3. Implementing Expectation Propagation on Next Generation Wireless Systems

In this chapter, we provide two novel applications of EP detection algorithm for the next generation of wireless system. The first is applying EP on SCMA detection side, named EPA SCMA. EPA SCMA aims to solve the complexity problem of the original detection algorithm in SCMA. The second application is using EP to support massive MU-MIMO system. However, the implementation of conventional EP in MU-MIMO system will result an impractical problem regarding to its computational complexity. Therefore, we proposed a decentralized system in EP. The EP decentralized system outperforms the approximate message passing (AMP) decentralized system which is proposed in [6]. Furthermore, decentralized EP can be viewed as a low complexity version of the centralized one.

3.1 MPA SCMA and EPA SCMA

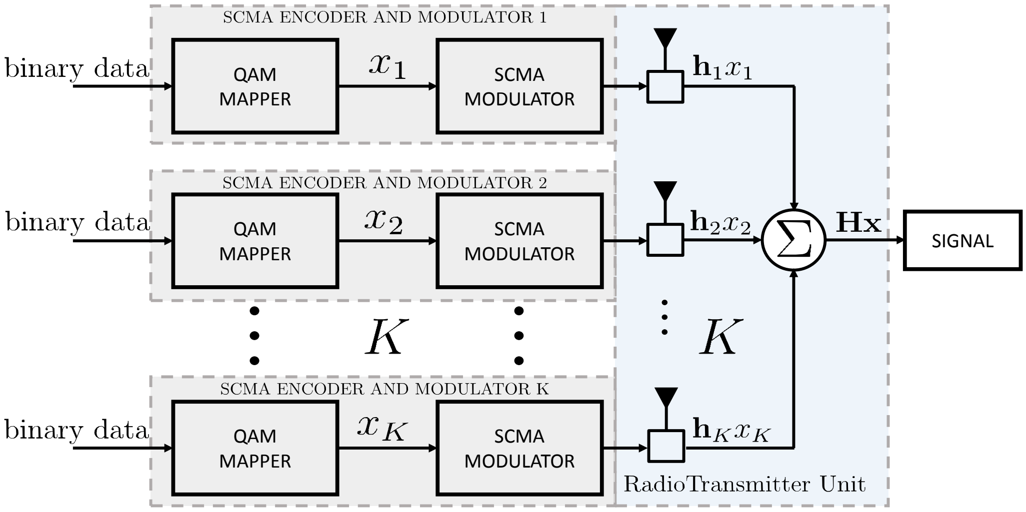
SCMA is a modulation technique that directly modulates each group of binary data into a complex multidimensional codeword. This codeword is taken from a codebook, which is created by combining QAM mapper and symbol spreader. A codebook is then formed sparsely. At the receiver side, the message passing algorithm (MPA) can be implemented to achieve near optimal detection performance [32]. MPA calculates marginal distribution for each transmitted signal, conditional on received signal. The completeness probability information in each MPA's node results an outstanding performance of MPA. Besides that, the sparsity of SCMA codeword makes a possibility of implementing MPA on SCMA. However, the complexity of MPA detection increases exponentially with the codebook size, because in MPA's structure feedback messages must be computed on every iteration.

To solve the complexity issue, many works have been completed either to reduce the complexity through the codebook design or consider several extensions of the MPA, such as max-log MPA [33], SIC MPA [34], and even combined extensions of the MPA technique. However, these MPA-based detectors are suffering from an exponentially incremental complexity because the structure of MPA is still maintained. Specifically, If the codebook size or the degree of freedom significantly increases, the MPAs for SCMA quickly becomes prohibitive due to its computational complexity.

In this work, we propose a low complexity detection method for the SCMA detector named the expectation propagation algorithm (EPA). The EPA approximates the marginal distribution of the posterior probability by using an exponential family [3]. Given that the probability in exponential family is easy to compute, the EPA is suitable to deal with high order and dimensional system. We also provide theoretical analysis to evaluate the performance of EPA SCMA. We show that the EPA for SCMA can achieve near optimal detection performance as the numbers of transmit and receive antennas grow. With the theoretical promise, we investigate the necessity of constellation rotation, which is used to increase the degree of freedom [4, 5]. We show that for the uplink scheme, channel responses from different users vary and thus increase the identifiability of each user. Therefore, appending a rotation value in SCMA encoder is unnecessary. Our hypotheses are also verified by the experimental results in Section 4. The removal of the rotation value can omit many unnecessary calculations not only in decoding but also in SCMA encoding.

