International Journal of Applied Science and Engineering

Optimized resource allocation in full-duplex cloud radio access network using firefly algorithm

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ABSTRACT

The main objective of the study is to allocate the resources in a Full-duplex cloud radio access network. Also, the use of C-RAN suppresses the self-interference because of the distributed behaviour of Remote Radio Head in C-RAN. Full-duplex communication system allows data to be transmitted and received between stations simultaneously. It has double the spectral efficiency of half-duplex communication system. The work aims to find the optimal value of the power that is allocated to the remote radio head when data rate is maximum. For the optimization, Firefly Algorithm is employed. It is an optimization algorithm that works similar to the firefly's attraction towards flashing light. The brighter firefly attracts the less bright one to move towards them. It is an iterative process and eventually, the population of firefly converges to brightest one. When maximum inverse data rate is achieved, the corresponding power value is noted and they are employed for the distribution among the single antenna and multiple antenna remote radio heads. In order to find the best cost value, power constraints are applied to it. Finally, the proposed work is compared with generalized benders decomposition (GBD)-based resource allocation (GRA) algorithm by plotting graphs using MATLAB.

Keywords: Base band unit, Best cost value, Cloud radio access network, Firefly algorithm, Full duplex communication, Interference cancellation, Inverse data rate, Remote radio head, Resource allocation, Self-interference.

1. INTRODUCTION

Full-duplex (FD) communication utilizes the same frequency band at the same time slot for transmitting and receiving the signal. Theoretically, this doubles the spectral efficiency of half-duplex (HD) system. But in reality, the dare that FD system will have to face is the strong power of self-interference (SI) from downlink signal to its uplink transmission.

Many signal processing schemes are currently used for suppression of SI but the presence of residual SI makes these schemes unsatisfactory. Sometimes, the SI from the downlink will be even larger than the received power of uplink information. This large power variations affect the FD communication system (Ng et al., 2016). Hence, the potential of FD system is not completely used. For exploring the full potential of FD system, several literatures are conducted. In spite of that, due to the presence of residual SI, the complete potential of a FD communication system cannot be completely utilized.

To promote the potential of FD system, many literatures (Lehmann and Berthet, 2017; Masmoudi and Le-Ngoc, 2017; Liu et al., 2016) studied the channel estimation schemes that eradicates the SI by eliminating them. Though, several studies were conducted for cancelling the SI from the communication system (Simeone et al., 2014), shows that it is possible to suppress SI naturally from the communication system by using cloud-radio access network (C-RAN) in which the remote radio heads (RRHs) are distributed. Distributed behaviour means the transmitting and receiving RRHs are placed distantly for eliminating SI from FD communication system. In practical case, data traffic will be

OPEN ACCESS

Received: August 31, 2020

Accepted: January 28, 2021

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Publisher:
Chaoyang University of Technology
ISSN: 1727-2394 (Print)
ISSN: 1727-7841 (Online)

asymmetrical (Malik et al., 2015; Alim and Watanabe, 2016; Liu et al., 2016). This asymmetrical traffic will lead to wastage of resourced allotted to them if symmetric allocation is used. The work considers asymmetric traffic. The main benefaction of the project is to allocate the power among the RRHs when the data rate is maximum. For reaching the optimal value of data rate, optimization algorithm called Firefly algorithm is employed. It is based on flashing pattern and behaviour of fireflies that have three simplified rules (Yang, 2009).

2. NETWORK SCENARIO

The following Fig. 1 shows the network setup for full duplex C-RAN. It has N_S number of single antenna-RRH (SA-RRH), N_M number of multiple antenna-RRH (MA-RRH), K mobile users and the base band unit (BBU) pool or BBU hotel where several BBUs are contained. RRHs and BBUs are connected via fronthaul link that can be optical fibres or mm wave radio links. Each multiple antenna RRH has α single antennas that are either scheduled for uplink transmission or downlink transmission. Let the number of downlink user equipement (DL-UE) be $K_D$and the number of uplink UE (UL-UE) be K_U. The BBU is the computational unit that allocate the resources for C-RAN.

