

## Distributed Beamforming Using Multi-Antenna Backscattering Network

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**Abstract:** - This paper proposes two novel beam-forming methodologies, which employ passive RF devices to enhance received signal through a passive, scattering based beam forming. Currently available backscattering systems, e.g. the radio frequency identification (RFID), suffer from a poor communication in an environment with multiple passive devices. The intermediate antennas create severe scattering environment with nulls. In contrast, the proposed approach changes the scattering properties of a subset of the multiple antennas such that the received signal strength and quality is maximized. The schemes employ Taguchi system and Learning Automaton to quickly identify such a suitable set of scattering intermediate devices. The theoretical limits of these schemes are studied mathematically and in simulations. For a 100-device network, the proposed schemes achieve power improvements over the line of sight equal to 37.5dB and 33dB for Taguchi and Learning Automaton-based schemes respectively. Moreover, the schemes are shown to perform well in an environment with the Rayleigh fading.

**Keywords:** - RFID networks, Beamforming, scattering, Learning automata, Taguchi method.

### I INTRODUCTION

In recent years, a passive scattering based wireless communication is an attractive alternative to the traditional, active transmission systems. The main benefits are a low power, inexpensive, and often battery-less design since the device requires less power to operate and can be implemented as a system-on-a-chip (SOC). The most commercialized backscattering solution is the *Radio Frequency Identification* (RFID) system with passive RFID tags that communicate a unique identification to an active reader. Furthermore, such systems are increasingly employed in sensing applications [1][2][3]. The low power, small form factor wireless sensors have potential to make the concept of a “smart dust” a reality. However, due to path loss and signal fading in wireless links, the communication range of passive systems is limited to no more than several tens of feet. Furthermore, such passive devices often harvest energy from the original RF signal transmitted by the reader/base station. There is a minimal amount of RF power required to wake and power such a passive device up. Consequently, in presence of fading channel, for example due to shadowing and multipath propagation, a passive device is often unable to receive sufficient energy to operate and successfully communicate. This limits the usage of backscatter-based communication to short-range wireless applications.

Several works studied this issue in the RFID systems with passive tags [1][2][3][23]. A typical deployment of RFID system includes a large number, densely placed passive devices, called RFID tags. Such scenario creates severe fading environment with number of nulls where tags cannot be read. The existing works focus on static design improvements, for example a tag’s antenna redesign, or experimentally test the performance in different system configuration, e.g. antenna types and placement. In contrast, the proposed work aims at dynamically adjust the scattering properties of the multiple tags to improve the received signal and improve effective communication range.

Several approaches have been proposed in the literature to extend the range of communication in wireless networks including an active beam forming, a relaying network, and the RAKE receivers [4][7][8][9]. However, these works are not suitable for passive, backscatter-based systems since they often require active-transmission devices and precise synchronization. For instance, in a non-regenerative relaying network, the relay nodes scale the signal received from a source, and retransmit it to destination. However, passive devices are not capable of retransmitting an amplified signal due to power limitation; thus making the non-regenerative relaying approach unsuitable. Another approaches present in the literature include a RAKE receiver and an active beamforming. In general those relay on time-synchronization of the signal replicas such that they can be coherently combined together. For example, RAKE receiver collects and coherently adds time-delayed replicas of the received signal. While it could be implemented at a capable, advanced reader/base station, the passive devices have neither sufficient energy nor time resolution capabilities to implement such a RAKE receiver. Similarly, antenna-array based beamforming cannot be implemented at the passive devices. Moreover, a distributed beamforming require significant time synchronization among the transmitters to achieve coherent

signal at the receiver. The inexpensive and energy-constrained design of passive devices, for example RFID tags, makes such beamforming approaches impractical. The main reason is that such passive, backscattering transceivers are unable to perform complex signal processing operations and computations.

In the past, the authors have proposed a passive beamforming method to improve SNR in a backscattering network [10]. This preliminary study employed a brute force (B-F), Taguchi-based, and Learning Automata (LA) based beamforming algorithms. It is assumed that the intermediate passive devices could be set to operate in one of two modes: *scattering* and *inhibition* where the device either scatters the reader's signal or minimizes the scattering. The proposed approach selects the states of intermediate devices such that the received signal strength and quality is maximized. In contrast to the preliminary results in [10], this paper revises the proposed approach and introduces two novel beamforming methods: a Taguchi- and LA-based, which increase SNR in a passive RFID network under realistic, large-scale scenarios with random topologies. Also, the selection of the scheme's design parameters is studied here. The exhaustive search of the brute force (B-F) method, while impractical for more than few tags, provides a reference, optimal selection of scattering tags.

The main contributions of this paper are: (1) development of a model that describes RF signal propagation between two nodes in the presence of scattering devices distributed, (2) development of a scheme for distributed beamforming using Taguchi system and LA that achieve the maximum power possible using individual scattering devices, and (3) theoretical study of the performance, and (4) a comparative performance study for the discussed schemes.

The paper is organized as follows. In section II, the background is presented. Section III defines the problem statement. The proposed algorithms are discussed in details in Section IV. The simulation results are presented in Section V, and conclusions are given in Section VI.

## II BACKGROUND

In a wireless passive scattering scenario an original RF signal impinges antennas of all intermediate devices and is scattered on all of them. Consequently, at the destination, the original signal is received as a summation of several components, including line-of-sight signal (LOS), multipath, and scattering copies. In the best scenario, these components may constructively interfere thus increase strength and quality of the received signal. However, more often a destructive interference occurs thus impeding the communication. In general, to compensate for phase difference of replicas of an original signal in a distributed beam forming, synchronization has been studied in the literature [11][12][13][14]. The method of random phase adjustment at the transmitter is discussed in [11] a feedback signal is sent indicating whether the signal-to-noise ratio has improved or worsened and the transmitters adjust their phases accordingly. The concept of division of nodes into master and slave nodes is discussed in [12] where the slave nodes estimates the distance from the master node and calculate the delay and phase. The problem is addressed in [13] by using a 1-bit feedback register at the receiver and the phase adjustment is done according to the feedback from it. The work in [14] starts with the correlation of noise and the design of the relay gains based on the addition of copies of desired signal. While most of the previous works focus on the time synchronization to compensate for the scattering induced fading, the added complexity and overhead of the synchronization renders those methods impractical.

Conversely, the same scattering phenomenon could be used to boost the SNR at the destination. In general, scattering devices can be divided in two groups: (a) the devices that have constructive interference, and (b) the ones that have destructive interference. Instead of correcting phase errors, the system could activate scattering only for the intermediate devices that create the constructive interference. The rest of devices should be set to absorb the signal to avoid injecting a destructive scattering. When the appropriate passive devices are selected the constructive interference does improves the received signal. As a result, a distributed, passive beamforming is realized. The increased signal strength and quality allows for either higher transmission (modulation) rates or extended communication range or reduce power consumption.

The main challenge addressed by the proposed approaches is the selection of the best set of the scattering intermediate devices while minimizing the overhead and convergence time. The schemes have to maximize the received power and SNR. In contrast to traditional beamforming, which employs an antenna array, the proposed approach does not require precise timing and synchronization among the individual antennas.

