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A Hybrid Algorithm based on Machine Learning for Channel Network Optimization in 5G Wireless Network

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ABSTRACT: Network Selection is one of the difficult mechanisms in cognitive radios, when moving from 4G to 5G technologies to address spectrum shortage issue and by achieve Fast delivery handover route with high speed data rate access, and also maintain the quality of service (QoS). The meddle (interference) occurred by all secondary users (SUs) in licensed network's must be minimum. Neural Networks are essentially a part of Deep Learning, which in turn is a subset of Machine Learning. So, Neural Networks are nothing but a highly advanced application of Machine Learning that is now finding applications in many fields. We Proposed Neural Network–Particle Swarm Optimization (NN-PSO) method for network selection and Fast Delivery Route mechanism in order to increase system efficiency by consider more number of SUs in network and providing to their preferences, and respect the criteria of primary network operators, at the same time. Experimental results and numerical parameters represent the effectiveness of the proposed NN-PSO methods to finding a near-optimal solution for network selection.

KEYWORDS: QoS, SU, PSO, Neural Network, 5G, Machine learning, Deep Learning.

I. INTRODUCTION

The requirement of spectrum resources is predicted to increase significantly in 5G LTE wireless networks. This requires wireless system designers to suggest an efficient spectrum management technique for improving QOS. Different point of views on 5G architecture are resented in [3][5] with key technologies such as massive MIMO, micro cells, energy efficient communications, cognitive radios etc. The 5G networks will mainly contain of network densification (the act of becoming more dense), i.e., densification over space and frequency. To enhance the available capacity of spectrum band by adding more cell sites, called network densification. Cell sites is mostly positioned in capacity-strained areas for adding more capacity where it is most needed and would be help offload traffic from surrounding sites. There are two terms defined as; Densification over space: defined closed connection of n number of small cell. Densification, self-fish spectrum sharing plays an important role in order to achieving hard goals for 5G environment. Spectrum would be also divided between n numbers of devices present in network with multiple applications and also ensures the coverage of 5G networks all over [8].



Figure 1: 5G Wireless Networks



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In addition, it is spectrum efficient as it can use all non-communicated spectrum, can achieve better system capacity, reduce energy consumption, and increase cell efficiency. Dynamic spectrum access (DSA) has appeared as key for spectrum sharing in an opportunistic way [9], [10]. A cognitive radio network (CRN) used Dynamic Spectrum Access to coexist with a licensed network (primary network) for ease of spectrum allocation [11]. A users have licensed of primary networks are known as primary users (PUs). A user which can operate licensed band (PU band) with the permission of licensed user (PU) and respect the criteria of PU's, called Secondary user (SU's) or unlicensed user. Unlicensed Spectrum is the open frequency bands to be utilized by an unlimited number of users. There is multiple primary networks incorporates with 5G network. so, there may be possible, that SUs have a problem to selecting one of the primary network for network selection problem with characteristics in terms of bandwidth, price, and capacity [12], [13]. Most of the time, for accessing the spectrum, Price is a main criterion for selecting any PU network with specific operator. In [14], represents an approach management of interference in cognitive femto cell through joint price based spectrum sharing and power allocation mechanism.

There is an interaction between PU (licensed user) and SUs (unlicensed user) and spectrum sharing algorithm is presented price based scheme, through the particle swarm optimization (PSO). The difficulty of sub-carrier sharing through discrete rate allocation to solve price-based spectrum sharing and rate allocation method. The network selection problem solved through PSO technique. But, there is problem of unmanageable nature of the network selection having large processing time in 5G networks, so, it is necessary to develop better algorithms for solving the network selection problems. So that, to improve the previous work, it is necessary to study network selection problem.

II. RELATED WORK

A. Mughees et al., [1] presents an up-to-date review of future wireless system concepts such as 6G and role of ML techniques in these future wireless systems. In particular, we present a conceptual model for 6G and show the use and role of ML techniques in each layer of the model. We review some classical and contemporary ML techniques such as supervised and un-supervised learning, Reinforcement Learning (RL), Deep Learning (DL) and Federated Learning (FL) in the context of wireless communication systems. We conclude the paper with some future applications and research challenges in the area of ML and AI for 6G networks.

