Dynamic Channel Allocation in Small Cells

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***Abstract*— The inter-cell interference coordination techniques which include frequency reuse and Dynamic Channel Allocation (DCA) play a vital role in improving the spectrum efficiency. The techniques of frequency reuse are very sophisticated. Depending on the traffic demand, channels allocated to each cell is varied in DCA. In OFDM based cellular systems, the channel information and interference signals can be measured easily whose knowledge is essential for DCA. Hence, in OFDM systems, DCA can improve the spectral efficiency to a great extent. The next generation cellular systems would incorporate small cell (Micro, Pico and Femto) base stations for extensive frequency reuse and spectrum utility. They would also include millimeter wave (mmWave) for communication i.e. 5G cellular networks. DCA techniques in such a HetNet would improve the efficiency to a great extent. With the development of Software Defined Mobile Networking (SDMN), the protocol-specific features of mobile networks for various radio access technologies can be carried out with software improving the functionality of network. Thus, the implementation of DCA techniques becomes less complex. In this paper, DCA in small cells with respect to three cases namely spatial, temporal and spatio-temporal allocation is proposed. The problem formulated for DCA is solved using integer linear programming (ILP) technique and the solution is an effective prediction based model to optimize the channel allocation problem. Simulation results show the performance for various number of available resources and number of cells for allocation.**

***Keywords*—** DCA, Small Cell, ILP, HetNet, 5G, SDMN.

I. Introduction

This The telecom operators are putting in more efforts to accommodate the increasing mobile users while data intensive applications are emerging. With the evolution of 4G cellular networks providing high data rates, increasing efforts are made to innovate enabling technologies for 5G. HetNets are proposed as one among the technologies that will enable integration of micro, pico and femto cells with the macro cells. With high frequency reuse in small cells, the available spectrum for communication is efficiently utilized. The realization of Internet of Things (IoT) requires novel communication paradigms that enable connection of billions and trillions of devices. Thus, the need to be able to utilize the mmWave bands from 3 GHz to 300 GHz for communication is increasing [1].

Researchers, thus are actively investigating the design and implementation of millimeter-wave communication, especially in small cells. There are efforts to integrate such communication systems with fiber-optic backbone based wide area networks in 4G. The property of high attenuation experienced by millimeter waves is capitalized to enable high frequency reuse, also enabling high spectral efficiency [2]. But, it is expected that the deployment of IoT (with cyber physical systems integrated with it) will certainly require efficient utilization of available channels [3]. Thus, in this research paper, dynamic channel allocation (DCA) in small cells is proposed which can aid in realizing next generation cellular technologies. Software defined networking (SDN) enables a logically centralized controller which plays a key role in DCA technique proposed in this paper. Software defined cellular networking allows to carry out SDN operations to mobile users at a low management cost, called the software defined mobile networks (SDMN) [4]. This enables complex DCA technique practical improving the spectrum utility.

II. Literature Review

A. Concept of Channel Allocation

The geographical area is assumed to be covered by hexagonal cells. The center of a cells are base stations interconnected by wired network. The available bandwidth is divided into channels for communication that can be reused at cells without interference if their separation is greater than or equal to the minimum reuse distance. In recent years, with the increasing demand for channels, the need for efficient spectrum usage and more reliable techniques for channel allocation has become an interesting area for research. For more efficiency, frequency reuse with decreasing the cell coverage area (small cells) is used. Channel allocation in small cells encounters more number of hand-offs which leads to the development of channel allocation schemes that can achieve high performance and compatibility with macro cell techniques. The two main areas of interest is knowledge of the environment i.e. historical data of the traffic and allocating appropriate number of channels based on the data [5].

1) Static Allocation or Fixed Channel Allocation
2) Dynamic Channel Allocation

Fixed Channel Allocation: Each cell is permanently allocated a set of channels to handle the calls [6]. One approach to such a channel allocation is graph multi-coloring [7].