In this paper, the learning automata (LA) and Taguchi approaches are proposed and studied for scenarios with over 100 intermediate, passive devices, e.g. RFID tags. The proposed LA-based scheme randomly selects combinations of tags and analyses the corresponding outcomes (signal strength and quality). Subsequently, this scheme learns which actions are more beneficial and adjusts the probability of their selection next time. The second proposed scheme employs a Taguchi system, where for subsequent periods carefully selected sets of tags are selected for scattering. The Taguchi-based system optimizes tradeoff between number of experiments and the optimality of the device selection. The Taguchi-based analysis indicates which devices

improve the received signal strength and SNR. In contrast to other approaches, the Taguchi-based scheme takes the non-linear interactions among the individual devices into account.

### III PROBLEM STATEMENT

First, the scattering is discussed in the context of the proposed beamforming approach. Then, the received signal composition is modeled and the device selection problem is defined.

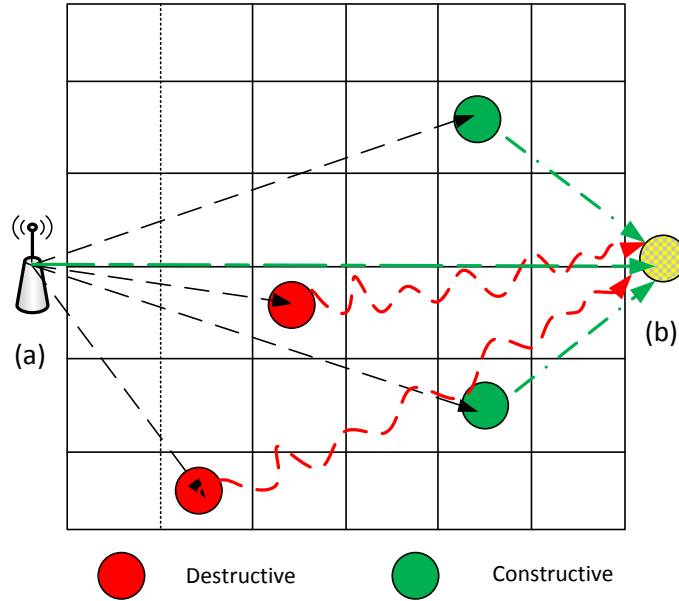


Figure 1. An efficient algorithm should select constructive tags and deactivate destructive ones.

#### III.1 A scattering network of passive RFID tags

The concept of a distributed beam forming using a scattering network is shown in Fig. 1. We consider a communication link between the transmitter,  $\mathcal{A}$ , and the receiver,  $\mathcal{B}$ . In between there are  $N$  scattering devices, which are assumed to be passive components whose scattering properties can be varied. Notably, such passive devices, for example the RFID passive tags, are small and inexpensive since they have simple, integrated design, and require *no batteries* to operate. When the transmitter,  $\mathcal{A}$ , interrogates a target device,  $\mathcal{B}$ , the intermediate devices will generate scattered copies of the signal. The  $N$  non-unisonous signals interfere with the LOS signal at the receiver,  $\mathcal{B}$ . These signals arrive with variable delays, or offsets, depending on their position and scattering property, i.e. the antenna and chip impedance. Such a scattering based multipath propagation contributes to the already existing channel fading and lowers overall signal quality. Potentially, the combined signal at the destination will become stronger when the phase shifts align. However, in a random topology the effect is often negative due to phase mismatch among the signals. Generally, variation of phase occurs due to three factors: (a) *distance*: scattered signals propagate through a different-length paths thus introducing phase variation; (b) *medium*: channel properties variation may also cause phase shift; and (c) *reflection/scattering*: the reflecting/scattering object may cause a phase shift due to electric properties. It is well understood that when an electromagnetic field encounters an object, transmitted and reflected fields will be produced:

$$E_r = \Gamma E_i \tag{1}$$

$$E_t = T E_i = (1 + \Gamma) E_i \tag{2}$$

where  $E_i$ ,  $E_r$  and  $E_t$  are respectively incident, reflected, and transmitted fields, and  $\Gamma$  is reflection coefficient.

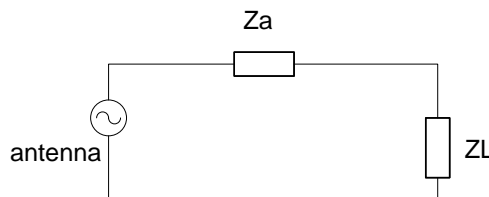


Figure 2. Simplified circuitry of RFID tag

A simplified model of the internal circuits of a RFID tag is depicted in Fig. 2; where  $Z_a$  is the complex impedance of tag's antenna and  $Z_L$  is the complex impedance of chip of the tag. The reflection coefficient  $\Gamma$  is equal to:

$$\Gamma = \frac{Z_L - Z_a}{Z_L + Z_a} \quad (3)$$

Two modes of operations are expected from a RFID tag: *scattering* and *inhibition*. In scattering mode, the tag switches to  $Z_L = \infty$  acting as a reflecting object. In  $Z_L = \infty$  reflection coefficient will be  $\Gamma = 1$ , giving no amplitude or phase shift to the reflecting signal. In inhibition mode, the scattered energy should be minimized by setting its impedance  $Z_a = Z_L$ . Overall, the reflected signal energy and its phase shift is modeled as:

$$E_r = \Gamma E_i \left( \frac{Z_L - Z_a}{Z_L + Z_a} \right) E_i \quad (4)$$

### III.2 Signal propagation in a scattering network of passive devices

Consider a single tone transmitted from an active transmitter, for example an RFID reader. The received signal in a presence of a network of scattering passive devices can be written as

$$s(t) = c_0 \cos(\tau) + c_1 \cos(t - t_1) + c_2 \cos(\tau - t_2) + \dots \quad (5)$$

where  $s(t)$  is received signal at destination,  $c_0, c_1, c_2, \dots, c_n$  are attenuation coefficients and  $t_1, t_2, \dots, t_n$  are related time delay of received signal from reader (LOS). Then, the received power of the signal (1), can be written as

$$P_{rc}(t) = \sum_{i=1}^n P_i(t) e^{j\theta_i(t)} \quad (6)$$

where  $P_i$  and  $\theta_i$  are the power and phase shift related to the  $i^{\text{th}}$  scattering node. Assuming the intermediate passive devices are scattering the signal, the power attenuation from each node at destination is calculated by

$$P_i(t) = \Gamma \left( \frac{\lambda}{4\pi r} \right)^2 P_t(t) G_r G_t g_i(t) \quad (7)$$

where  $P_t(t)$  is transmitted power from reader,  $G_r, G_t$  are antenna gains of the reader and tag respectively,  $\lambda$  is operating wavelength, and  $g_i$  is the fading coefficient. Let  $r = d_1 + d_2$  with  $d_1$  and  $d_2$  are respectively the distance from reader to intermediate node and from the intermediate and the destination node. Applying (7) to (6) the received signal power can be modeled as

$$P_{rc}(t) = P_t(t) G_r G_t g_i(t) \left( \frac{\lambda}{4\pi} \right)^2 \sum_{i=1}^N r_i^{-2} e^{j2\pi f_c t_i} \quad (8)$$

where  $f_c$  is the carrier frequency. The passive devices, for example the passive RFID tags, harvest energy from the RF signal to power internal circuitry. For a passive receiver, there is a minimum power,  $P_{th}$ , that is required to activate it, that is  $P_{rc}(t) > P_{th}$ . This constraint can be used to derive a theoretical limit on the distance between the active reader and passive receiver:

$$P_t G_r G_t \left( \frac{\lambda}{4\pi} \right)^2 \sum_{i=1}^N r_i^{-2} e^{j2\pi f_c t_i} > P_{th} \quad (9)$$