J. Kaur et al., [2] present taxonomy of machine learning applications in 5G networks for improving energy efficiency. We discuss several issues that can be solved using machine learning regarding energy efficiency in 5G networks. Finally, we discuss various challenges that need to be addressed to realize the full potential of machine learning to improve energy efficiency in the 5G networks. The survey presents a broad range of ideas related to machine learning in 5G that addresses the issue of energy efficiency in virtualization, resource optimization, power allocation.

N. Ul Hasan et al.[3] presents exhibits a network determination and direct assignment system so as to expand income by obliging more SUs and taking into account their inclinations, while in the meantime, regarding the primary network administrator's strategies. An advancement issue is defined so as to limit gathered obstruction acquired to authorized users and the sum that SUs need to pay for utilizing the primary network.

D. Wu et al. [4] propose a joint channel designation calculation for the coordinating coalitional amusement hypothetical plan. We demonstrate that the proposed calculation merges to a steady channel assignment profile. Reproduction results demonstrate that the proposed calculation accomplishes higher worldwide SUs' fulfillment than the littlest obstruction channel determination and irregular allotment.

M. Bukvić et al. [5] Applying intellectual radio network standards prompt the notable issue of Network Determination and Channel Assignment. CNP needs to tackle this NP-difficult issue by considering similarly the requests of the heterogeneous PNs just as the best enthusiasm of SUs. In this paper we propose two distinctive bi-target models and fathom them by producing their non-ruled focuses.

A. BenMimoune et al. [6] propose a novel transfer choice technique dependent on Markov Choice Procedure (MDP) for multi-bounce hand-off networks. We will likely accomplish noteworthy execution improvement against inheritance, brought together hand-off determination systems, for example, the disjoint-way choice plan. Recreation results



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demonstrate that our structure has the upside of diminishing between cell handoff recurrence and bringing down handoff delay.

T. Bi et al. [7] propose RLoad, a novel Notoriety based Burden adjusting Network Choice Procedure for heterogeneous remote situations, based over the IEEE 802.21 Media Autonomous Handover (MIH) standard. The proposed arrangement makes utilization of a notoriety based component to choose the most proper arrangement of networks for the portable client and a heap adjusting instrument to disseminate the traffic load among the networks by making utilization of the Multipath TCP (MPTCP) convention. Starter reproduction results show critical advantages when utilizing the proposed RLoad arrangement.

C. Chen et al. [8] this work researches the asset distribution (RA) issue for the downlink different information various yield based non-symmetrical numerous entrance (MIMO-NOMA) framework, which is typically explained through a beamforming (BF) process and a client determination (US) process. In this paper, we propose the different client channel state data (CSI)- based solitary esteem decay (MU-CSI-SVD) BF plot and the minimization of intensity (Min-Power) US conspire. Under impeccable CSI situations, the proposed MU-CSI-SVD accomplishes close ideal entirety rate execution with the high-intricacy BF conspire while has a similar dimension computational multifaceted nature as the low-unpredictability BF plot.

D. Saliba et al. [9] propose in this paper a precise calculation for the estimation of WiFi 802.11n physical channels load through 3 channels perceptions as it were. When the channel load is evaluated utilizing the proposed calculation, the channel task dependent on the negligible burden esteem is procured, subsequently giving quicker reaction of an AP channel determination and quicker end client association for better Nature of Experience (QoE).

T. Zeng et al. [10] In this way, so as to acquire a problematic arrangement, the improvement issue is decayed into two subproblems: seed determination and subchannel allotment. For the seed determination sub-issue, a novel D2D network examination (DNA) structure is proposed to investigate visit correspondence designs crosswise over D2D users, known as spatial themes, to decide the ideal number of gadgets which can scatter substance. Besides, to take care of the second sub-issue, a heuristic calculation is presented.

T. Salam et al. [11] In this vein, a conveyed MDA choice calculation is additionally proposed to assign proper client hardware as aggregator. The proposed CDA conspire adequately caters the huge access and gives omnipresent accessibility of the amassing gadgets in the MTC network. What's more, the constrained channel assets induce a FDA to plan assets other than information total. Along these lines, an asset distribution plot is additionally proposed to progressively dispense channels to the MTC gadgets subject to their QoS necessities.