Dynamic Channel Allocation: To use the bandwidth more efficiently, taking the traffic demand into consideration, the channels can have mobility between cells, i.e. channels are allocated to cells based on their demand. [8] Any channel can be used in any cell, maintaining the interference levels below threshold. This involves additional computing for tracking the changes in traffic and assigning channels to cells [7].

Dynamic Channel Allocation can be centralized or distributed. In centralized dynamic channel allocation, the channels are assigned to the cells through a central computer which has a central pool of channels. The channels are returned to the central pool once the traffic goes down. The disadvantage with this type of allocation is a single point of failure at the central computer can halt the communication sessions. In distributed dynamic channel allocation, channel reuse is maximized within the minimum reuse distance at the expense of some interference below a certain threshold provided neighboring cells are not using the channel simultaneously. This can be formulated as a resource sharing problem [5]. The resource sharing problem is similar to mutual exclusion problem but with number of resources (channels) [5]. Token and non-token based distributed mutual exclusion algorithms are used in the design of distributed dynamic channel allocation [7] [9].

There exist other channel allocation schemes like hybrid channel allocation and flexible channel allocation [10] [11]. Hybrid channel allocation is a combined technique incorporating both fixed and dynamic channel allocation where it has a fixed set of channels assigned to each cell and a dynamic set of channels which are assigned only when a cell in the system has all the channels in fixed set exhausted [10]. Flexible channel allocation is similar to hybrid channel allocation. The channels are divided into fixed sets for handling low traffic and flexible sets for the varying traffic demand.

In summary, the channel allocation problem is to assign the channels using the spectrum efficiently and minimizing the interference. The assignments can be made to satisfy the immediate future requirement i.e. static channel allocation. The other way is to dynamically assign the channels based on the traffic environment. The optimization problems can be solved using neural networks [12]–[14], other optimization techniques like [15] Linear programming etc.

B. Need for Frequency Reuse in Channel Allocation

Spectrum management can be done by choosing proper location of BTS and efficient carrier assignments [16]. The carrier assignment can be done either as frequency reuse or as fractional frequency reuse. In frequency reuse, the frequencies are reused in cells after the minimum reuse distance. In case of fractional frequency reuse, the main portion of spectrum is reused everywhere except at the cell edge and the remaining spectrum is divided for orthogonal reuse at the cell edge [17].

C. Small Cells and Their Importance

Small cells (micro or femto) can increase the capacity of macro cell. Small cells are deployed in WPANs and WLANs as an underlay with macro base stations. Dense deployment of small cells is a method of overcoming the shortage of spectrum resources. HetNets with dense deployment of small cells can deliver high data rates per unit area. HetNets with different sizes and overlapping coverage areas in least interference performance can be achieved by considering the dynamic traffic and optimization based spectrum allocation schemes [16]. With the development of millimeter wave technology for wireless communication, aggressive frequency reuse is possible as propagation loss is high for mm Waves.

The demand for cellular access in HetNets is increasing giving rise to new radio access technologies (RAT) which are more effective with higher spectral efficiency and utilization [18]. Co-deployment of multiple RATs and use the licensed spectrum, still demanded for additional capacity and higher throughput. The solution with a great potential was the deployment of self-configuration access points densely which are termed as small cells. The interference in HetNets containing macro cells and small cells can occur between small cells and macro cells called the cross-tier or may occur between small cells called the intra-tier [19]. Macro cell base station and small cell base station are analogous to the primary and secondary user in the dynamic spectral access model [19]. According to [19], the small cells must have the spectral knowledge so that they avoid interference with the macro cell. Small cells may use the same band used by macro cell or on its own dedicated bands. While dedicated bands reduce interference with macro cells, due to spectrum scarcity, they share the spectrum with macro cells. Resource allocation technique in small cells can be centralized or distributed [18]. Centralized resource sharing minimizes the interference but increases the system complexity with the increase in the number of small cells.