After transformation we get following condition

$$\sum_{i=1}^N r_i^{-2} e^{j2\pi f_c t_i} > \frac{4\pi}{\lambda} \sqrt{\frac{P_{th}}{P_t G_r G_t}} \quad (10)$$

**Remark 1:** The condition (10) simplifies to  $r < \left( \frac{4\pi}{\lambda} \sqrt{\frac{P_{th}}{P_t G_r G_t}} \right)^{-1}$  when only LOS signal is considered.

**Remark 2:** In a realistic, random topology, the phase shifts,  $\theta_i$ , are not aligned coherently thus adding to the destructive interference. The resulting fading and low read-rate is widely observed for the RFID systems in scenarios with multiple tags.

### III.3 Problem formulation

Let's consider scattering network of  $N$  passive devices, e.g. RFID tags, randomly placed in a square of  $m \times m$  meters as shown in Fig. 1. The target device, which the reader wants to communicate with, is located at the farthest distance to the reader. The desired goal is to maximize the power available at the destination tag. Let's define  $X$  as a random variable taking values from a set  $\mathcal{S} = \{0, 1\}$ , where "1" indicates that the corresponding passive device is scattering, and "0" indicates that the device has a negligible scattering power. Then,  $\mathbf{X} = \{X_1, X_2, \dots, X_N\}$  indicates the set of variables which shows the scattering status of all tags. For two tags,  $j$  and  $k$ , the received power can be written as

$$P(\mathbf{X}) = \alpha_j X_j + \alpha_k X_k + \beta X_j X_k \quad (11)$$

where  $\alpha_j$  and  $\alpha_k$  are power coefficient related to tag  $j$  and  $k$  respectively, and  $\beta$  is the power coefficient related

to the interaction of these two signals at destination tag. Also,  $X_j$  and  $X_k$  are the variables taken from  $\mathcal{X}$  and are equal to 1.

**Remark 3:** The power coefficients are typically unknown in real deployments. Hence, a set of experiments would have to be carried out to determine their values.

In general, there can be  $M$  out of  $N$  tags that do scatter the reader's signal to the destination tag and the generalized power equation can be rewritten as

$$P(\mathcal{X}) = \prod_{i=1}^M \alpha_i X_i + \prod_{i=1}^{\binom{M}{2}} \alpha_i^2 X_{\binom{M}{2},i} + \prod_{i=1}^{\binom{M}{3}} \alpha_i^3 X_{\binom{M}{3},i} + \dots + \prod_{i=1}^{\binom{M}{M}} \alpha_i^M X_{\binom{M}{M},i} \quad (12)$$

**Remark 4:** For  $k = \binom{M}{m}$ , we use below notation to show a total  $k$  states  $\bar{k} = \{(X_{k,1})_1, (X_{k,2})_2, \dots, (X_{k,k})_k\}$ , where  $X_{k,i} = [^1X_{k,i}, ^2X_{k,i}, \dots, ^mX_{k,i}]$  is an  $m$  element array of the  $i^{\text{th}}$  state from the total of  $k$  states. The variable  $^{m,i}X_{k,i}$  is the  $j^{\text{th}}$  element out of the total  $m$  elements of the  $i^{\text{th}}$  state out of a total  $k$  states, i.e.  $X_{k,i}$ .

Each term in (12) shows summation of received power from the  $\binom{M}{m}$  tags and  $m=1,2,\dots,M$ . The term  $\alpha_i$  indicates the power coefficient related to that set of tags in the received power model. Equation 12 can be written as

$$P(\mathcal{X}) = \sum_{i=1}^M \prod_{i=1}^{\binom{M}{i}} \alpha_i^i X_{\binom{M}{i},i} \quad (13)$$

By substituting  $M$  with  $N$  in 13,  $P(\mathcal{X})$  will be a function of  $\mathcal{X}$ .

$$P(\mathcal{X}) = \sum_{i=1}^N \prod_{i=1}^{\binom{N}{i}} \alpha_i^i X_{\binom{N}{i},i} \quad (14)$$

We are interested in maximizing equation 15.

$$\varphi(\mathcal{X}) = \max\{P(\mathcal{X})\} = \left\{ \varphi(\mathcal{X}) = \max\left(\sum_{i=1}^N \prod_{i=1}^{\binom{N}{i}} \alpha_i^i X_{\binom{N}{i},i}\right) \right\} \quad (15)$$

To maximize (16), all combination of tags for  $N=1,2,\dots$ , should be examined to find the combination which achieves maximum possible power

$$S = \{X | X \subset \mathcal{X}, X = 1 \rightarrow P(\mathcal{X}) = \max\} \quad (16)$$

The simple, brute force approach is to evaluate all possible combination and select the best combinations of intermediate devices. In ideal channel condition, this will determine the optimal solution to (15). It requires knowing all  $\alpha$  parameters in (15), which are not known in a realistic scenario. Moreover, the number of combination to be evaluated increase at the order of  $\mathcal{O}(2^N)$ . Consequently, the brute force approach is impractical for large networks due to the time and processing overheads.

## IV THE PROPOSED BEAM FORMING SCHEMES

### IV.1 Taguchi-based method

Taguchi system evaluates the effect of multiple variables on a performance metric [19][20][21]. It employs orthogonal arrays to minimize number of experiments that have to be carried out while maximizing the amount of available information. The analysis of the results corresponding to the orthogonal array leads to the selection of the variables that optimize performance. The proposed Taguchi-based method of selecting the best set of scattering tags is shown next. The performance and low overhead is demonstrated in both theoretical and simulation analysis. Although Taguchi method does not guarantee the optimal solution all possible scenarios, it does approach the optimal solution. In concert with the quick convergence it is an appropriate solution for realistic deployment.

#### IV.1.1 Orthogonalisation in the Taguchi method

Vectors in an orthogonal array form a basis, i.e. any vector can be expressed as a linear combination of the basis vectors. In the proposed scheme, the vectors correspond to the states of the intermediate devices, as in (14). Hence, the orthogonal array will form the basis for any combination of scattering devices.

**Lemma.** A combination of a particular set of  $N$  tags can be shown by

$$P(\mathcal{X}) = \prod_{i=1}^N \alpha_i \beta_i Y_i \quad (17)$$

where  $\alpha$  is the power coefficient,  $\beta$  also takes value from  $\{0,1\}$ , indicating whether  $Y_i$  is included in showing this set of tags and  $U$  is the operator for XOR.

