UNO | No Multipath | Working | Working | Working |
| MEGA | No Multipath | working | Working | Working |
| NANO | One Multipath | Working | Working | Working |
| UNO | One Multipath | Working | Working | Working |
| MEGA | One Multipath | Working | Working | Working |
| NANO | Two Multipaths | Working | Memory Error | Memory Error |
| UNO | Two Multipaths | Working | Working | Working |
| MEGA | Two Multipaths | Working | Working | Working |

## 3.5 Parallel Implementation with Working Improvement

In parallel implementation, the computationally incapable and inexpensive platforms are capable to work in parallel manner and provide much lesser processing time. The memory improvements comparison on different MIMO systems with one, two and no multi-path components are shown in the Table.3.3. It is observed that the distributed strategy effectively runs the sequential algorithm for different MIMO systems with multi-path components without any complication of memory error. However, NANO among all three sensor nodes is unable to work for $3 \times 3$ and $4 \times 4$ MIMO communication system with two multi-path components due to limited memory availability.

# Chapter 4

# Results Description

In this chapter, measurement results are presented by considering various MIMO communication systems with direct and multi-path components. The MIMO BPSK communication system with and without multi-path components are modeled in MATLAB software by considering an SNR=30$dB$. The received signal vector that has been generated in MATLAB environment is then given to low complexity MIMO channel estimation algorithm. The low complexity MIMO channel estimation algorithm is deployed on low cost wireless sensor nodes to substantiate the validation of PDASP technique. The performance outcomes of PDASP technique are presented in subsection of this chapter.

## 4.1 Complexity Comparison

In this section, the computational complexity of sequential and distributed adaptive filtering technique for different MIMO communication systems is discussed. The low complexity MIMO channel estimation algorithm sequentially provides $2M^2 + 2M(N+1) + 1$ multiplications and $2M^2 + 2MN$ additions per iteration. Where $N$ shows the MIMO spatial streams and $M$ represents the filter order. However, by using the PDASP architecture, the computational complexity respective to each processing node is much lesser than that of sequentially operated low complexity MIMO estimation algorithm which is clearly envisioned in Table. 4.1.

TABLE 4.1: Computational complexity relative to each processing node

| Processing Node | Multiplication Complexity | Addition Complexity |
|---|---|---|
| Node M1 | $M^2 + 2M + 1$ | $M^2$ |
| Node S1 | $M^2$ | $M^2$ |
| Node S2 | $MN$ | $MN$ |
| Node S3 | $MN$ | $MN$ |

Likewise, the multiplication and addition complexity with direct and multipath components for various MIMO systems are shown in Table. 4.2 and Table. 4.3, respectively. Furthermore, the percentage improvement of computational complexity between sequential algorithm and maximum computational cost occupied by node $M_1$ of PDASP technique is shown in Table. 4.4. It can be seen that the multiplication and addition complexity provided by the PDASP architecture is much lesser than the sequentially operated low complexity MIMO channel estimation algorithm. Moreover, the percentage improvement more than of 50% in reduction of computational complexity show a superlative improvement in terms of low energy consumption.

## 4.2 Processing Time Comparison

The processing time with respect to sequentialy operated low complexity MIMO estimation algorithm and its implementation on PDASP architecture is shown in Table. 4.5. It is realized that the processing time obtained by using PDASP technique provides parallely much lesser processing time than the sequentialy operated low complexity MIMO channel estimation algorithm. In case of no multipath components, the processing time taken by node $M_1$ is comparatively greater than the other slave nodes. The increased processing time taken by node $M_1$ is on the basis

Table 4.2: Sequential and distributed multiplication complexity for different MIMO systems with and without multipath components

| Processing Algorithm | Multipath Components | $2 \times 2$ MIMO | $3 \times 3$ MIMO | $4 \times 4$ MIMO |
|---|---|---|---|---|
| Sequential Algorithm | No Multipath | 21 | 43 | 73 |
| Node M1 | No Multipath | 9 | 16 | 25 |
| Node S1 | No Multipath | 4 | 9 | 16 |
| Node S2 | No Multipath | 4 | 9 | 16 |
| Node S3 | No Multipath | 4 | 9 | 16 |
| Sequential Algorithm | One Multipath | 57 | 121 | 209 |
| Node M1 | One Multipath | 25 | 49 | 81 |
| Node S1 | One Multipath | 16 | 36 | 64 |
| Node S2 | One Multipath | 8 | 18 | 32 |
| Node S3 | One Multipath | 8 | 18 | 32 |
| Sequential Algorithm | Two Multipaths | 109 | 235 | 409 |
| Node M1 | Two Multipaths | 49 | 100 | 169 |
| Node S1 | Two Multipaths | 36 | 81 | 144 |
| Node S2 | Two Multipaths | 12 | 27 | 48 |
| Node S3 | Two Multipaths | 12 | 27 | 48 |

of larger computations involvement than the other nodes in the PDASP architecture. However, in case of multipath components, the time taken by node $S_1$, takes a lead because of larger memory utilization than the processing node $M_1$. Therefore, the equivalence processing time relative to node $S_1$ in case of multipath components can be expressed as