3.1.1 System Model

We consider a SCMA system with U users operating on S orthogonal subcarriers. Each user equipment features N_t transmit antennas and the base station (BS) possesses N_r receive antennas. Let $K = UN_\mathrm{t}$ and $N = SN_\mathrm{r}$. In the SCMA, each transmit symbol x_k is transmitted over S subcarriers using d degree, and different



(a) Transmitter side

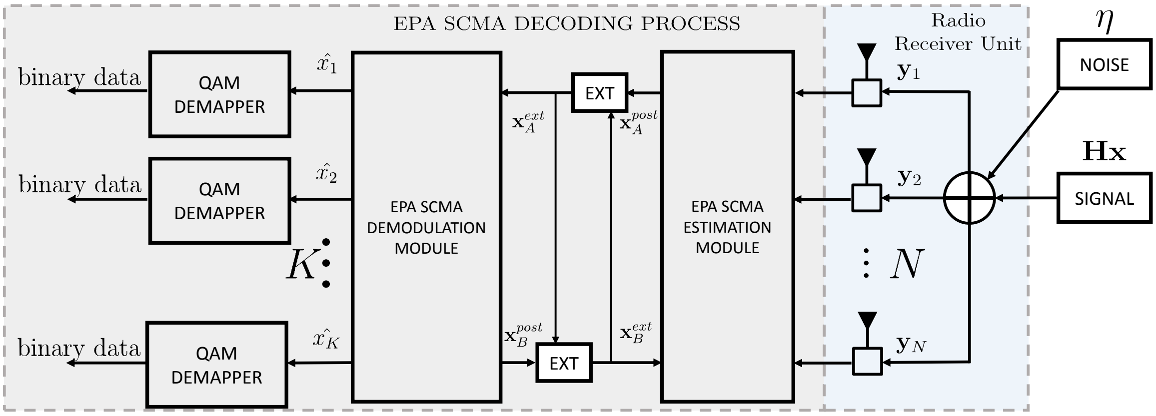


Figure 3.1. Block diagram of uplink scheme SCMA transceiver

phase rotation values are introduced at different subcarriers [35]. For example, if $S = 4$ and $d = 2$, the mapping can be

$$\boldsymbol{\phi}_k = [\phi_{k,s}] = \begin{bmatrix} e^{-j2\pi\Delta_1} \\ e^{-j2\pi\Delta_2} \\ 0 \\ 0 \end{bmatrix},$$

where $\Delta_i \in [0, 1)$. Let $\mathbf{h}_{k,s} \in \mathbb{C}^{N_{\mathrm{r}}}$ denote the channel vector from the k-th transmit antenna to the BS at the s-th subcarrier, and we define

$$\mathbf{h}_k = \begin{bmatrix} \phi_{k,1}\mathbf{h}_{k,1} \\ \phi_{k,2}\mathbf{h}_{k,2} \\ \vdots \\ \phi_{k,S}\mathbf{h}_{k,S} \end{bmatrix}.$$

Therefore, at the BS, the N-dimensional channel output vector $\mathbf{y}$ is expressed as

$$\mathbf{y} = \sum_{k=1}^{K} \mathbf{h}_k x_k + \boldsymbol{\eta}$$

where $\boldsymbol{\eta}$ is the additive white Gaussian noise (AWGN) vector with zero mean and covariance matrix $\sigma^2\mathbf{I}$. Let

$$\mathbf{H} = \begin{bmatrix} \mathbf{h}_1 \ \mathbf{h}_2 \ \cdots \ \mathbf{h}_K \end{bmatrix}, \quad \mathbf{x} = \begin{bmatrix} x_1 \ x_2 \ \cdots \ x_K \end{bmatrix}^T.$$

Finally, we obtain

$$\mathbf{y} = \mathbf{H}\mathbf{x} + \boldsymbol{\eta}. \tag{3.1}$$

The input-output relationship of the SCMA can be viewed as a MIMO communication system with K inputs and N outputs. Figure 3.1 illustrates a block diagram of the SCMA transceiver.

3.1.2 MPA SCMA

MPA has known as a powerful detection algorithm which also brings a great performance even near to the maximum likelihood performance. Evaluating our system model, SCMA matrices should be formed in sparse matrices model. This sparsity makes a possibility to apply MPA for SCMA technique especially uplink case.