M. A. Gadam et al. [12] the low-control level is under-used though, UEs having poor channel quality expend huge measure of accessible assets in the network. The proposed joined channel increase and nature of administration (QoS)-based access-mindful (CCGQA) cell choice plan accentuates on the significance of consolidated measurements to accomplish improved execution through burden adjusting in HetNets.

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III. PROPOSED METHODOLOGY

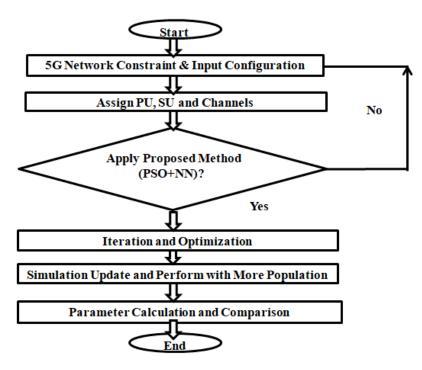


Figure 2: Flow Chart

In our proposed system, we consider a 5G heterogeneous system that consolidates numerous essential systems. At any given moment, every essential system has an alternate number of channels accessible for the SUs, and each channel has an alternate limit. Each system has a few imperatives as far as obstruction, membership expenses, and limit. SUs determine their necessities as far as the base information rate and the most extreme membership charge that they will pay. Based on SU requirements and primary network constraints, we employ the PSO and the NN to find a near-optimal solution. The goal of this paper is to find a solution such that the overall less no of iteration to optimize fitness value and decision weight, in terms of RSSI, Loss, bandwidth, Speed, crossover rate and cost. Particle Swarm Optimization and Neural Network are used to solve the optimization problem and Network Selection and Fast Delivery Handover Route.

ALGORITHM -

PSO-NN algorithm for simultaneous optimization of weights Error and Fast Delivery Handover Route

Section 0: Make a Loop - Create a matrix for PSO to use 'RSSI', 'Loss', 'BW', 'Speed', 'RTT',' Cost' These are the six equivalent RF environments for each deficit above
Section I: Make a Name - Initialization matrix index
Section II: Make a Connection -connection matrix, nothing connected
Section III: Make a Route - Prune the connection matrix with limited multiple connection M
Section IV: Make a Bang-Now the random change of route or schedule happen!
Section V: Make a Rescue-Now trying to hand over the system, using hope matrix
Section VI: Make an Exit-Now trying to go with new network, using exit matrix
Section VII: Make a Final -RDBMS server fails rate Ms
Section VIII: NN Train -run many times, to train neural network



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The proposed 5G LTE wireless network, where, multiple primary networks present and cooperating each other. Where each primary network has a different number of channels with a different capacity are available for the SUs. Each network has some limitations in terms of interference, subscription cost, and capacity. SUs specify their conditions and demands in terms of the maximum data rate and the minimum subscription fee that they are capable to pay. The proposed PSO and NN algorithms use to find a closed-optimal solution based on SU requirements. The goal of this work is to optimized channel network, free route and select network such that the overall cost for all SUs is minimized and the overall interference acquired to the PUs is also reduced of different primary networks and provide more number of SU's in channel.

A. Machine Learning Neural Network (NN)

Machine Learning based Neural Network is a network for computation and an intelligently compute system; by consisting multiple connected processing elements (nodes) in wireless communication. It is motivated by the human nervous systems. Where neurons represent as nodes and nervous systems are represented as a network of interconnections between nodes, having an activation functions. Neural networks have different classes, which would be obtained by changing the activation functions of the neurons and the structure of the weighted interconnections between them. Neural Network having one or more layers of nodes (neurons). This is created for the interaction of multiple connected processing elements. A Neural Network can perform any tasks in system either linear network or non-linear network. The desired linear connection between the input and the output represented by approximated straight line, which trained by neural network. In each iteration, the square of the error (also called mean square error) is measured between the actual and desired output, during the training; and applied to a weight algorithm which is updating after each iteration. Due to their parallel structure where each node connected with each other, neural network can continue processing without any problem even when some elements of neural network not work (or failed). Main element (or part) of the neural network is sensor nodes; that's by NN is also referred as sensor network. Data communication between WSN must be an efficient and sensor node must be absorbed less power during processing.