**Proof.** It is well proven that, to show any combination of  $N$  elements we can find  $P$  sets from themselves so that

$$\begin{cases} Y_1 & \gamma_1^1 X_1 + \gamma_2^1 X_2 + \dots + \gamma_N^1 X_N \\ Y_2 & \gamma_1^2 X_1 + \gamma_2^2 X_2 + \dots + \gamma_N^2 X_N \\ \dots & \dots \\ Y_p & \gamma_1^p X_1 + \gamma_2^p X_2 + \dots + \gamma_N^p X_N \end{cases} \quad (18)$$

In a matrix format (18) can be expressed as

$$\mathbf{Y} = \mathbf{\gamma} \mathbf{X} \quad (19)$$

where  $\mathbf{Y}$  takes values from  $\{0,1\}$  and we define  $\mathbf{Y} = \{Y_1, Y_2, \dots, Y_P\}$ . Using  $\mathbf{Y}$ , any set of different combination of tags can be written using XOR operator. Thus, Equation (14) can be shown as

$$P(\mathbf{X}) = U_{i=1}^{\mathbf{Y}} (\alpha_i \beta_i Y_i) \quad (20) \blacksquare$$

In (17),  $\mathbf{Y}$  is defined based on  $N$  tags or  $N$   $X$ 's. As  $N$  increases, however, using (19) might not be very easy since the length of  $\mathbf{Y}$  also would increase. To solve this problem, in this paper, we used orthogonal arrays of table 1 to write equation (14) based on orthogonal combination of tags. Thus, according to  $OA(8,5,2,2)$ , introduced in table 1, we divide all tags in groups of 5. By using 8 orthogonal arrays in table 1, we write equation (14) as

$$P(\mathbf{X}) = f(\mathbf{X}) \cdot g(\mathbf{Y}) = \sum_{i=1}^{N_g} U_{i=1}^{N_g} \alpha_i \beta_i Y_i^j \quad (21)$$

where  $N_g$  is the number of groups and  $Y_i^j$  is the  $j^{th}$  orthogonal array in the  $i^{th}$  group of tags.

Table 1. Orthogonal array in Taguchi scheme

Y	X <sub>1</sub>	X <sub>2</sub>	X <sub>3</sub>	X <sub>4</sub>	3X <sub>5</sub>	
O	Device	Device	Device	Device	Device	SNR
A	1	2	3	4	5	
Y <sub>1</sub>	1	1	1	1	1	SNR <sub>1</sub>
Y <sub>2</sub>	1	1	1	0	0	SNR <sub>2</sub>
Y <sub>3</sub>	1	0	0	1	1	SNR <sub>3</sub>
Y <sub>4</sub>	1	0	0	0	0	SNR <sub>4</sub>
Y <sub>5</sub>	0	1	0	1	0	SNR <sub>5</sub>
Y <sub>6</sub>	0	1	0	0	1	SNR <sub>6</sub>
Y <sub>7</sub>	0	0	1	0	1	SNR <sub>7</sub>
Y <sub>8</sub>	0	0	1	1	0	SNR <sub>8</sub>
	T <sup>x1</sup>	T <sup>x2</sup>	T <sup>x3</sup>	T <sup>x4</sup>	T <sup>x5</sup>	

#### IV.1.2 The proposed Taguchi-based device selection approach

The proposed scheme selects the passive devices for scattering if their Taguchi coefficient, which is presented below, is positive. Considering the power at the destination devices written as (21), we proceed to detailing the Taguchi approach. The search for solution in a large domain  $X$  faces scalability issues in convergence time and complexity. Instead, we proposed to transform the problem into a smaller domain  $\mathbf{Y}$  (orthogonal array).

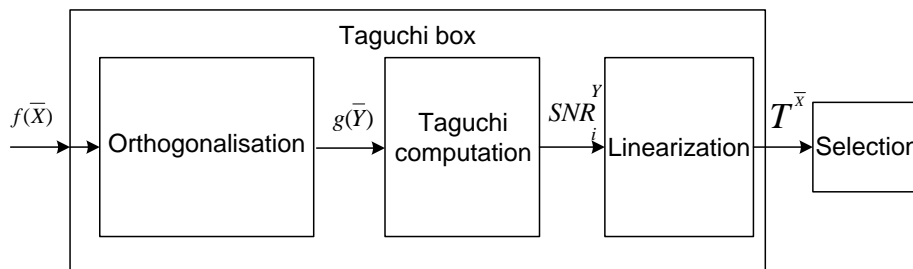


Figure 2. Taguchi block diagram

A block diagram of Taguchi method is depicted in Fig. 2. The Taguchi analysis estimates the weighted coefficient corresponding to each  $X_i$ , i.e. tag. The coefficient orders the devices based on their impact on the combined power at the receiver. In fact, the Taguchi algorithm transforms the nonlinear formulation (15) to a



linear problem. In this paper, we name this coefficient as a *Taguchi coefficient* and represent as  $T^X$ . The SNR value is calculated for each set of  $Y_i^j$  as follows:

$$SNR_i^j = 10 \log \left\{ \sum P_{scatter} \right\} - 10 \log \left\{ \sum P_i e^{-\mu_i} \right\} \quad (22)$$

where  $SNR_i^j$  is calculated upon the status of  $X$ 's in  $Y_i^j$  array. The Taguchi coefficient of  $X_k$  device is calculated as

$$T^{X_k} = \sum \varphi_i SNR_i^j |k \text{ present} - \sum \varphi_i SNR_i^j |k \text{ not present} \quad (23)$$

Taguchi coefficient is a measure of being effectiveness of variable  $X_k$  in comparison to the other  $X$ 's. The effect of the  $X_k$  device increases with its Taguchi coefficient. All devices whose Taguchi coefficient is negative should be considered as negatively contributing devices since their presence in a given set reduced the received power.

$$\begin{cases} T^{X_k} \geq 0 & \rightarrow \text{effective tag} \\ T^{X_k} < 0 & \rightarrow \text{non effective tag} \end{cases} \quad (24)$$

Accordingly, all devices are sorted on the Taguchi coefficient  $\{S'\}$  first  $\left[ \left( \min\{K, N\} \right) \text{ tags } S, T^{X^m} > 0 \right] \subset \{S\}$ , where  $S'$  is the set of scattering nodes, and  $K$  is a number to be chosen. Table 1 shows an example Taguchi array with 8 orthogonal vectors. The vectors model the  $S$  space,  $S = \left\{ \begin{pmatrix} 1 \\ 0 \end{pmatrix}, \begin{pmatrix} 0 \\ 1 \end{pmatrix}, \dots, \begin{pmatrix} 1 \\ 1 \end{pmatrix} \right\}$ . The equivalent  $T^{X^k}$  are calculated based on SNR of each set of  $Y$ .

#### IV.2 Learning Automata

Learning automata is a feedback oriented, adaptive algorithm for a system whose input has to be selected in such a way that its output performance is maximized. In this paper, the LA is applied to search the best combination of passive devices to be used in scattering to the destination node. The proposed LA-based scheme selects a set of devices based on corresponding probabilities. The probabilities are updated based on the received power when the selected devices are set to scatter the signal. The update equations are chosen such that the probability of the positive, desired devices increases over time. We have considered and studied performance of several variants of the LA-based schemes with varying group sizes and update gains. The details of the scheme are presented next.