In a BBU pool, contains a router which provides inter-connections. It is located either in cloud or a data center. It has multiple BBU nodes which have very high capability for computation and storage. BBUs are capable of processing resources and dynamically allocating them to RRHs based on current network requirements.

Fronthaul link connects BBU and RRHs which provides high bandwidth so as to satisfy the needs of multiple RRHs. This can be realized using various technologies such as optical fiber communication and cellular communication. Optical fiber communication in ideal for C-RAN since it gives highest bandwidth requirement. But it is expensive and not flexible for implementation whereas cellular communication is cheaper and easy to execute.

A locality of network is divided into several sectors to manage traffic. When a communication system faces traffic it severely affects the communication. In order to avoid overloading of services, areas are separated into various pools.

3. SIGNAL MODEL

In the implementation part of the work, a random binary data is generated and modulated using binary phase shift keying (BPSK) modulation before transmitting. The data is received in the other end as a corrupted version. This is due to the interference that the signal may face in its transmission.

The received signal for k^{th}downlink user equipment can be represented as y_{D_k} which is given by

$$y_{D_k} = d_{S,k} + d_{M,k} + I_{S,k} + I_{M,k} + I_{CCI,k} + n_k \tag{1}$$

where n_k is the additive white gaussian noise at the k-th DL-UE and $d_{S,k}$ and $d_{M,k}$ are the desired signals from SA-RRH and MA-RRH respectively.

$$d_{S,k} = \sum_{i=1}^{N_s} \alpha_{S_i} p_{S_{i,k}}^{1/2} g_{D_{i,k}}^{H} v_{i,k} x_{D_k} \tag{2}$$

$$d_{M,k} = \sum_{i=1}^{N_M} \alpha_{M_i} p_{M_{i,k}}^{1/2} g_{D_{i,k}}^{H} v_{i,k} x_{D_k} \tag{3}$$