The MPA can be classified as a iterative decoding algorithm. Its working principle is based on the message passing between information nodes and variable nodes. initializing that the prior - probability is equal and the variable nodes message as

$$m_{i\to a}^{0} = \frac{1}{M} \tag{3.2}$$

The updater messages of information nodes and variable nodes are sequentially given by

$$m_{i\to a}(x_i)^{l+1} \propto P_X(x_i) \prod_{b=1,b\neq a}^{N} m_{b\to i}^{l}(x_i) \tag{3.3}$$

$$m_{a\to i}(x_i)^{l} \propto \int \prod_{j=1,j\neq i}^{K} [dx_j m_{j\to a}^{l}(x_j)] P(y_a \mid x) \tag{3.4}$$

After doing L iteration, the approximation value of x_i $(\hat{x})$ is

$$\hat{x_i} = \text{arg max} \left(\prod m_{a\to i}^{L}(x_i) \right) \tag{3.5}$$

Despite the successful implementation of MPA SCMA particularly on the detection side, as the transceiver antennas grow, the computational complexity significantly increase. Recently, many researches have been done in order to reduce the MPA SCMA computational complexity. One of them, as proposed in [36] is called threshold-based MPA.

The main idea is set a belief threshold in order to ensure that the codewords are reliable or not. The evaluation of these codewords is going to be done in every iteration. If a user has a reliable codeword, this corresponding user will be decoded right away. Thus, the user will not be given a message update anymore after the decoding process. In this way, the threshold-based MPA will remove many unnecessary calculations.

Nevertheless, the threshold-based MPA have not fixed the exponential complexity problem on MPA algorithm. It means the MPA still grows exponentially with the codebook size, and quickly becomes prohibitive.

3.1.3 EPA SCMA

The input vector $\mathbf{x}$ to the equivalent MIMO channel $\mathbf{H}$ is a combined constellation $\Omega_1 \times \cdots \times \Omega_K$, where Ω_k is the set of constellation of the th transmission. Our target is to detect $\mathbf{x}$ based on $\mathbf{y}$ given the full knowledge of the channel matrix $\mathbf{H}$. The complexity of the optimal detection increases exponentially with the size of the transmission and becomes prohibitive. To solve this problem, we adopt the EPA (Algorithm 1). Noting that, we have configured our SCMA system model following the linear form in (3.1). Therefore, we can directly apply the EPA to fine the approximated signals as mentioned in chapter 2.

3.1.4 MPA and EPA Complexity Analysis

We compare the computational complexity of the three different algorithms: MPA, threshold-MPA, and EPA. Let I_t denotes the number of Iteration. Table 3.1 shows

Table 3.1 Computational Complexity Comparison.

Comparison Setting1	$M = 4$, $N = 128$, $K = 196$, I_t=10, d=2
MPA	$\mathcal{O}(7.63617 \text{ X } 10^{64})$
Threshold-MPA	$\mathcal{O}(5.71086 \text{ X } 10^{64})$
EPA	$\mathcal{O}(62914560)$

Comparison Setting2	$M = 4$, $N = 64$, $K = 96$, I_t=10, d=2
MPA (BL)	$\mathcal{O}(1.24128 \text{ X } 10^{35})$
Threshold-MPA	$\mathcal{O}(9.25765 \text{ X } 10^{34})$
EPA	$\mathcal{O}(7864320)$

the complexity orders of two comparison settings. The implementation of MPA is prohibitive. Although threshold-MPA can decrease approximately 25% of the original MPA complexity, its implementation remains prohibitive. The EPA for SCMA successfully handles these situations, and its complexity is less than $10^{-20}\%$ of the MPA complexity.

3.2 Decentralized Expectation Propagation in massive MU-MIMO System

As mentioned in chapter 1, massive MU-MIMO will be a core of next generation wireless systems (5G). Considering the receiver side, simple linear processing such as minimum mean square error (MMSE) or zero forcing (ZF) can be use for maximizing the benefits of massive MU-MIMO system [28]. The challenge of massive MU-MIMO implementation is regarding to its complexity [37]. Many works have been done in order to reduce the complexity of massive MU-MIMO implementation.

Maximum ratio combining (MRC) [38], full dimension MIMO [39], and decentralized equalization in massive MU-MIMO [6] are recognized as the previous works for supporting massive MU-MIMO and also solve its complexity problem at once. Furthermore, we investigate that the prior art in [6] is the most efficient way to reduce the massive MU-MIMO complexity.