##### IV.2.1 The proposed LA-based approach

Our model is represented using a quintuple  $\{\alpha, \varphi, \beta, S(+,+), O(+)\}$  as it is described hereafter. Let's consider  $1, 2, \dots, N$  RFID tags as it is depicted in Fig. 1. Tags are randomly set in groups of size  $G_S$  which leaves  $k = \lfloor \frac{N}{G_S} \rfloor + 1$  groups. We define  $k$  groups as  $k$  actions,  $\alpha = \{\alpha_1, \alpha_2, \dots, \alpha_k\}$ , taken by system. Next, we define  $k$  system states for our model by  $\varphi = \{\varphi_1, \varphi_2, \dots, \varphi_k\}$ . Current state of system shows the last action taken by the system and it is updated each time a response is received from the environment to determine next action by the system. The response from environment is called  $\beta$  and is measured at reader side. A response is considered a rewarding ( $\beta = 1$ ) when the total measured power is higher than LOS; and a penalty ( $\beta = 0$ ) when it is lower than LOS. The feedback from environment is exerted to the system by updating current state and through *State Transition Function*,  $S(\varphi_i, \beta_i)$ , which is a function of current system state and the response from environment. State transition function is composed of a set of probabilities representing the probability of a transition between a state  $i$  and any other state, say  $j$ , and is shown by  $S_{ij}^k$ . Thus, at each state  $\sum_{\alpha, \beta} S_{ij}^k(\alpha) = 1$  should be held. State transition function is updated each time a response is received from environment to rather intensify or weaken the probability of sets.

**Corollary.** The described passive RFID network is a P-model, variable structure automaton.

**Proof.** A P-model LA is a model in which the input from environment takes only two values. Further, a LA whose state transition coefficients are variable over time is categorized in variable structure automaton, contrary to fixed-structure automaton where state transition coefficients are independent of time intervals. ■

The proposed LA based approach starts as a *pure chance automaton*. Since no prior information is available, no action preferred. Hence, the algorithm starts with  $p_i(n = 1) = \frac{1}{k}$ , for  $i = 1, 2, \dots, k$ . Let's assume action  $\alpha_p$  is taken. Consequently, we set  $\varphi(n = 1) = \varphi_p$  and  $p^{\text{th}}$  group will scatter to destination and the rest will be silent. Based on the received response from environment, a transition among states is performed by *State Transition Function*  $\varphi(n + 1) = S(\varphi(n), \beta(n))$ , where  $\varphi(n)$  and  $\beta(n)$  are state and response of environment at time  $n$ . At this stage, our model is changed to a *variable structure automaton* and State Transition Function is updated consequently based on a *linear Reinforcement Scheme* with probability update gain  $\delta$ . Upon receiving a constructive response from environment, a last action is rewarded by increasing its probability:

$$\beta = 1 \rightarrow \begin{cases} S_{ik}^u(n+1) = S_{ik}^b(n) + \delta S_{ik}^u(n) \\ S_{ij}^u(n+1) = S_{ij}^u(n) - \frac{\delta S_{ij}^u(n)}{k-1}, j \neq i \end{cases} \quad (25)$$

When the received power decreases, that is the interference is destructive, the last (“failed”) action is penalized by decreasing its probability:

$$\beta = 0 \rightarrow \begin{cases} S_{ik}^u(n+1) = S_{ik}^b(n) + \delta S_{ik}^u(n) \\ S_{ij}^u(n+1) = S_{ij}^u(n) + \frac{\delta S_{ij}^u(n)}{k-1}, j \neq i \end{cases} \quad (26)$$

The state transition matrix (STM) is calculated as  $\mathcal{S}(n+1) = [S_{11} \ S_{12} \ \dots \ S_{kk}]^{-1}$ . If during updating process a state transition coefficient, e.g.  $S_{ik}^u(n+1)$ , reduces to zero, that action, in this case  $p$ , is omitted from state transitions. To maintain  $\sum_{\varphi_1, \varphi_2} S_{ij}^u(n) = 1$ :

$$\begin{cases} S_{ij}^u(n+1) = S_{ij}^u(n) + \frac{S_{ij}^u(n)}{k} \\ S_{ik}^u(n+1) = S_{ik}^u(n) - \frac{S_{ik}^u(n)}{k-1}, j \neq p \end{cases} \quad (27)$$

Since a transition to a state means the same action should be taken state transition coefficients can be viewed as  $S_{ij} = Pr\{\alpha(n) = \alpha_j | \varphi(n) = \varphi_i\}$ . The output of the system is characterized by *Output Function*:  $\alpha_1 = \mathcal{O}(\varphi_1, \mathcal{S}, p_{\text{trans}})$ . By using state transition matrix, output coefficients are calculated as  $\alpha_2 = Pr\{\alpha(n) = \alpha_j | \varphi(n) = \varphi_i\}$ . This implies  $\alpha_2 = \mathcal{S}_{ij}$ , where  $S_{ij}$  is the probability of a transition from state  $i$  to  $j$ . By choosing a  $p_{\text{trans}}$  next action is determined by LA and this process will iteratively continue. After several iterations, device groups with negative effect on the received power have their probability decreased and are omitted. In contrast, the probabilities increase for groups that improve the received power, and they will be selected for scattering. When a state transition coefficient reaches a design threshold,  $\sigma$ , i.e.:  $S_{ij}^u(n+1) \geq \sigma$ , the updating process stops. The groups with probabilities higher than the desired threshold  $\sigma$  are selected for scattering:  $\{\alpha_i | S_{ij}^u(n+1) \geq \sigma, S_{ij}^u(n+1) \geq \sigma\}$ .

### V SIMULATION RESULTS

The performance of the proposed schemes is evaluated in simulations using MATLAB. The convergence time and the received power are two main metrics used for comparison. A network of passive scattering devices is considered, as illustrated in Fig. 1 with network and cell dimension set to 4m, 0.25m respectively. We assume that there is a communication link that controls scattering of the devices. The simulations assume the following parameters:  $P_T = 0.1W$ ,  $G_T = 20$ ,  $G_R = 1$ ,  $\Gamma = 0.1$  and  $f = 100\text{ MHz}$ .

For Taguchi method we used  $OA(8, 5, 2, 2)$ , shown in Table 1, to orthogonalize the space of  $N$  scattering variables of RFID tags. All tags with  $T^k \geq \sigma$  are considered as scatterers to destination tag.