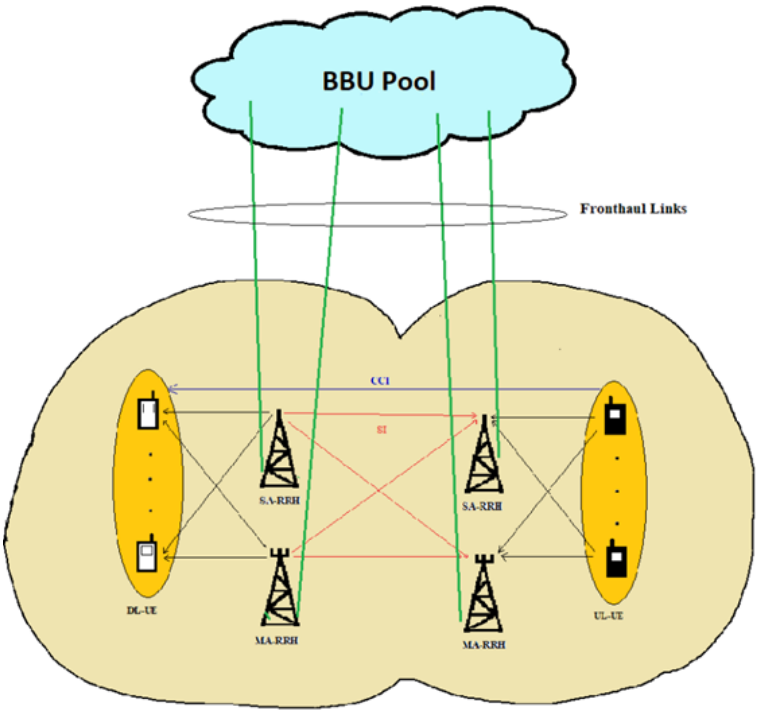

Fig. 1. Full duplex system in C-RAN

α_S and $\alpha_M \in \{0,1\}$ are binary indicators for selection where 1 indicates corresponding RRH implements DL transmission and 0 indicates UL reception for RRH. $p_{S_{i,k}}$ and $p_{M_{i,k}}$ are the allocated power from i^{th} SA-RRH and i^{th} MA-RRH to the k^{th} DL UE respectively. $v_{i,k}$ represents maximum ratio transmission precodig at the *i*-th SA-RRH and *i*-th MA-RRH to the *k*-th DL UE. $g_{D_{i,k}}$ is the channel gain from the i^{th} SA-RRH to the k^{th} DL UE and channel vector from i^{th} MA-RRH to the k^{th} DL UE.

x_{D_k} indicates data symbols that are transmitted to the k^{th} DL UE, where power of data symbol satisfies E $[|x_{D_k}|^2] = 1$.

Parameters $I_{S,k}$ and $I_{M,k}$ are the inter-user-interference (IUI) from both SA-RRH and MA-RRH in the k^{th}downlink UE. They can be given by

$$I_{S,k} = \sum_{i=1}^{N_S} \sum_{j=1,j\neq k}^{K_D} \alpha_{S_i} p_{S_{i,j}}^{1/2} g_{D_{i,k}}^H v_{i,j} x_{D_j} \quad (4)$$

$$I_{M,k} = \sum_{i=1}^{N_M} \sum_{j=1,j\neq k}^{K_D} \alpha_{M_i} p_{M_{i,j}}^{1/2} g_{D_{i,k}}^H v_{i,j} x_{D_j} \quad (5)$$

$I_{CCI,k}$ is the co-channel interference (CCI) from the uplink UE to k^{th}downlink UE. It can be written as

$$I_{CCI,k} = \sum_{i=1}^{K_U} p_{U_i}^{1/2} h_{C_{i,k}}^H x_{U_i} \quad (6)$$

where $p_{U_i}$is the transmit power from the *i*-th UL-UE and $h_{C_{i,k}}$ is the channel gain from the *i*-th UL-UE to the *k*-th DL UE. x_{U_i}represents the data symbols sent from *i*-th UE.

The maximum capacity of DL transmission that can be achieved for the k^{th} DL-UE is

$$R_{D_k} = \log_2(1 + \gamma_{D_k}) \quad (7)$$

γ_{D_k} in above equation is the received signal-to-interference-plus-noise ratio (SINR) in DL-UE

$$\gamma_{D_k} = \frac{|d_{S,k}|^2 + |d_{M,k}|^2}{|I_{S,k}|^2 + |I_{M,k}|^2 + |I_{CCI,k}|^2 + \sigma_k^2} \quad (8)$$

Data rate is calculated from the received signal y_{D_k}. A maximum limit of power is assigned to SA-RRH, MA-RRH and UE. The concept is to allocate this fixed power among the SA-RRHs and MA-RRHs separately as a constraint and the data rate is maximised. Also, spectral efficiency is calculated.

The optimization problem can be given as

$$\max_{\alpha_S,\alpha_M,p_S,p_M,p_U} R_D \quad (9)$$

subject to $\sum_{k=1}^{K_D} p_{S_{i,k}} \leq p_{S_{max}}, \quad \forall i$

$\sum_{k=1}^{K_D} p_{M_{i,k}} \leq p_{M_{max}}, \quad \forall i$

$p_{U_i} \leq p_{U_{max}}, \quad \forall i$

$R_{U_k} \geq R_{req}, \quad \forall k$

$\alpha_S,\ \alpha_M \in \{0,1\} \quad \forall$ i,j

α_S, α_M, p_S, p_M, p_U are the notations for design varibles representing SA-RRH selection, MA-RRH selection, transmission power of SA-RRH, transmission power of MA-RRH, and transmission power of UL-UEs respectively.