TABLE 4.3: Sequential and distributed addition complexity for different MIMO systems with and without multipath components

| Processing Algorithm | Multipath Components | $2 \times 2$ MIMO | $3 \times 3$ MIMO | $4 \times 4$ MIMO |
|---|---|---|---|---|
| Sequential Algorithm | No Multipath | 16 | 36 | 64 |
| Node M1 | No Multipath | 4 | 9 | 16 |
| Node S1 | No Multipath | 4 | 9 | 16 |
| Node S2 | No Multipath | 4 | 9 | 16 |
| Node S3 | No Multipath | 9 | 9 | 16 |
| Sequential Algorithm | One Multipath | 48 | 108 | 192 |
| Node M1 | One Multipath | 16 | 36 | 64 |
| Node S1 | One Multipath | 16 | 36 | 64 |
| Node S2 | One Multipath | 8 | 18 | 32 |
| Node S3 | One Multipath | 8 | 18 | 32 |
| Sequential Algorithm | Two Multipaths | 96 | 216 | 384 |
| Node M1 | Two Multipaths | 36 | 81 | 144 |
| Node S1 | Two Multipaths | 36 | 81 | 144 |
| Node S2 | Two Multipaths | 12 | 27 | 48 |
| Node S3 | Two Multipaths | 12 | 27 | 48 |

$$
\begin{aligned}
\mid T_{\mathbf{\Psi}-T_{\mathbf{g}}} \mid &= \Delta T_{\mathbf{g}} \\
\mid T_{\mathbf{\Psi}-T_{\mathbf{e}}} \mid &= \Delta T_{\mathbf{e}} \\
\mid T_{\mathbf{\Psi}-T_{\mathbf{W}}} \mid &= \Delta T_{\mathbf{W}}
\end{aligned}
\tag{4.1}
$$

The working procedure of PDASP architecture with multipath components is shown in Table. 4.6. Moreover, the percentage improvement in decreased processing time using PDASP architecture is shown in Table. 4.7. It can be seen that

TABLE 4.4: Percentage improvement of multiplication and addition complexity for different MIMO systems

| Complexity | Multipath Components | $2 \times 2$ MIMO | $3 \times 3$ MIMO | $4 \times 4$ MIMO |
|---|---|---|---|---|
| Multiplication Complexity | No Multipath | 57.14% | 62.79% | 65.75% |
| Multiplication Complexity | One Multipath | 56.14% | 59.50% | 61.24% |
| Multiplication Complexity | Two Multipaths | 55.04% | 57.44% | 58.70% |
| Addition Complexity | No Multipath | 75.00% | 75.00% | 75.00% |
| Addition Complexity | One Multipath | 66.66% | 66.66% | 66.66% |
| Addition Complexity | Two Multipaths | 62.50% | 62.50% | 62.50% |

the PDASP architecture provides a significant improvement in decreased processing time parallely than the sequentially operated low complexity algorithm. This decreased processing makes a critical impact on the efficiency of the processing device as well as on the power consumption.

## 4.3 Memory Utilization Comparison

It is observed that the distributive strategy effectively runs the sequential algorithm for different MIMO systems without any complication of memory error. However, NANO among of all three sensor nodes unable to work for $3 \times 3$ and $4 \times 4$ MIMO system with two multi-path components because of lesser memory specification. Likewise, the percentage improvement of memory utilization is shown in Table. 4.8.