D. Related Work and Motivation

In [9], authors proposed a strategy for optimal scheduling based on the queue state information and channel state information. The problem is solved using non-convex combinatorial optimization using two step heuristic algorithm. The simulation results for dynamic user scheduling shows better performance than other basic and improved algorithms. Similarly in [5], authors proposed a dynamic cell selection scheme for small cells using quasi-nash equilibrium. The scheme works on sensing based mechanism to optimize the cell selection. In [20], authors proposed a queue-aware scheduling algorithm for small cells which is similar to traffic sensing and dynamic scheduling algorithms. The main focus in this paper is on energy saving through efficient scheduling of spectrum. A "Dynamic Strict Fractional Frequency Reuse (DSFFR)" method is proposed [21] based on dynamic division of small cell areas. A joint scheduling problem is been formulated having two schedulers operating on different time granularity for the transmission of downlink packets. With simulation it is shown that DSFFR is better than static scheduling schemes in 5G small cells. In [22] a cluster based scheme for small cells is 5G is proposed that focuses on power efficiency and QoS for users. It is based on non-cooperative game between the clusters to make inter-cluster competition in the absence of inter-cluster communication. The proposed algorithm comprises of epsilon-coarse correlated equilibrium. Simulation results demonstrate that the proposed scheme is efficient than older schemes available. Another game theory based scheme is proposed in [23]. Authors proposed a solution for joint channel allocation in small cell networks. Dynamic stochastic game-theoretic learning is used to solve the problem with dynamic active BS sets. A "Dynamic Joint Channel and Power Selection - Stochastic Learning Algorithm (DJCPS-SLA)" is used for proving the convergence in active BS sets. The proposed algorithm is better than random algorithm as proved by simulation results. Similarly [24] also proposed a game based solution for resource allocation in small cells. The solution allows to take decisions distributively on the basis of past learning and present situation of other cells. It's a competitive approach to solve the problem. Further in

[25], another game theoretic approach is proposed for small cells to manage interference. In this approach, Nash-equilibrium minimizes the interference between cells. It also proposes a dynamic and distributed algorithm for channel selection. In [26], authors proposed a dynamic spectrum access scheme for small cells networks based on load. It is a distributed learning algorithm and results proved that proposed learning algorithm can resolve the problem of channel allocation and interference. A dynamic crowd formation algorithm is proposed in [27] for activating small cells. This algorithm also is based on present state of load on several crowded places and balances the load by activating small cells to divide the load dynamically, if required.

Motivated by above discussed works, this paper proposes dynamic channel allocation in small cells. The solutions in literature are based on game-theory, real-time traffic sensing, queue awareness, and load awareness. The problem of DCA is formulated and an efficient solution using integer programming is provided.

III. Optimal Dynamic Channel Allocation

As discussed in the previous section, the introduction of small cells helps in extensive frequency reuse. The spectral efficiency can be maximized by introducing efficient techniques of channel allocation dynamically.

The cells are separated spatially from each other, i.e. the base stations are spatially separated. The available channels are distributed among these base stations based on the traffic demand. Hence, the traffic data is collected from different cells over an interval of time and within each cell over regular intervals of time. The data collected is analyzed and the channels are distributed among the cells dynamically. The dynamic channel allocation problem is formulated in three steps i.e. for spatial allocation, temporal allocation and then spatio-temporal allocation.

A. Optimal Spatial Dynamic Allocation of Channels

Consider the total number of cells be $N$and the total number of available channels be M. The temporal unit is chosen to capture the call traffic variations across the cells. Based on the call traffic data collected across cells over a period of time, let $p_1,\ p_2,\ldots,p_N$ be the probabilities corresponding to the call density in cells $1,2,\ldots,N$ respectively. The allocation of channels spatially among the cells depends on their respective probability of channel requests. The allocation by maximizing the available channels is formulated as an integer linear programming problem. So, the problem is to maximize average number of channels allocated to a cell i.e.

$$E[X] = \sum_{i=1}^{N} n_i p_i \qquad (1)$$

where, X is a random variable corresponding to the number of cells or the cell index. The constraint imposed on the maximization in (1) is subject to the total available channels being M, i.e. $\sum_{i=1}^{N} n_i = M$. If there are no constraints imposed, then the problem becomes trivial. Assume that $p_1,\ p_2,\ldots,p_N$ are sorted in increasing order of probabilities. Then, the following cases are possible:

Case 1: If the values of $n_i's$ are such that $n_1 = 0, n_2 = 0, \ldots, n_N - 1 = 0, n_n = M$which maximizes $E[X]$ but leads to a trivial solution.