$p_{S_{max}}$, $p_{M_{max}}$, $p_{U_{max}}$ are transmission power constraints of SA-RRH, MA-RRH and UL-UEs. R_{req} is the QoS constraint of *k*-th UL-UE.

The previous work chosen for comparison was based on a GBD based resource allocation (GRA) algorithm where the particular problem was decomposed into subproblems for ease. But the newly proposed method to approach this scenario is to utilize the firefly algorithm which gives a better efficient result. It is an optimization algorithm which resembles the firefly's attraction toward flashing light. The objective of the problem in hand is to find the optimal value of power in which maximum data rate is obtained. The current problem considers the 'best cost' value as inverse data rate and when inverse data rate is minimum, its corresponding power value is the best value.

The power value corresponds to the absorption coefficient in the algorithm and the algorithm chooses the efficient firefly from the group so as to get the optimized value. The complete population of fireflies is considered which have fireflies having varying brightness. The main rule of this algorithm is that the less bright firefly will be attracted by the brighter one. So, the algorithm compares all pairs of fireflies in terms of their brightness and brightest one among them is found. If the new firefly is brighter than the current brightest one, then the new firefly is updated as the brightest one ignoring the previous selection. Likewise, each new firefly is compared with the firefly with current maximum brightness. This iteration continues for the whole population till it converges to the brightest firefly.

The three main rules of firefly algorithm are:

Primarily, all fireflies are unisex, that means any firefly can get attracted to any brighter one in the population regardless of their sex. Secondly, the brightness of firefly is determined from the encoded objective function. Thirdly, attractiveness is directly proportional to brightness and they both decreases as their distance increases which means the firefly will move towards the brighter one, and if here is no brighter one in the population, it will move randomly.

It's already known that the intensity of light is inversely proportional to the square of the distance, r from the source.

So, the variation of attractiveness, β with distance rcan be represented as

$$\beta(r) = \beta_0 e^{-\gamma r^2} \quad (10)$$

where β_0 is constant that represents attractiveness at r = 0; initial condition, $\beta(0) = \beta_r$

If a firefly located at X_j is more attractive than another firefly located at X_i, the firefly located at X_i will move towards X_j.

Then the position updating formula of the firefly location at X_i is

$$X_i^{t+1} = X_i^t + \beta_0 e^{-\gamma r_{ij}^2} (X_j^t - X_i^t) + \alpha_t \in_i^t \quad (11)$$

where t is the number of iterations.

The second term in the equation is due to attractiveness whereas the last term with α_t being a randomization parameter with $0 \leq \alpha_t \leq 1$ and $\in_i^t$ is a vector of random numbers drawn from a uniform, gaussian or other distributions at time t.

When $\beta_0 = 0$, it becomes a simple random walk. Then, above Equation (11) reduces to

$$X_i^{t+1} = X_i^i + \alpha_t \in_i^t \quad (12)$$

Here, X_i^i is the previous position and X_i^{t+1} is the updated position. Final term represents randomness which makes this equation a simple random walk.

If γ = 0, then Equation (11) reduces to standard particle swarm optimization (PSO).

In the present context, each iteration will result a set of inverse data rate and a best cost versus iteration graph is plotted. Best cost here, refers to inverse data rate (IDR). Also, efficiency of firefly algorithm is determined by comparing it with GRA method.

4. RESULT

In this section, in order to evaluate the performance of firefly algorithm, the obtained result is compared with GRA algorithm (Fang et al., 2019) via simulation.

Fig. 2, best cost versus iteration shows the intermediate graph of the firefly algorithm which describes the variation in best cost i.e., inverse data rate with the number of iterations. The aim is to minimize the inverse data rate. It is evident from the graph that the value of inverse data rate decreases as iteration progresses. It shows the speed of convergence is very high for firefly algorithm and inverse data rate reaches a stable value at almost 30 iterations.