It can be observed that the PDASP architecture while running the sequential

TABLE 4.5: Sequential and distributed processing time in $\mu sec$ for different MIMO systems with and without multipath components

| Processing Algorithm | Multipath Components | $2 \times 2$ MIMO | $3 \times 3$ MIMO | $4 \times 4$ MIMO |
|---|---|---|---|---|
| Sequential Algorithm | No Multipath | 696 | 1420 | 2396 |
| Node M1 | No Multipath | 196 | 348 | 512 |
| Node S1 | No Multipath | 112 | 276 | 508 |
| Node S2 | No Multipath | 84 | 176 | 336 |
| Node S3 | No Multipath | 108 | 268 | 476 |
| Sequential Algorithm | One Multipath | 1780 | 3532 | 6116 |
| Node M1 | One Multipath | 524 | 1008 | 1612 |
| Node S1 | One Multipath | 508 | 1000 | 1772 |
| Node S2 | One Multipath | 164 | 332 | 680 |
| Node S3 | One Multipath | 212 | 508 | 920 |
| Sequential Algorithm | Two Multipaths | 3272 | 6852 | 11816 |
| Node M1 | Two Multipaths | 1004 | 1992 | 3080 |
| Node S1 | Two Multipaths | 1020 | 2268 | 4544 |
| Node S2 | Two Multipaths | 248 | 504 | 884 |
| Node S3 | Two Multipaths | 332 | 772 | 1232 |

algorithm parallely provides lesser memory utilization in sense of variable storage. This can also makes a critical impact on the efficiency of the processing device.

TABLE 4.6: Working procedure of PDASP with multipath components for MIMO communication system

| | |
|---|---|
| Initilize: $\mathbf{W}_{k-1}, \mathbf{a}_{k-2}, \hat{\mathbf{r}}_{k-1}, \mathbf{\Psi}_{k-1}, \mathbf{\Psi}_{k-2}, \mathbf{e}_{k-2}, \mathbf{g}_{k-2}$ | |
| parallel procedure for $M_1$, $S_1$, $S_2$ and $S_3$ | |
| for k=0:N | |
| Process node $S_2$ | |
| at time $t_1$: | $\hat{\mathbf{r}}_k^T = \mathbf{x}_k^T \mathbf{W}_{k-1}$ |
| at time $t_1$: | $\mathbf{e}_{k-1} = \mathbf{r}_{k-1} - \hat{\mathbf{r}}_{k-1}$ |
| at time $t_1$: | wait $\Delta T_{\mathbf{e}}$ |
| Process node $M_1$ | |
| at time $t_1$: | $\mathbf{a}_{k-1} = \mathbf{x}_{k-1}^T \mathbf{\Psi}_{k-1}$ |
| at time $t_1$: | $\mathbf{g}_{k-1} = \dfrac{\mathbf{a}_{k-1}}{\mathbf{a}_{k-1}^T \mathbf{x}_{k-1} + \sigma_{v,k}}$ |
| at time $t_1$: | wait $\Delta T_{\mathbf{g}}$ |
| Process node $S_1$ | |
| at time $t_1$: | $\mathbf{\Psi}_k = \mathbf{\Psi}_{k-2} - \mathbf{g}_{k-2} \mathbf{a}_{k-2}^T$ |
| Process node $S_3$ | |
| at time $t_1$: | $\mathbf{W}_k = \mathbf{W}_{k-1} + \mathbf{e}_{k-2} \mathbf{g}_{k-2}^T$ |
| at time $t_1$: | wait $\Delta T_{\mathbf{W}}$ |
| at time $t_2$: | Transmit $\mathbf{g}_{k-1}$ from $M_1$ to $S_3$ and $S_2$ |
| at time $t_3$: | Transmit $\mathbf{e}_{k-1}$ from $S_2$ to $S_3$, $\mathbf{a}_{k-1}$ from $M_1$ to $S_1$ |
| at time $t_4$: | Transmit $\mathbf{\Psi}_{k-1}$ from $S_1$ to $M_1$, $\mathbf{W}_k$ from $S_3$ to $S_2$ |
| end for | |

## 4.4 Communication Time Comparison

The complete time taken by the PDASP architecture for one iteration including the communication burden is shown in Table. 4.9. It is observed that the communication burden is directly dependent on the number of MIMO streams and number of multipath components. The time difference of one complete iteration and maximum processing time taken by any node in PDASP architecture is shown in Table. 4.10. It is realized that the communication burden is much higher than the maximum processing time of any specific node in the PDASP architecture. So, there must be a trade off between the communication burden and the number of MIMO spatial streams.