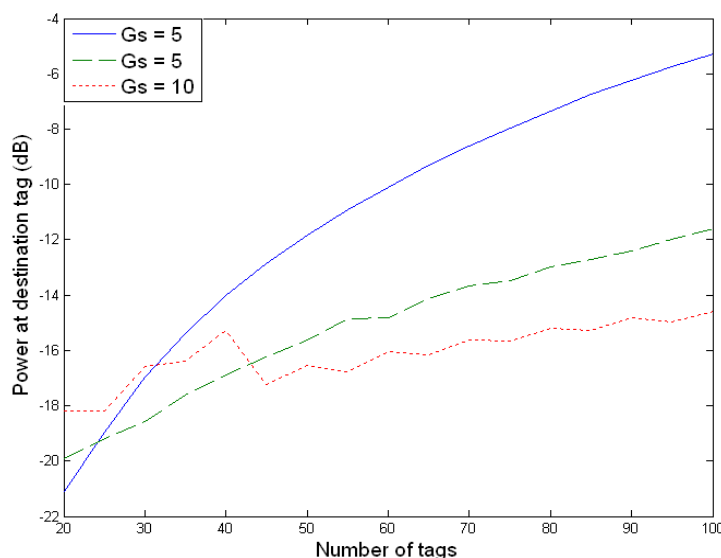


Figure 4. Signal strength for the LA-based scheme with varying grouping scheme,  $\sigma = 0.2$



On the other hand, successful application of the LA requires tuning of its design parameters: group size ( $G_s$ ), probability update gain ( $\delta$ ), convergence criteria ( $\sigma$ ) and  $\vartheta$ . Optimal values of these parameters depends on number of factors including network size and topology, channel conditions, etc. In this work, we varied these parameters to understand their impact on the performance. Overall, there is a general guidance for selecting the LA design parameter selection. For a large “stop” threshold,  $\sigma$ , the LA will take longer to converge and only the strongest groups will be selected. The groups with smaller constructive interference will be omitted thus resulting in a suboptimal solution. On the other hand, for a very small  $\sigma$ , LA converges quickly thus preventing the LA from discovering all the groups that improve the signal strength. Thus, a careful and informed selection of  $\sigma$  is needed. Also, the group size has an impact on the proposed beamforming performance. For small group size,  $G_s$ , the number of groups is high and they start with low probability. Consequently, the convergence time increases with the number of groups. However, the final selection can be more precise if smaller groups are considered. In contrast, for large group sizes,  $G_s$ , the convergence is faster since they start with high initial probability.

Fig. 4 shows performance of LA using groups of  $G_s = 1, 5, \text{ and } 10$  devices, while “stop” threshold is set to  $\sigma = 0.25, 0.5 \text{ and } 0.6$  respectively. The final selection threshold is set to  $\vartheta = \frac{1}{2\lambda}$ . The LA variant with  $G_s = 1$  achieves the highest power since the selection considers each individual devices. The devices are evaluated independently from each other and only those that contribute positively to received power will have high probability at the end of the learning period. In contrast, the larger groups contain randomly selected devices that do not have coherent phase shift.

We also examined performance of using different probability update gain ( $\delta$ ) in LA. Large gain  $\delta$  results in larger changes in the state coefficients thus speeding up the convergence time. However, as convergence time decreases the performance of the final device set decreases, as observed in Fig. 5 illustrates for varying network size. The LA-based scheme achieves the lowest power for  $\delta = 0.4$ . In such case, the final selection includes only few groups, which cannot achieve more than -24dB power. In contrast, for  $\delta = 0.1$  the probability update steps are small thus increasing convergence time. However, the extended learning period may result in LA singling out only the strongest groups due to the absorbing behavior of LA [4][5][6]. In contrast, cases with  $\delta = 0.2$  and  $0.3$  result in best balance between convergence speed and selection accuracy.

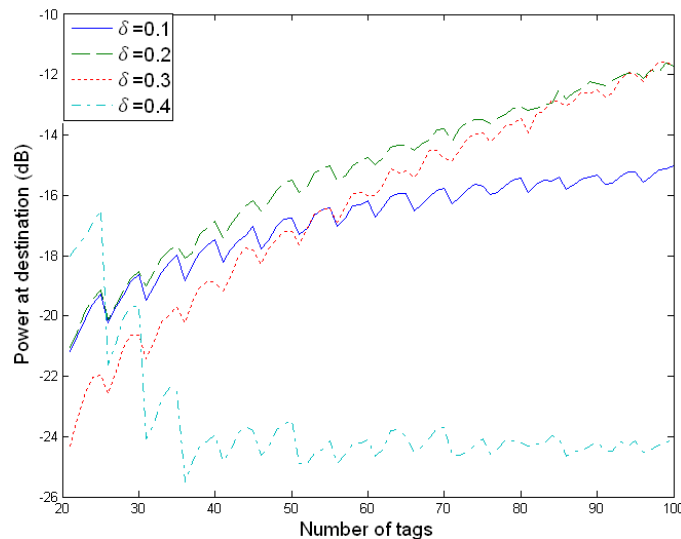


Figure 5. Signal strength for the LA-based scheme,  $G_s=5$

### V.1 Random topology results in ideal and fading channel

Next, the performance of proposed schemes is compared for both ideal (free space) and Rayleigh fading channel. For Rayleigh fading case, the power is averaged over three measurements before using in the calculations to address the volatility of the fading channel. For Taguchi-based scheme, all devices with  $T_{x,m} > 0$  are selected. For LA-based scheme, the following parameters and gains are used:  $\delta = 0.2, G_s=1, 5, \text{ and } N/4$ . The latter corresponds to dividing the network in four random groups, LA-1/4. Convergence criteria is set to  $\sigma = 0.25, 0.5, \text{ and } 0.5$  respectively for LA-1, LA-5, and LA-1/4. For comparison, we simulate cases for schemes (a) “ALL” where all devices scatter to the destination, (b) LOS with only direct signal present (no scattering), (c) a brute force (B-F) method that selects the optimal device set, and (d) a *Constructive Phase algorithm* (Cns-PH). The *Constructive Phase algorithm* (Cns-PH) approach assumes that the phase shift for all

scattering devices had been measured individually. Then, it selects only the devices with a constructive phase with respect to LOS, i.e.  $\varphi \in \pm \frac{\pi}{2}$ .

**Remark:** Both the brute force (B-F) and *Constructive Phase algorithm* (Cns-PH) approaches while resulting in large received power have significant limitations when practical implementation is considered. For larger networks, the brute force (B-F) scheme is extremely slow and requires large memory and time overhead. Hence, it is evaluated for less than  $N < 15$  device networks. In case of Cns-PH, the precise phase measurements are required, which is difficult due to complexity of the hardware and relatively small signals from individual scattering devices.