As presented in [6], decentralized architecture is introduced in order to obtain higher spectral efficiency than the maximum ratio combining (MRC) method. Moreover, it also naturally enables distributed processing. However, we indicate that the performance of approximated message passing algorithm (AMP) [6] is unacceptable. Furthermore, if the performance of the original centralized algorithm could not satisfy the expectation performance, the decentralized architecture would be useless.

Considering the uplink data detection case, we proposed several improvements of [6]. First, we propose decentralized expectation propagation algorithm (EPA) to support massive MU-MIMO system which outperforms decentralized AMP. Second, we significantly reduce the complexity of EPA [3] itself by implementing the partial decentralized of EPA. Originally, the dimension of the EP inverse matrix is equal with the dimension of transmitter antennas. By implementing the partial decentralized system, we significantly reduce the dimension of the inverse matrix to become C times smaller than the original one, where C denotes the number of decentralized system we have.

Next, we aim to improve the fully decentralized architecture performance while maintaining a low latency system. Therefore, we introduce semi fully decentralized architecture. Finally, we provide a theoretical verification to prove that our algorithms perform well.

3.2.1 System Model

We consider an up-link cellular network with K users. The base station (BS) is equipped with N receive antennas. In this paper we focus on the $K \leq N$ system model. The input vector $\mathbf{x}$ is a combined constellation $\Omega_1 \times \cdots \times \Omega_K$, where Ω_k is the set of constellation of the kth transmission. Therefore, the cardinality of the transmitted signal is $|\Omega|$.

On the other hand, the received signal of an uncoded massive MU-MIMO uplink system is given by

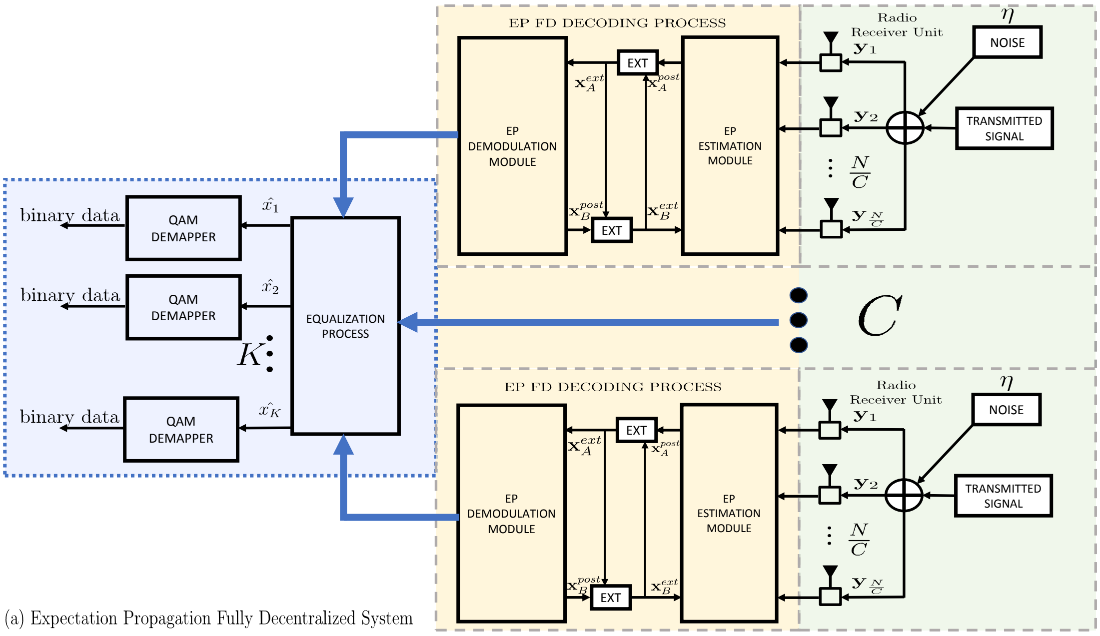
$$\mathbf{y} = \mathbf{H}\mathbf{x} + \mathbf{n} \tag{3.6}$$

where $\mathbf{y} \in \mathbb{C}^N$ denotes the received signal , $\mathbf{H} \in \mathbb{C}^{N\text{x}K}$ denotes the channel vector from the transmit users antennas to the BS antennas, and lastly, $\mathbf{n} \in \mathbb{C}^N$ denotes the additive white Gaussian noise (AWGN) vector with zero mean and covariance matrix $\sigma^2\mathbf{I}$