B. Particle Swarm Optimization (PSO)

An intelligent optimization which based on population or the moving of particle in swarm is called Particle swarm optimization (PSO). It having multiple agents (*kth* particles) that form a swarm and moving around in search space for searching best solution. The location of each and every particle which shows a solution is represented in a vector. The PSO algorithmic technique starts with an initialize parameter of *n* random number of particles. Each particle allot with a random position (X_k) and random velocity (V_K) in the search space. PSO Inertia weight (w); where,

- Big value w- greater global search ability
- ► Lower w- greater local search ability.

PSO is a developmental algorithm. At each iteration, every particle is update or changes its velocity (V_k^{new}) and position (X_k^{new}) by using eq. (1) and eq. (2). Particle place or position in a swarm found through the Fitness function. It describes best position (called *pbest*) and quality of each particle. The velocity of each particle is compaired continuously with its current value and previous value, until reach the optimum value. If previous value is better than present value than it changed its value with own best previous position (*Pbest*) that, best position found by particle itself (fitness value).

- Global best (gbest): When every particles in a swarm are considered as best to one particle than, that particle called "gbest".
- Local best (*lbest*): if some particle (i.e. only particle in a group) considered as best neighbor of one particle than, that particle called "*lbest*".

PSO used for channel selection in CRN other than using other stochastic algorithms- The PSO has huge advantages compared to others that make using it very attractive:

• Easy to implement.

- Requires a few parameters needed to be adjusted by the user.
- It provides fast convergence and this will save the spectrum sensing process.

• It provides high accuracy.



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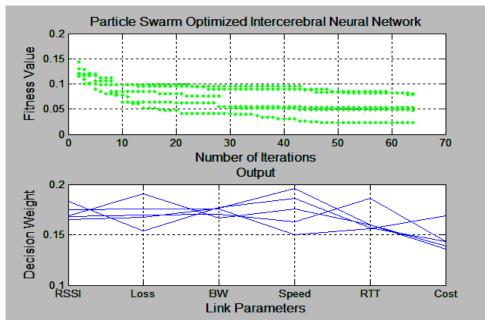
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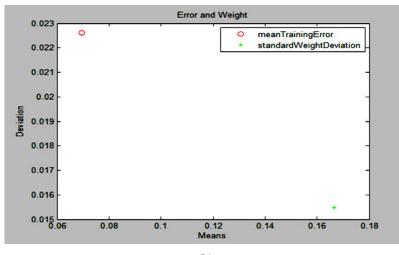
•It requires less computational time compared to others heuristics.

IV. SIMULATION AND RESULT

For simulating the results, the software that is being used is the MATLAB R2018a. The following are the simulation results for Network Selection and Fast Delivery Handover Route in the PSO-NN. The machine learning based Neural Network iteration method is capable of calculating the maximum of the thousand's of the nodes. In this each node depends on the previous node for the optimal power allocation. For example consider a single node and let us assume 10secs as duration for each node and if we consider for the 10 nodes then the time should be of 100secs. So in this it calculates for each and every node and assumes the value itself when there is the multiple numbers of the nodes. In the random instances method the calculation will be done completely in the random manner and finally from the above graph the optimal power allocation is obtained.