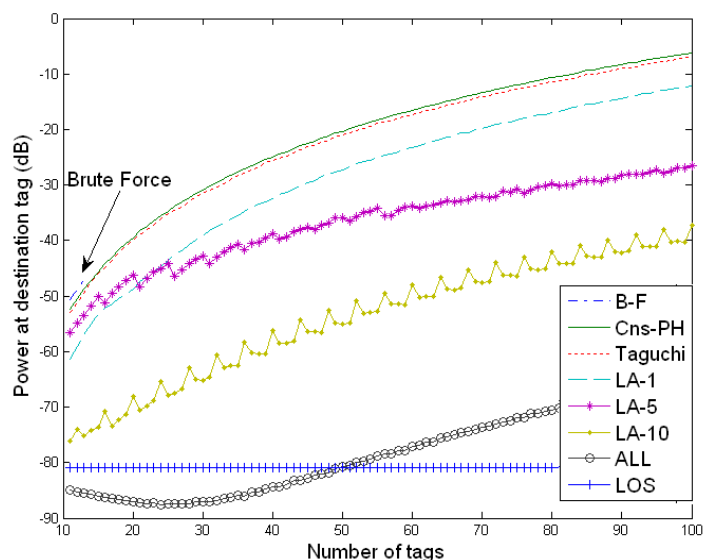


Fig. 5. Performance of algorithms in ideal conditions

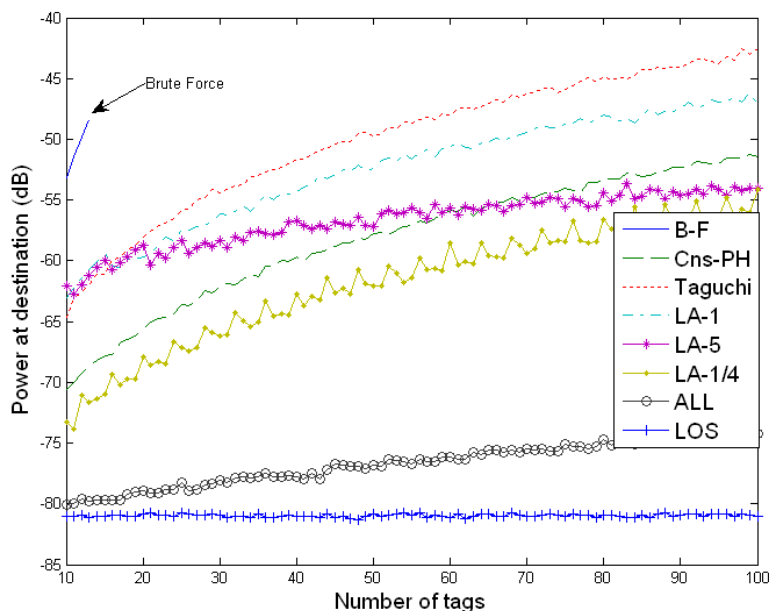


Figure 6. Performance in Rayleigh fading

Figs 6 and 7 show the performance of all algorithms based on the number of devices for the ideal and the Rayleigh fading. In those cases it determines the optimal selection with the most power for both ideal and fading environment. Overall, it is observed that all algorithms achieve more power than LOS. Fig. 6 shows that the Cns-PH approaches the optimal solution given by the B-F scheme for  $N < 15$ . Moreover, the Taguchi-based scheme achieves similar performance as the Cns-PH. This illustrates that Taguchi coefficient for tags is a good approximation of the accurate, non-linear solution (15). In small networks,  $N < 20$ , the LA-5 achieves more power than other LA schemes. If  $N > 20$ , the LA-1 outperforms the LA-5. For LA-1/4, it is observed that since only  $\frac{1}{4}$  of randomly grouped tags are selected as scatterers its achieved power is lower than for other algorithms.

For the “ALL” baseline, it is observed that when  $N < 30$  tags are destructively added while by increasing  $N$ , the cumulative power at destination tag slightly increases.

Fig. 7 illustrates the results for a fading channel. In general, the fading of a realistic channel results in reduction of the power when compared with Fig. 6. Also, all but Cns-PH schemes maintain relative performance to each other. In case of Cns-PH, the phase shift of each device cannot be estimated precisely; hence, the device selection is not accurate. Also, the B-F achieves the highest power even in the fading environment.

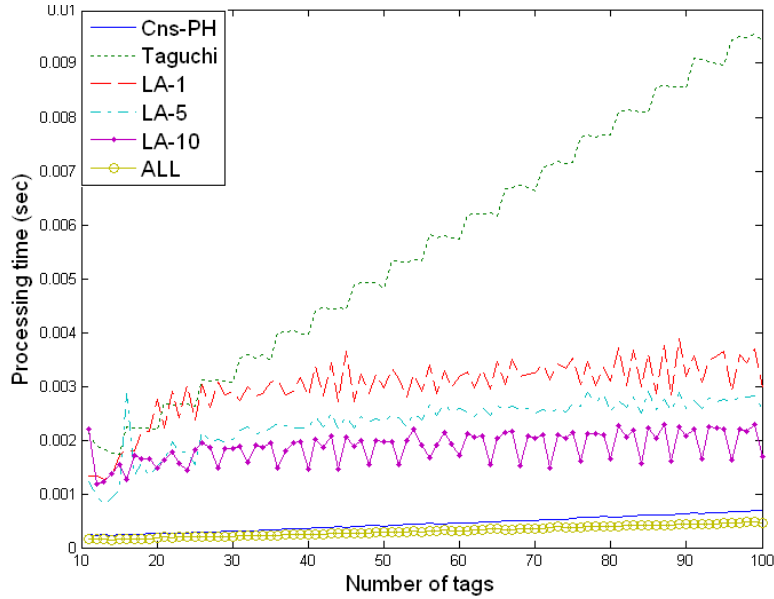


Figure 8. Processing time

Fig. 8 shows the required time for all algorithms to select their scatterers including both convergence time for algorithms (simulation iterations) and propagation delays. It is observed that Taguchi algorithm requires more time than the other algorithms, and increases with network size. In contrast, the LA needs a relatively constant time to determine the solution since the convergence criterion for LA is not adaptive. Consequently, it converges faster at the expense of a lower, achieved power level. For the ALL and Cns-PH cases, the required time is approximately propagation time since no repeated trials have to be performed.

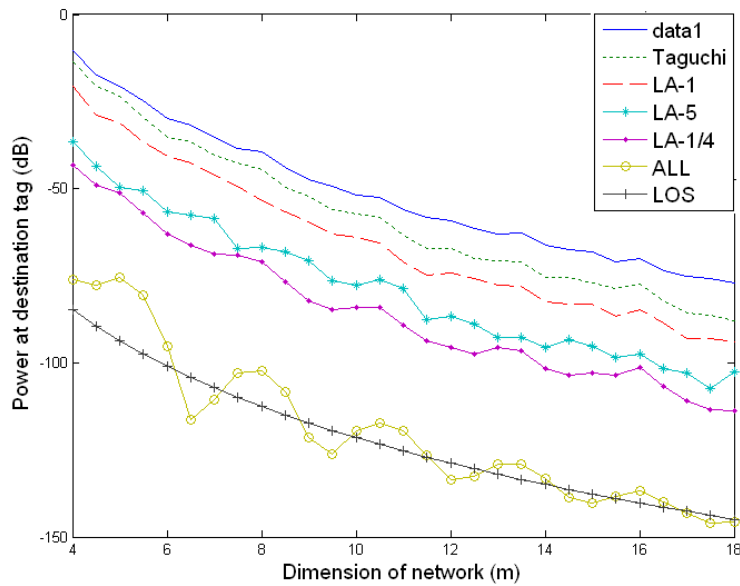


Figure 9.  $N=100$ ,  $f=100$  MHz

Fig. 9 shows achieved power at destination based on the dimension of network when  $N=100$ . As network dimension increases the scatterers are able to attain less power at destination. Also, the relative order of algorithms based on performance is the same as in Fig. 6. One interesting phenomenon is that for algorithms

which do not select individual devices, i.e. ALL, LA-1/4, and to some extent LA-5, the decrease in power is periodically fluctuating. The reason is that as the network dimension increases, the average number of positive and negative scatterers varies. Thus, for certain network dimensions the devices are more likely to cause a constructive interference at destination. This phenomenon is more pronounced in the ALL scenario.