In the decentralized system, as proposed in [6], [40], we follow to partition N BS antennas into $C \geq 1$ independent antenna clusters. The writing style of decentralized system is given as CxNxK. Wireless equipment has been already provided for each cluster. The cth cluster, $\forall c \in C$ will has an access to the local state channel information (CSI). Finally, in clustering overview, we define $\mathbf{y} = [\mathbf{y}_1^T, \mathbf{y}_2^T, \cdots, \mathbf{y}_C^T]^T$, $\mathbf{H} = [\mathbf{H}_1^T, \mathbf{H}_2^T, \cdots, \mathbf{H}_C^T]^T$, and $\mathbf{n} = [\mathbf{n}_1^T, \mathbf{n}_2^T, \cdots, \mathbf{n}_C^T]^T$. Rewriting (3.6) in decentralized manner, the input output relationship of uncoded massive MU-MIMO system is

$$\mathbf{y}_c = \mathbf{H}_c\mathbf{x} + \mathbf{n}_c, \forall c \in C. \tag{3.7}$$

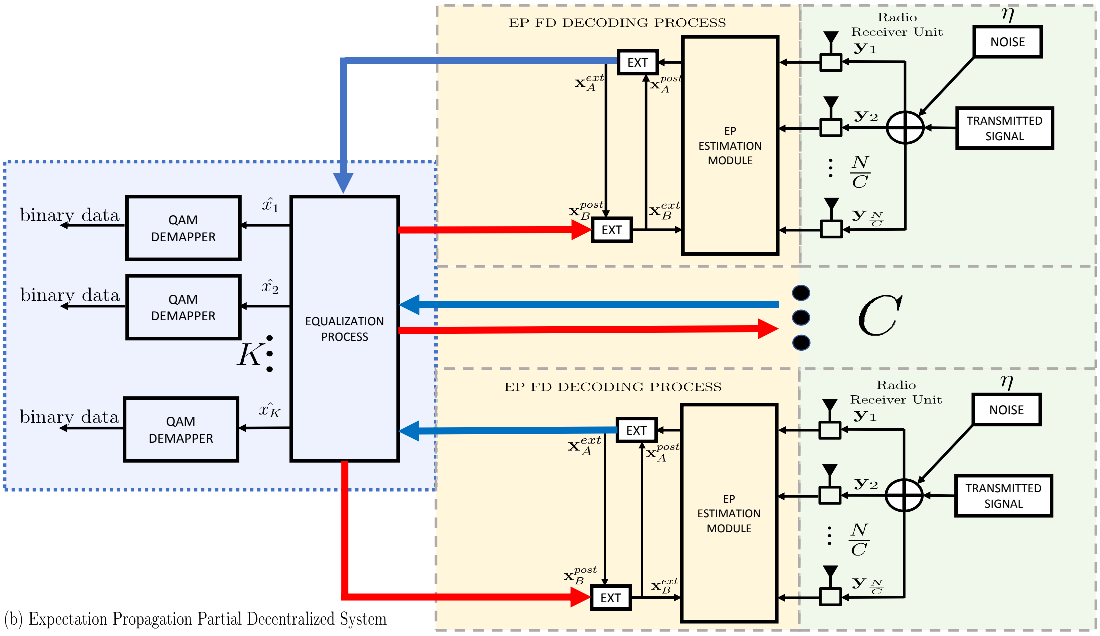
3.2.2 Fully Decentralized Expectation Propagation (FD-EP) Algorithm



(a) Expectation Propagation Fully Decentralized System

As illustrated in Figure 3.2a, FD-EP structure can be viewed as a group of C EP modules that works identically and independently. At the beginning, all of the signals which contain of the noise are received in EP decentralized modules. Specifically, each module will receive $\frac{N}{C}$ signals as we have C decentralized modules. Then, each EP module will begin their own iteration. After the iteration converge, the EP demodulation modules will send their approximation results $(\mathbf{x}_{B,c}^{\text{post}}, \forall c \in C)$ to the equalization process module. Once the equalization process has been done, the hard decision is performed in order to estimate the transmitted signal.