Fig. 3 is a data rate comparison graph between the previous work, GRA algorithm and the proposed work firefly algorithm. The data rate versus number of users graph shows that the proposed firefly algorithm provides better data rate than the existing GRA algorithm. Figure shows both the cases of SA-RRH and MA-RRH.

Fig. 4 shows the comparison of the performance of system on both the algorithms in terms of spectral efficiency (SE) and is found that the SE has increased when firefly algorithm is applied. The figure indicates the performance of both SA-RRH and MA-RRH.

Firefly algorithm uses non-linear updating equation which produce rich behavior and high convergence than the linear updating equations used in standard PSO and differential equation. Always a non-linear equation has higher convergence than linear equation. It isnoted that the better performance of firefly algorithm is due to the fast convergence. Also, the algorithm has an advantage of integration with other optimization techniques to generate a better hybrid tool for solving any optimization problem. FFA do not need a strong initial solution for starting its iteration.

Firefly algorithm is swarm-intelligence-based algorithm so, it has comparable advantages that other algorithms of that category possesses. Automatic subdivision and ability for dealing with multimodality are two main advantages of firefly algorithm that makes this algorithm more efficient than others.

Automatic subdivision: This algorithm is based on attraction and the decrease of attractiveness with distance. This makes the whole population to automatically divide into subgroups. That is, fireflies are considered to be in several subgroups according to its distance from the source and the more distant subgroups are discarded while computation.

Ability for dealing with multimodality: Ability of automatic subdivision of population allows the fireflies to find all optima simultaneously if the population size is sufficiently higher than the number of modes. This makes the searching space to be small and the subgroups swarm around each local optimum or mode. From these modes, the optimal global solution can be found.

In addition, some parameters in the FFA can be tuned to control the randomness as iteration proceeds that makes the convergence to speed up. β_0, γ and α ar e the thr ee unknown parameters in the equation of FFA which can be set according to the application. In Equation (11), α_t controls the randomness which can be tuned during iterations.

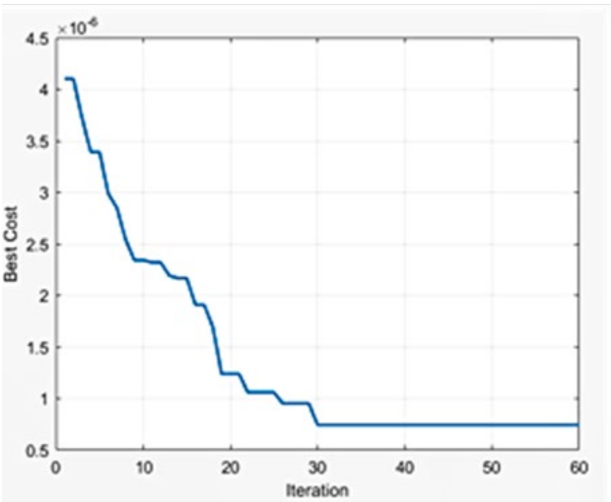

Fig. 2. Convergence of firefly algorithm for inverse data rate

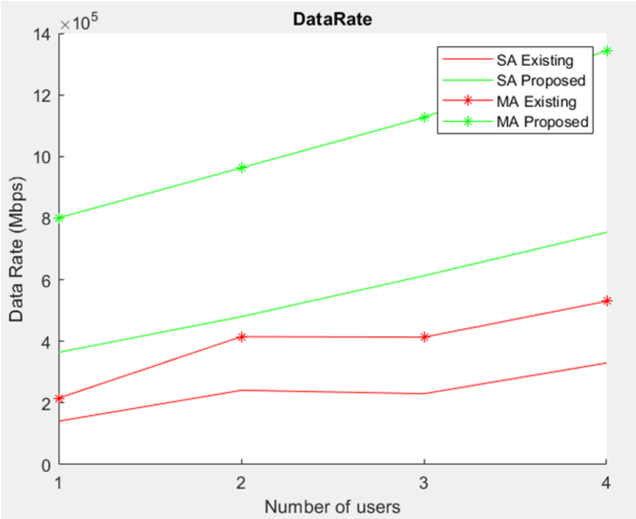

Fig. 3. Comparison of GRA (exiting algorithm) and FFA (proposed algorithm) showing data rate versus number of users