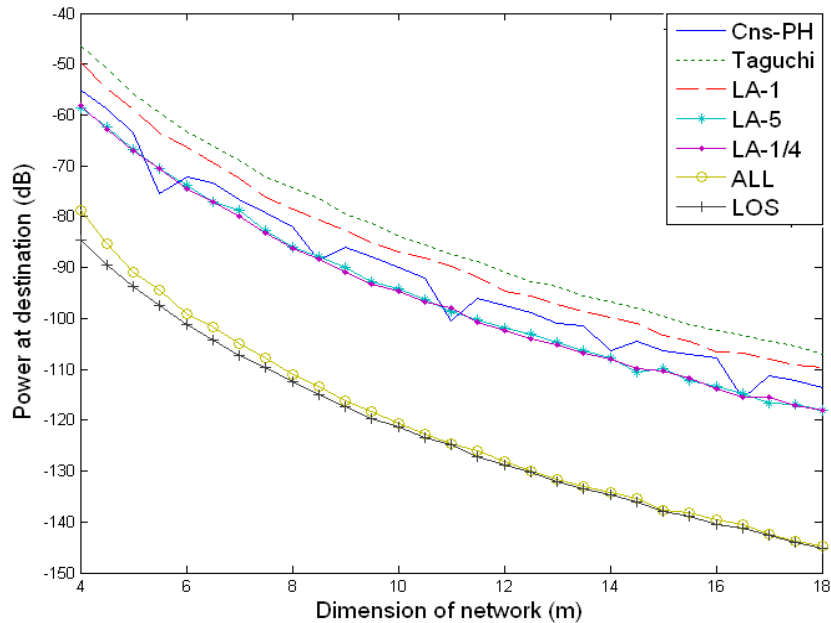


Figure 10. Rayleigh fading,  $N=100$ ,  $f=100$  MHz

However, in Fig. 10, where a Rayleigh fading is included, these periodic variations are no longer observed since the changes due to fading overshadow the dimension impact. Further, the Cns-PH faces a significant decline in received power since the fading prevents it from accurately estimating the phase shifts. Consequently, the set of selected devices is sub optimal in realistic scenarios.

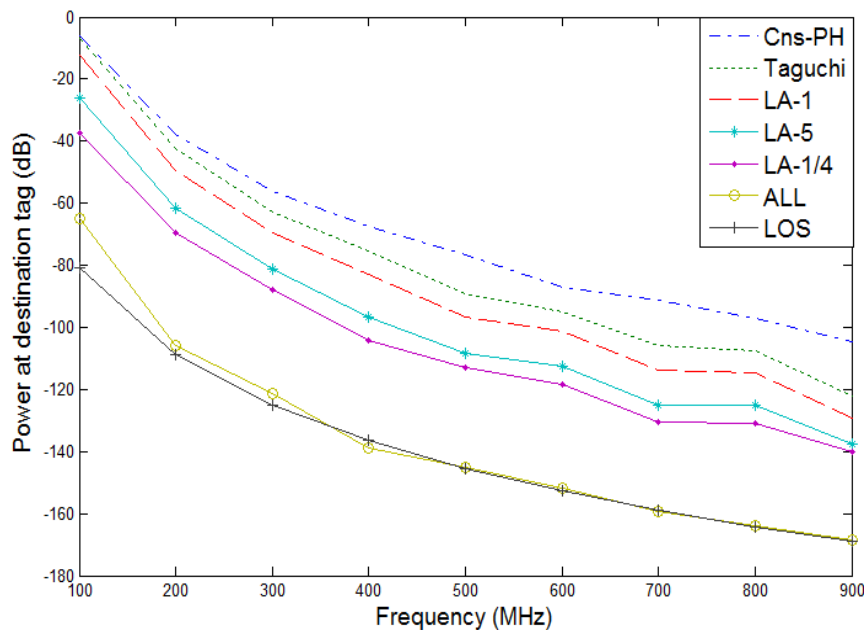


Figure 11.  $N=100$ ,  $M=4$

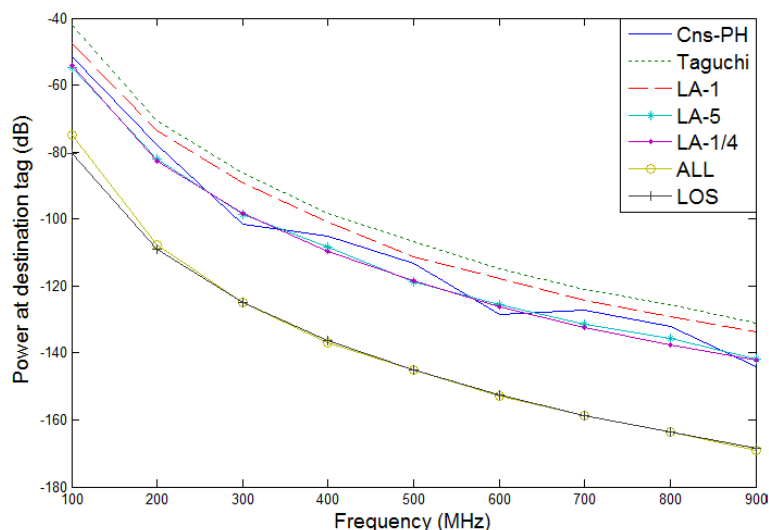
Figure 12.  $N=100$ ,  $M=4$ 

Fig. 11 shows the variation of power based on frequency at destination. Again, the order of performance is kept as in Fig. 6. Moreover, it is understood that by increasing frequency the achieved power decreases. This phenomenon can be verified through Equation (7) whereas there is a direct relationship between wavelength and achieved power. Again in fading environment, as shown in Fig. 12, the algorithms achieve less power with Cns-PH suffering the largest decrease.

## VI CONCLUSIONS

We proposed and evaluated two novel beamforming schemes based on the *Learning Automaton* and *Taguchi system* frameworks. The schemes have been shown to improve the received signal strength and quality for multi-device, passive RFID network. We demonstrated that in ideal condition the achieved performance for Learning Automaton with  $G_s=1$  is 68 dB higher than LOS for  $N=100$  devices. Moreover, we showed that in ideal condition the Taguchi-based approach achieves 75dB higher power than the LOS but requires more processing time than other methods. In Rayleigh fading environment with 100 nodes, we observed the 37.5 dB and 33dB improvement over LOS respectively for Taguchi-based and LA-1 schemes. Future works include studying the effect of using orthogonal arrays of different lengths in the Taguchi method, and adaptively setting design parameters of the Learning Automata based scheme.

## VII ACKNOWLEDGEMENTS

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