Table 4.7: Percentage improvement in processing time for different MIMO systems

| Multipath Components | $2 \times 2$ MIMO | $3 \times 3$ MIMO | $4 \times 4$ MIMO |
|---|---|---|---|
| No Multipath | 71.84% | 75.49% | 78.63% |
| One Multipath | 70.56% | 71.46% | 71.02% |
| Two Multipaths | 68.82% | 66.90% | 61.54% |

Table 4.8: Percentage improvement in memory utilization using PDASP architecture

| Processing Time | Multipath Components | $2 \times 2$ MIMO | $3 \times 3$ MIMO | $4 \times 4$ MIMO |
|---|---|---|---|---|
| Sequential Algorithm | No Multipath | 696 | 1420 | 2396 |
| Combined Time of $M1, S1, S2, S3$ | No Multipath | 500 | 1068 | 1832 |
| Percentage Improvement | No Multipath | 28.16% | 24.78% | 23.53% |
| Sequential Algorithm | One Multipath | 1780 | 3532 | 6116 |
| Combined Time of $M1, S1, S2, S3$ | One Multipath | 1408 | 2848 | 4984 |
| Percentage Improvement | One Multipath | 20.89% | 19.36% | 18.50% |
| Sequential Algorithm | Two Multipaths | 3272 | 6852 | 11816 |
| Combined Time of $M1, S1, S2, S3$ | Two Multipaths | 2604 | 5536 | 9740 |
| Percentage Improvement | Two Multipaths | 20.41% | 19.20% | 17.56% |

Table 4.9: Maximum time taken for One complete iteration using PDASP architecture for different MIMO systems

| Multipath Components | $2 \times 2$ MIMO | $3 \times 3$ MIMO | $4 \times 4$ MIMO |
|---|---|---|---|
| No Multipath | 9520 $\mu sec$ | 11449$\mu sec$ | 15633$\mu sec$ |
| One Multipath | 16934$\mu sec$ | 26320$\mu sec$ | 38986$\mu sec$ |
| Two Multipaths | 27143$\mu sec$ | 43380$\mu sec$ | 66898$\mu sec$ |

Table 4.10: Communication Burden specified for One Complete Iteration using NRF for Different MIMO Systems

| | | | |
|---|---|---|---|
| No Multipath | 9324 $\mu sec$ | 11101$\mu sec$ | 15121$\mu sec$ |
| One Multipath | 16410$\mu sec$ | 25312$\mu sec$ | 37214$\mu sec$ |
| Two Multipaths | 26123$\mu sec$ | 41212$\mu sec$ | 62354$\mu sec$ |

# Chapter 5

# Conclusion and Future work

## 5.1 Conclusion

In this thesis, the validation of PDASP architecture for various MIMO streams deployed on low cost sensor nodes has been presented. The validation of PDASP architecture has been evaluated on the basis of processing time, computational complexity and communication delay. Processing time and computational complexity of PDASP with low complexity MIMO channel estimation algorithm have been compared with sequentially operated low complexity MIMO algorithm. It has been realized that the PDASP architecture utilizes much lesser processing time and computational complexity than the sequentially operated low complexity algorithm. Moreover, by using the PDASP architecture, the memory utilization in sense of variable storage has also been improved than the sequentially operated low complexity MIMO estimation algorithm. Furthermore, It has been realized that the communication burden for one complete iteration using PDASP architecture is much higher than the individual processing time of any node in the network. It has been observed that the communication burden may increase as increase in number of MIMO streams or multipath components. For efficient communication, there must be a trade off between the communication burden and the number of MIMO spatial streams.

## 5.2 Future Work

By using the PDASP architecture, it has been observed that the communication burden for one complete iteration is much higher than the individual processing time of any node in the distributed architecture. In future this increased communication delay can be reduced by considering the following plane.

### 5.2.1 Plan 1: WIFI Transceiver

In PDASP architecture, the information interchanges among the processing nodes is possible by using the NRF24l01 transceiver. The maximum data rate provided by the NRF24l01 is 2Mbps. Therefore, the communication burden provided by the PDASP architecture is much higher than the processing time of the algorithm when it runs on single unit. To makes the fast communication among the nodes, there is scope to use the WIFI transceiver module that provide a maximum data rate of 54Mbps.

### 5.2.2 Plan 2: The Network Simulator - ns-2

Ns is a discrete event simulator targeted at networking research. Ns provides substantial support for simulation of TCP, routing, and multicast protocols over wired and wireless (local and satellite) networks. NS2 provides the packet transmitting rate, end-to-end delay, index number of packet, protocol types and so on. It records the detailed data of packets flow passing through the intermediate nodes. The PDASP architecture can be simulated on NS2 and compare the results with this thesis results from which we can draw bigger picture.

### 5.2.3 Plan 3: Use of MIMO antennas

In time varying channel environment, due to high Doppler rate the channel shows adverse behavior. For instance, at 50HZ of Doppler the channel is constant for

20msec. It is necessary to estimate the time varying channel condition and therefore, the communication burden must be reduced as much as possible. By using MIMO antennas, the communication may be reduced.

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