To simplify our explanation on EP decentralized system, we first consider cth EP module and its detail algorithm. We describe the equalization process which results the $\hat{\mathbf{x}}$ afterwards. In cth EP module, the EP algorithm is started by replacing the



(b) Expectation Propagation Partial Decentralized System

Figure 3.2. Block diagram Decentralized Expectation Propagation systems.

prior input distribution of the received signal by an indepedent Gaussian distribution, such that

$$q(\mathbf{x}) \propto \mathcal{N}(\mathbf{y}_c : \mathbf{H}_c\mathbf{x}, \sigma^2\mathbf{I}) \prod_{i=1}^{K} e^{x_i^{\mathbf{H}}\gamma_{i,c}+\gamma_{i,c}^{\mathbf{H}}x_i-\lambda_{i,c}|x_i|^2} \tag{3.8}$$

where, $q(\mathbf{x})$ is EP approximation, $\gamma_{i,c} \in \mathbb{R}^K$, and $\lambda_{i,c} \in \mathbb{R}^K, \forall i \in K$. We define $\boldsymbol{\gamma}_c = [\gamma_{1,c}, \gamma_{2,c}, \cdots, \gamma_{K,c}]^T$ and $\boldsymbol{\lambda_c} = [\lambda_{1,c}, \lambda_{2,c}, \cdots, \lambda_{K,c}]^T$ as updating parameters. Equation (3.8) fulfills the MMSE approximation to the posterior distribution $p(\mathbf{x}|\mathbf{y})$ as presented in [14], [15].

Performing Gaussian product Lemma on (3.8), we can define $q(\mathbf{x})$ by its Gaussian mean vector $\boldsymbol{\mu}_c$ and covariance matrix $\boldsymbol{\Sigma}_c$ as given in (3.10a) and (3.10b). Before passing the messages to the next module, the prior information has to be removed from the estimation value, this process is called the calculation of cavity distribution.

Calculating the cavity distribution from estimation module is the same as finding the extrinsic values of $\mathbf{x}_{A,c}^{\text{ext}}$ and $\mathbf{v}_{A,c}^{\text{ext}}$, which are given in (3.11a) and (3.11b), respectively. In the demodulation module, the expectation and variance of the posterior estimator $(\mathbf{x}_{B,c}^{\text{post}}, \mathbf{v}_{B,c}^{\text{post}})$ are computed by calculating conditional expectation from the extrinsic information of $\mathbf{x}_{A,c}$.

Consider kth user $\forall k \in K$, the expectations in (3.12a) and (3.12b) are with respect to $P(x^k|x_{A,c}^k)$, which can be obtained by the Bayes rule

$$P(x_k|x_{A,c,k}) = \frac{P(x_{A,c,k}|x_m)P_x(x_m)}{P(x_{A,c,k})}, \tag{3.9}$$

where

$$\begin{aligned} P(x_{A,c,k}|x_m)P_x(x_m) &= \frac{1}{M}\frac{1}{\pi v_{A,c,k}} \exp\left(-\frac{|x_{A,c,k} - x_m|^2}{v_{A,c,k}}\right), \\ P(x_{A,c,k}) &= \frac{1}{M}\frac{1}{\pi v_{A,c,k}} \sum_{m=1}^{M} \exp\left(-\frac{|x_{A,c,k} - x_m|^2}{v_{A,c,k}}\right). \end{aligned}$$

Next, the extrinsic values of the demodulation module, i.e., $\mathbf{v}_{B,c}^{\text{ext}}$ and $\mathbf{x}_{B,c}^{\text{ext}}$, are calculated in (3.13a) and (3.13b), respectively. The value of $\mathbf{v}_{B,c}^{\text{ext}}$ may return a negative. In this case, we simply use the previous value of $\mathbf{v}_{B,c}^{\text{ext}}$ and $\mathbf{x}_{A,c}^{\text{ext}}$ as a new pair of updating parameters. After the iteration converges, the conditional expectation that given by (3.12a) is expected to be the estimated signals. The complete algorithm is shown in Algorithm 2.

After the EP iteration for every module converge, we expect to extract the approximation results i.e. $(\mathbf{x}_{A,c}^{\text{ext}}, \mathbf{v}_{A,c}^{\text{ext}})$, $c = [1, \cdots, C]$. Noting that, the extrinsic value of $\mathbf{x}_{A,c}$ is chosen because it is a Gaussian distribution.

Now, we proceed the equalization process to result the final approximation of transmitted signal $\hat{\mathbf{x}}$. There are two steps in equalization process. Those are, equalization computation and expectations computation. We define the outcome of equalization and expectations computation as $\hat{\mathbf{x}}_e$ and $\hat{\mathbf{x}}$. For kth user, the equalization equation given as

$$x_{e,k} = v_{e,k} \sum_{c=1}^{C} \frac{x_{A,c,k}^{\text{ext}}}{v_{A,c,k}^{\text{ext}}} \tag{3.14}$$

where,

$$v_{e,k} = \sum_{c=1}^{C} \frac{1}{v_{A,c,k}^{\text{ext}}}. \tag{3.15}$$

Initialization: $\boldsymbol{\gamma}^0_{c,B\to A} = 0, \boldsymbol{\lambda}^0_{c,B\to A} = \frac{1}{E_s}\mathbf{I}, d(\mathbf{Q}) = \text{diag}(\mathbf{Q})$;

for $l = 1 : L_{max}$ **do**

Estimation Module (Module A):