Case 2: If the minimum number of channels in each cell has a lower bound by at least R, the channel allocation will be as follows:

$$n_1 = R, n_2 = R, \ldots, n_N = M - (N-1)R \text{ with } n_{N \geq M}$$

Case 3: If the minimum number of channels in each cell has a lower bound by at least R and the other channels must differ by at least 1, the allocation will be as follows:

$$n_1 = R, n_2 = R+1, \ldots, n_N - 1 = R + (N-2), n_N = M - S \text{ with } (M - S \geq R) \text{ where}$$

$$S = R + (R+1) + \cdots + \big(R + (N-2)\big)$$

Case 4: If the minimum number of channels in each cell has a lower bound by at least R and the other channels must differ by at least d, the allocation will be as follows:

$$n_1 = R, n_2 = R+d, \ldots, n_N - 1 = R + (N-2)d, n_N = M - S \text{ with } (M - S \geq R) \text{ where}$$

$$S = R + (R+d) + \cdots + (R + (N-2)d)$$

Thus, it is natural to lead to impose realistic (practical) constraints on the integer values of n_i.

Constraint: Let $n_i's$ are in Arithmetic Progression (AP) series, i.e. the series $n_1,\ n_2,\ldots,n_N$ can be written as $a, a+d, a+2d, \ldots, a+(N-1)d$. The sum of this series i.e. the total number of available channels must add up to M.

$$Na + d\frac{(N-1)N}{2} = M \qquad (2)$$

The equation (2) is a Linear Diophantine Equation whose solution is the greatest common divisor (GCD) of N and $\frac{(N-1)N}{2}$, where a and d are variables. This hold true only when $M$is a multiple of GCD. Moreover, if a_0 and d_0 are one solution then, the general expression for other solution is

$$a = a_0 + k\frac{\frac{(N-1)N}{2}}{GCD},\ \ d = d_0 - k\frac{N}{GCD} \qquad (3)$$

where, k is any integer constant.

Let $p = M\frac{(N-1)N}{2} = q.$ Now, two cases arise when N is odd and when N is even. If N is odd, GCD of N and $\frac{(N-1)N}{2}$ is N, then the solutions are expressed as follows:

$$a = a_0 + k\frac{(N-1)}{GCD}, \qquad d = d_0 - k \qquad (4)$$

If N is even, GCD can be found using Extended Euclidean algorithm. By using this algorithm, for given p and q, integers m and n can be found such that,

$$(mp) + (nq) = \big(GCD(p,q)\big) \qquad (5)$$

where m and n are not unique. One pair of m and n is needed. As, it is assumed that $GCD(p,q)$ divides M, an integer $l$can be such that, $\big(GCD(p,q)\big)l = M$. Then (5) can be written as,

$$(mp)l + (nq)l = \big(GCD(p,q)\big)l \qquad (6)$$

This gives one solution, $a_0 = ml \, and \, d_0 = nl$. If $px_0 + qy_0 = c$ is a solution then the solutions form a general expression as follows:

$$a = a_0 + k\frac{q}{GCD(p,q)}, \qquad d = d_0 - k\frac{p}{GCD(p,q)} \quad (7)$$

There exists infinitely many solutions but the solution of interest is the one which maximizes $E[X]$ with real and positive values of a and d i.e. a >0 and d >0. The expected value expression in (8) is,

$$E[X] = \sum_{i=1}^{N} n_i p_i = ap_1 + (a+d)p_2 + \cdots + (a + (N-1)d)p_N = a + d\sum_{j=1}^{N}(j-1)p_j = a + \square d \quad (8)$$

where $\square = \sum_{j=1}^{N}(j-1)p_j$.