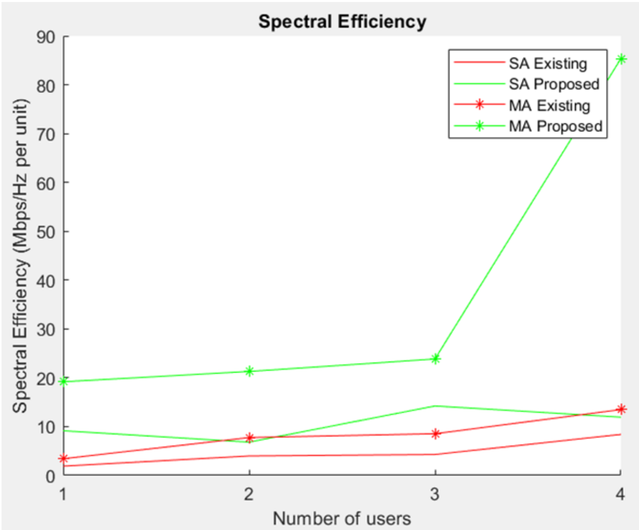

Fig. 4. Comparison of existing and proposed algorithms showing improvement in spectral efficiency

β_0 controls the attractiveness and parameter studies suggests that it is set to unity for most of the applications. Many simulations show that firefly algorithm gives more efficiency when initial α_0 is associated with scaling of design variables. Assuming L as the average scale of the problem of concern. Then we can set α_0 as 0.001 L initially. Factor 0.001 is because random walk requires a number of steps to reach the target while balancing the local exploitation without jumping too far in a few steps. Now, γ is also related to scaling L where its value is usually set to $\frac{1}{\sqrt{L}}$.

This is another advantage of firefly algorithm in which its parameters can be varied to control the randomness when iteration progresses. With this, convergence can be accelerated even more.

For solving an optimization problem, the algorithm is chosen after considering its complexity. Most of the metaheuristic algorithms are less complex and are easy to implement. Algorithm with less complexity is chosen.

The algorithm has two inner loops throughout the population, n and one outer loop for total iteration t which gives its complexity at extreme case as $O\ (n^2 t)$ means the complexity is linear with respect to total iteration t and non-linear with respect to population n. If population n is small (say $n = 50$) and t is very large (say $t = 4000$), the computational cost is relatively inexpensive since algorithm complexity is linear in terms of t whereas if n is large, it is possible to use one inner loop for ranking the attractiveness (brightness) of the fireflies using sorting algorithms. In that case, the complexity of FFA will be $O\ (nt \log n)$.

Thus, the computational cost is relatively less. This algorithm allows to find the optimum value of power for RRHs by maintaining a high data rate. So, this solves the problem that arises when the power is high. This algorithm allows to find the optimum value of power for RRHs by maintaining a high data rate. So, this solves the problem that arises when the power is high.

5. CONCLUSION

The work discusses the allocation of resources in C-RAN with an implementation of firefly algorithm being applied on it. Also, the FD C-RAN has a suppressive behavior of SI cancellation due to the distributive nature of RRH which utilizes the potential of FD communication for a good extend. The main objective of the work was to find the optimal value of power in which maximum data rate is obtained. For optimization, the inverse data rate is found and the corresponding power is determined. Graphs are plotted by comparing the GRA algorithm with the proposed firefly algorithm in terms of data rate and spectral efficiency. It can be concluded that the FFA has exhibited a better performance in allocating the resources. The algorithm has fast convergence and was observed that the spectral efficiency has been improved by 10 % and data rate is better from the work that is compared.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

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