(1) Compute the a posteriori mean/variance of $\mathbf{x}_{A,c}$:

$$\mathbf{v}^{\text{post}}_{A,c,l} = \boldsymbol{\Sigma}^l_c = \left(\sigma^{-2}\mathbf{H}^H_c\mathbf{H}_c + d(\boldsymbol{\lambda}^{l-1}_{B\to A,c})\right)^{-1} \tag{3.10a}$$

$$\mathbf{x}^{\text{post}}_{A,c,l} = \boldsymbol{\mu}^l_c = \boldsymbol{\Sigma}^l_c\left(\sigma^{-2}\mathbf{H}^H_c\mathbf{y}_c + \boldsymbol{\gamma}^{l-1}_{B\to A,c}\right) \tag{3.10b}$$

(2) Compute the extrinsic mean/variance of $\mathbf{x}_{A,c}$:

$$\mathbf{v}^{\text{ext}}_{A,c,l} = \left(\frac{1}{d(\boldsymbol{\Sigma}^l_c)} - d(\boldsymbol{\lambda}^{l-1}_{B\to A,c})\right)^{-1} \tag{3.11a}$$

$$\mathbf{x}^{\text{ext}}_{A,c,l} = d(\mathbf{v}^{\text{ext}}_{A,c,l})\left(\frac{\boldsymbol{\mu}^l_c}{d(\boldsymbol{\Sigma}^l_c)} - \boldsymbol{\gamma}^{l-1}_{B\to A,c}\right) \tag{3.11b}$$

Demodulation Module (Module B):

(3) Compute the a posteriori mean/variance of $\mathbf{x}_B$:

$$\mathbf{x}^{\text{post}}_{B,c,l} \leftarrow \mathsf{E}\{\mathbf{x}|\mathbf{x}^{\text{ext}}_{A,c,l}, \mathbf{v}^{\text{ext}}_{A,c,l}\} \tag{3.12a}$$

$$\mathbf{v}^{\text{post}}_{B,c,l} \leftarrow \text{Var}\{\mathbf{x}|\mathbf{x}^{\text{ext}}_{A,c,l}, \mathbf{v}^{\text{ext}}_{A,c,l}\} \tag{3.12b}$$

(4) Compute the extrinsic mean/variance of $\mathbf{x}_B$:

$$\mathbf{v}^{\text{ext}}_{B,c,l} = \boldsymbol{\lambda}^l_{B\to A,c} = \left(\frac{1}{\mathbf{v}^{\text{post}}_{B,c,l}} - \frac{1}{\mathbf{v}^{\text{ext}}_{A,c,l}}\right)^{-1} \tag{3.13a}$$

$$\mathbf{x}^{\text{ext}}_{B,c,l} = \boldsymbol{\gamma}^l_{B\to A,c} = \left(\frac{\mathbf{x}^{\text{post}}_{B,c,l}}{\mathbf{x}^{\text{post}}_{B,c,l}} - \frac{\mathbf{x}^{\text{ext}}_{A,c,l}}{\mathbf{v}^{\text{ext}}_{A,c,l}}\right)^{-1} \tag{3.13b}$$

end

Algorithm 2: EP Algorithm for cth decentralized EP module

Collecting the $x_{e,k}$ and $v_{e,k}, \forall k \in K$, we have $\mathbf{x}_e = [x_{e,1}, x_{e,2}, \cdots, x_{e,K}]$ and $\mathbf{v}_e = [v_{e,1}, v_{e,2}, \cdots, v_{e,K}]$. The final step is to perform the expectations calculation. The process is quite similar to the (3.13a) and (3.13b), where the equation is given by

$$\hat{\mathbf{x}} \leftarrow \mathsf{E}\{\mathbf{x}|\mathbf{x}_e, \mathbf{v}_e\}, \hat{\mathbf{v}} \leftarrow \text{Var}\{\mathbf{x}|\mathbf{x}_e, \mathbf{v}_e\} \tag{3.16}$$

The expectations are with respect to $P(\mathbf{x}|\mathbf{x}_e)$, where for each kth user, the detail of calculation is similar to that in (3.9).