The expected value $E[X]$ is an increasing function, more channels are allocated to the cell which has maximum probability. Hence, the solution of the Linear Diophantine Equation is selected such that it maximizes the value of d, in turn, the value of (a, d) is selected which satisfies the equation.

Theorem: If $\{(a_1,d_1),\ldots,(a_l,d_l),\ldots,(a_k,d_k)\}$ are a set of solutions out of the infinite solutions of the Linear Diophantine Equation, such that all are non-negative integers and also, if $a_1 < \cdots a_l < \cdots < \cdots a_k$ then, $d_1 < \cdots d_l < \cdots < \cdots d_k$. Now, the solution which maximizes $E[X]$ is (a_1, d_1).

Proof: To prove that the solution which maximizes $E[X]$ is (a_1, d_1), it should be proved that,

$$a_i + \square d_l \leq a_1 + \square d_1 \; for \; l = 2,3,\ldots,k \quad (9)$$

$$\frac{a_l - a_1}{d_1 - d_l} \leq \square \quad (10)$$

The Linear Diophantine Equation in (2) is satisfied by $(a_1, d_1)$and (a_l, d_l).
Therefore,

$$a_1 N = M - d_1\frac{(N-1)N}{2}, a_l N = M - d_l\frac{(N-1)N}{2} \quad (11)$$

Multiplying (10) with N on both sides and substituting (11),

$$\frac{\left[M - d_1\frac{(N-1)N}{2}\right] - \left[M - d_l\frac{(N-1)N}{2}\right]}{d_1 - d_l} \leq \square N \quad (12)$$

$$\frac{N-1}{2} \leq \square \quad (13)$$

Substitute $\square = \sum_{j=1}^{N}(j-1)p_j$,

$$\frac{N-1}{2} \leq \sum_{j=1}^{N}(j-1)p_j \quad (14)$$

This implies that the proof of the expression in (14) proves that (a_1, d_1) is the solution which maximizes $E[X]$. We now prove that the eq. (14) holds.

Proof: To prove the maximum value of $\sum_{j=1}^{N}(j-1)p_j$ occurs only for uniform distribution, i.e. $p_1 = p_2 = \cdots = p_N = \frac{1}{N}$, we use the proof of contradiction. Suppose the probability masses $p_1 = q - \epsilon, p_2 = p_3 = \cdots = p_{N-1} = q = 1/N$ and $p_N = q + \epsilon$gives the minimum value of $\sum_{j=1}^{N}(j-1)p_j$, where $\epsilon > 0$ is a small positive real number. Using the given probabilities, we can calculate value of the expression $\sum_{j=1}^{N}(j-1)p_j$, as given below:

$$\sum_{j=1}^{N}(j-1)p_j = 0*(q-\epsilon) + \sum_{j=1}^{N}(j-1)q + (N-1)(q+\epsilon) \quad (15)$$

$$\sum_{j=1}^{N}(j-1)p_j = \sum_{j=1}^{N}(j-1)q + (N-1)(q+\epsilon) = \sum_{j=1}^{N}(j-1)q + (N-1)(\epsilon) \quad (16)$$

$$\sum_{j=1}^{N}(j-1)p_j = \frac{1}{N}*\sum_{j=1}^{N}(j-1) + (N-1)(\epsilon) \quad (17)$$

$$\sum_{j=1}^{N}(j-1)p_j = \frac{1}{N}*\frac{(N-1)N}{2} + (N-1)(\epsilon) = \frac{(N-1)}{2} + (N-1)(\epsilon) \quad (18)$$

Since, $\epsilon > 0$, contradicts our supposition, therefore, we can conclude that the value of $\sum_{j=1}^{N}(j-1)p_j > \frac{(N-1)}{2}$ for any probability distribution and minimum value occurs for uniform distribution.