(a)





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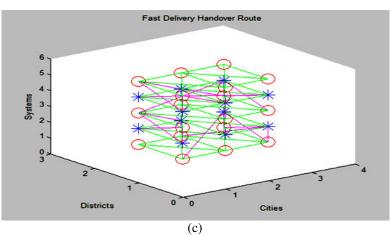


Figure 3: (a) PSO -NN for Iteration and Error (b) Training Error and SWD (c) Fast Delivery HR

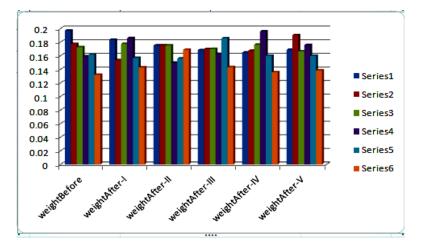


Figure 4: Weight Before and weight after-I to V

| Table 1: Weight before and after till process end | | | | | | | |
|---|-------------------|---|--|--|--|--|--|
| | eight After- I | Weight After- II | Weight After- III | Weight After- IV | Weight After-V | | |
| | 0.1834 | 0.1752 | 0.1683 | 0.1647 | 0.1688 | | |
| | 0.1536 | 0.1752 | 0.1698 | 0.1673 | 0.1903 | | |
| | 0.1774 | 0.1752 | 0.1701 | 0.1763 | 0.1666 | | |
| | 0.1859 | 0.1498 | 0.1626 | 0.1959 | 0.1758 | | |
| | 0.1568 | 0.1559 | 0.1858 | 0.1601 | 0.1599 | | |
| | 0.1429 | 0.1688 | 0.1433 | 0.1357 | 0.1385 | | |
| | | Weight After-I 0.1834 0.1536 0.1774 0.1859 0.1568 | Weight After- I Weight After- II 0.1834 0.1752 0.1536 0.1752 0.1774 0.1752 0.1859 0.1498 0.1568 0.1559 | Weight After- I Weight After- II Weight After- II Weight After- III 0.1834 0.1752 0.1683 0.1536 0.1752 0.1698 0.1774 0.1752 0.1701 0.1859 0.1498 0.1626 0.1568 0.1559 0.1858 | Weight After- I Weight After- II Weight After- III Weight After- III Weight After- IV 0.1834 0.1752 0.1683 0.1647 0.1536 0.1752 0.1698 0.1673 0.1774 0.1752 0.1701 0.1763 0.1859 0.1498 0.1626 0.1959 0.1568 0.1559 0.1858 0.1601 | | |



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Table 2: Simulation Parameters value

| Sr No. | PARAMETERS | PROPOSED WORK |
|--------|-----------------|------------------|
| 1 | Method | Hybrid(PSO+NN) |
| 2 | Iteration | 65-70 |
| 3 | Population size | PSO- 30 & NN- 30 |
| 4 | Inertial Weight | 1-6 |
| 5 | Cross over Rate | 0.4 |

From the table-1 it can be said that as the number of the iteration is decreasing as well as population size is increasing, inertial weight balance is increasing and cross over rate is decreasing.

| Table 3: Mean and Standard value of Epoch, Erro | or and Weight |
|---|---------------|
|---|---------------|

| Parameters | Epoch | Error | Weight |
|------------|---------|--------|--------|
| Mean | 34.3529 | 0.0431 | 0.1667 |
| Standard | 19.5378 | 0.0214 | 0.0052 |

The output of the simulation is Mean Epoch, Mean Error, Mean Weight, Standard Epoch, Standard Error and Standard Weight values as represent in table 3. Where, Epoch represent time. Mean error represent average error of overall simulation signal values and Calculating variance of signal from mean value. After that, calculating standard values of Epoch, Error and Weight, which shows optimum value within one standard deviation of the mean. This process would be applied for finding mean and standard value of Epoch, Error and Weight. Mean error represent average of all error in a vector or set, which is used for measuring accuracy of system. Weight represents balance between exploration and exploitation. In which, overall mean weight is 0.1667 and standard weight is 0.0052.

V. CONCLUSION

In the 5G LTE wireless environment, QoS is important criteria for Network Selection and Spectrum sharing is the key solution to deal with the problem of spectrum scarcity. In this paper, we have proposed the network selection problem and fast delivery handover route in 5G LTE networks based on the PSO and machine learning neural network. The simulation results also shows the better performance in less no of iteration to optimize fitness value and decision weight, in terms of RSSI, Loss, bandwidth, Speed, crossover rate and cost to Network Selection and Fast Delivery Handover Route. As future works, we consider the fusion of the two interleaved tasks (inner PSO and outer PSO) in a single PSO searching for weights and architectures as a truly simultaneous optimization process.

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