3.2.3 Partial Decentralized Expectation Propagation (PD-EP) Algorithm

PD-EP system has a similar framework as the FD-EP system. The only difference is PD-EP structure needs to perform equalization process in every iteration. As depicted in 3.2b, each one of EP module is required to send their approximation values to the equalization process module in every iteration. Then, equalization module will send its output back to the EP modules. In this scenario, equalization module act as a demodulation module for each EP module. The given information that sent by the equalization module is identical for every EP module.

According to the Algorithm 2, the iteration of PD-EP system is described as follow. We first initialize the $\boldsymbol{\gamma}^0_{c,B\to A} = 0, \boldsymbol{\lambda}^0_{c,B\to A} = \frac{1}{E_s}$. Identical to the FD-EP system, first, we compute (3.10a), (3.10b), (3.11a), and (3.11b), respectively. Instantly, we get $(\mathbf{x}^{\text{ext}}_A, \mathbf{v}^{\text{ext}}_A)$ for each cth EP module. As described in above, PD-EP needs to perform equalization process in every iteration. Therefore, we compute the equalization equation for each cth module and kth user, as given in 3.14 and 3.15, respectively. Next, we calculate the expectations in 3.16. Noting that, the whole equalization process is identical to that in FD-EP. In order to get the updating parameters, we send back the result of 3.16 to the each cth EP module as a posterior value of $\mathbf{x}_{B,c}$ and compute (3.13a) and (3.13b), respectively. Finally, we close the loop by recalculating (3.10a), (3.10b), respectively, using the new updating parameters $(\boldsymbol{\gamma}^{l-1}_{c,B\to A}, \boldsymbol{\lambda}^{l-1}_{c,B\to A})$. After the iteration converge, the outcome of the equalization module $(\hat{\mathbf{x}})$ is extracted as the approximation of transmitted signals.

Regarding to the advantages of FD architecture, we wish to maintain the benefits of FD-EP while improving its performance. For this reason, we propose a semi fully decentralized (Semi-FD) architecture. The Semi-FD system is a combination between FD-EP and PD-EP. Furthermore, we define the equalization process and EP decen-

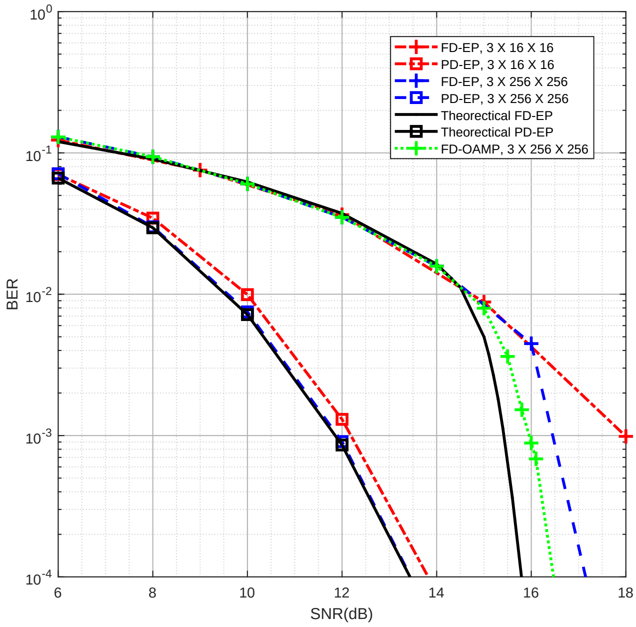


Figure 3.3. FD-EP and PD-EP Performance Analysis

tralized iteration as the outer loop and inner loop. Unlike the PD-EP that requires to perform equalization process in every iteration, the outer loop number of Semi-FD system can be set before. Therefore, the equalization process will be done as much as the given outer loop number. In this way, we achieve a better performance than the FD-EP and reduce the latency of PD-EP, at the same time.

3.2.4 Decentralized EP Performance Analysis

Figure 3.3 illustrates the theoretical analysis of FD-EP and PD-EP. For a small scale system, such as 3 x 16 x 16 massive MU-MIMO system, PD and FD-EP performance cannot achieve an optimal performance. However, as the transceiver antennas grow (3 x 256 x 256) the performance of FD-EP and PD-EP are significantly improving. Furthermore, PD-EP successfully reach the theoretical BER performance. Therefore, we have proved that PD-EP is able to reach the optimal performance. On the other hand, we indicate that FD-EP performance is not good enough because it cannot attain its theoretical BER performance.