B. Optimal Temporal Dynamic Allocation of Channels

The channels are allocated to each cell but more efficient use of resources is possible if within each cell, the available channels are allocated temporally. Historical data is collected at regular intervals of time over a day and based on the call traffic density, channels can be allocated. The total available channels in a cell are $L$and the intervals of time be labeled as $1,2,\ldots,T$. Let the channels available at a time interval j be n_j. Then, the traffic in each interval of time $1,2,\ldots,T$corresponds to probabilities $p_1, p_2, \ldots, p_T$ respectively. The temporal channel allocation problem is to maximize the number of channels available over an interval of time within a single cell i.e.

$$E[Y] = \sum_{j=1}^{T} n_j p_j \quad (19)$$

where, $Y$is a random variable corresponding to time unit. The constraint imposed on the maximization in (19) is subject to the total available channels being L.

$$\sum_{j=1}^{T} n_j = L$$

The problem of temporal channel allocation by maximizing the available channels over time is formulated as an integer linear programming problem. Assume that $p_1, p_2, \ldots, p_T$ are sorted in increasing order of probabilities. Then, as discussed in the previous section four cases arise and lead to impose constraint on the integer values of n_i.

Constraint: Let $n_i's$ are in Arithmetic Progression (AP) series, i.e. the series $n_1, n_2, \ldots, n_N$ can be written as $a, a+d, a+2d, \ldots, a+(N-1)d$. The sum of this series i.e. the total number of available channels must add up to L, i.e. $Na + d\frac{(N-1)N}{2} = L$; which looks similar to Linear Diophantine Equation as in the previous case of spatial allocation of channels. The solution to find the optimal values of (a, d) such that it maximizes the value of d in turn, the expected value $E[Y]$ is similar to the spatial allocation. (The readers are advised to refer to the Theorem and Proof of previous subsection.) It is inferred that the best solution (a_1, d_1) can maximize the allocation i.e. $E[Y]$ temporally.

C. *Optimal Spatio-Temporal Dynamic Allocation of Channels*

In previous sections, the spatial traffic information i.e. traffic information in various small cells, and the temporal traffic information i.e. traffic in the same cell at different times as being independent random variables.

The main observation here is that the spatial traffic information random variable and the temporal traffic information random variables are not necessarily independent random variables i.e. if X is spatial traffic information random variable and Y is temporal traffic information random variable then,

$$P\{X = n_i, Y = m_j\} \neq P\{X = n_i\}P\{Y = m_j\}$$

Hence, the problem of dynamic channel allocation is formulated spatiotemporally i.e. channel allocation among the cells and within a cell. To maximize the available channels, historical data is collected over time and across the cells and based on the call traffic information, the channels are allocated dynamically.

Data Collection Historical data is utilized to capture spatio-temporal correlations in data traffic in various small cells i.e. joint PMF is estimated based on call traffic data in various cells at different times.

$$E[XY] = \sum_i \sum_j (n_i)\,(m_j)\, P\{X = n_i, Y = m_j\}$$

The goal is to allocate available channels dynamically to various small cells at different times subject to the constraint that the total available channels are limited. This kind of problem can be solved using quadratic programming optimization.

IV. Maximizing the Channels Allocation based on Spatio-Temporal Correlations of Traffic

Let n_i i.e.$\{n_1, n_2, \ldots, n_r\}$ is the traffic in different cells and m_j i.e.$\{m_1, m_2, \ldots, m_r\}$ be the temporal traffic among them.

Goal: To formulate the Dynamic Channel Allocation (DCA) problem as Optimization of Quadratic Form associated with the weighting matrix being stochastic matrix.

$$E[XY] = X^T \tilde{C} X \qquad (20)$$

where, C are the joint Probability Mass Function (PMF) matrix showing that they need not be symmetric.

Objective Function is to optimize the maximum number of channels allocated spatially and temporally over a period of time such that,

$$\sum_{i=1}^{N}\sum_{j=1}^{N} n_i m_j P\{X = n_i, Y = m_j\} \neq \sum_{i=1}^{N}\sum_{j=1}^{N} n_i n_j P\{X = n_i, Y = m_j\} \qquad (21)$$

When n_i and m_j belong to the same set. The objective function in equation (20) is subject to the constraints similar to that mentioned in the previous sections, i.e.,

$$\sum_{i=1}^{N} n_i = M \qquad (22)$$

$$\sum_{j=1}^{N} m_j = M \qquad (23)$$

$$n_i, m_j \,\epsilon\, Integer\ Set \qquad (24)$$

The constraint (22) limits the total number of channels available spatially and the constraint (23) limits the total number of channels available temporally. The constraint (24) is imposed to have integer values for the variables n_i and m_j.

The problem thus formulated is to arrive at optimal number of channel units per day and per cell given the joint PMF matrix. The idea of channel units enables us to formulate the DCA problem as optimization of a quadratic form (unit size i.e. number of channel units in a day and over different cells are mostly different). $E[XY] = \sum_i \sum_j (n_i)\,(m_j)\, P\{X = n_i, Y = m_j\}$. The quadratic form based on joint PMF matrix which is not necessarily symmetric needs to be optimized over a constraint set. It is assumed that channel units per cell as well as per time unit belong to the same set e.g. $n_i \,\epsilon\, \{1,2,\ldots,M\}$. This assumption is made to ensure that the objective function becomes a quadratic form. The problem thus formulated in (20), falls into non convex class of optimization which is NP-hard. Generally, such problems are solved using either a heuristic algorithm or an exact and deterministic algorithm. In this work, the problem is solved using an exact algorithm called the interior-point-convex method. The simulation results are discussed in the next section.

V. Simulation Results

In order to maximize the channel availability to cells, it is necessary to allocate more number of channels for the cells which have more call density, in turn, high PMF value. Similarly, less number of channels to cells with lowers PMF value. Thus, the optimum allocation depends on the traffic data which is taken in the form of PMF matrix, $\tilde{C}$ in equation (20). The non-convex quadratic problem is solved using interior-point-convex-algorithm using solver. In DCA, there exists no relation between cells and channels. The channels are resources which are allocated when a cell is in need. Figure1 shows the variation in the optimized value for varying the total available channels to be allocated. The value n corresponds to the number of cells sharing the available channels. As the number of channels available for allocation increase, the optimized value also increases and a maximum is reached when $n = 10$. The number of cells for dynamic channel allocation in a small cell scenario is considered in this paper. As discussed earlier, the channel allocation generally requires more computation.

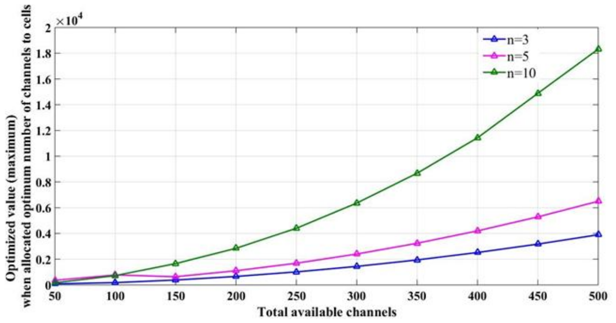

Fig.1. Result showing the allocation to varying number of cells

However, SDN enables centralized controller at low cost and complexity. Thus, relatively low value of n in simulation is considered for better performance of the scheme with less complexity. The channel allocation to the cells are constrained to be integers during the entire simulation. The results also vary with varying traffic data over a period of time.

VI. Conclusion

In this paper, DCA in a HetNet scenario in mmWave environment is considered. By incorporating DCA technique in the next generation cellular system, the advantage of spectral efficiency can be achieved. This paper emphasizes on using integer programming for solving the formulated problem. Firstly, the problem of spatial DCA and temporal DCA is formulated as an integer linear programming problem which is solved using the analytically tool. Next, depending on the spatio-temporal correlations, DCA problem is formulated as a quadratic optimization and is simulated. The proposed DCA scheme optimally allocates channels to available cells.

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