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Resource Allocation Using Particle Swarm Optimization (PSO) in Wireless Networks

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***Abstract* - Device-to-device (D2D) communications as underlays of cellular networks facilitate diverse local services and reduce base station traffic. However, D2D communication may cause interference with the primary cellular network. To avoid this problem, the network should flexibly allocate its resources and select a proper mode for users. Here, we formulate a joint mode selection and resource allocation problem to maximize the system throughput with a minimum required rate guarantee. A mode selection and resource allocation scheme based on particle swarm optimization (PSO) is proposed in which solutions are mapped onto particles and a fitness function embodies the constraints in a penalty function. Simulation results show its superiority over other schemes in terms of throughput and minimum required rate guarantee. This paper considers the design of optimal resource allocation policies in wireless communication systems which are generically modelled as a functional optimization problem with stochastic constraints. These optimization problems have the structure of a learning problem in which the statistical loss appears as a constraint, motivating the development of learning methodologies to attempt their solution. To handle stochastic constraints, training is undertaken in the dual domain. It is shown that this can be done with small loss of optimality when using near-universal learning parameterizations. In particular, since deep neural networks PSO and DNN are near-universal their use is advocated and explored. PSO are trained here with a model-free primal-dual method that simultaneously learns a PSO parameterization of the resource allocation policy and optimizes the primal and dual variables. Numerical simulations demonstrate the strong performance of the proposed approach on a number of common wireless resource allocation problems. The proposed system developed on MATLAB 2015b version.**

***Index Terms* – particle swarm optimization (PSO), DNN, Prime dual learning, Device-to-device (D2D) etc**.

I. INTRODUCTION

A Key consequence of the growth in video traffic is the competition for bandwidth to provide quality wireless support to video streaming. Compression techniques reduce the data rate required for video transmission. The time-varying nature of the wireless channel is supported by scalable video coding (SVC), which supports various quality levels linked to the available data rate. Within a video sequence, packet prioritization schemes exploit SVC using the encoding information to determine the relative importance of a packet in the com□pressed video and thus the order of packet transmission [1], [2]. In a similar way, the draft IEEE 802.11aa standard (MAC enhancements for robust audio/video streaming) [3] proposes to support graceful degradation of quality under deteriorating channel conditions by using packet drop precedence. However, to determine the rate allocation for multiple video scheduling, a means to differentiate between video sequences is required. The relationship between transmission data rate and video quality is well described by the distortion-rate (DR) model proposed in [4]. The higher the rate for which the audio/video is compressed, the lower the distortion of the material. This fits with the concept of utility representing the satisfaction of the user. The higher the rate at which the video can be transmitted, the better the quality perceived by the user and hence the higher the utility for the user. The DR curve depends on the characteristics of the video sequence. The difference in the DR curve between videos means that increasing the rate allocated to one video will not generate the same quality improvement as increasing another video's rate by the same amount. In the video resource allocation problem, Network Utility Maximization (NUM) allocates the resource to devices in order to maximize the video quality across the network devices. Solutions to the

NUM problem are the focus of much research. One seminal paper on the subject is [5] in which a Lagrangian dual algorithm solution is presented for a fair and stable rate allocation in the communication network. In [6] a Nash Bargaining Solution (NBS) is described, in which players cooperate to reach a fair allocation of resources. Each player has a minimum resource acceptable to it, known as the disagreement point. With the emergence of high-data-rate local services, IMT□Advanced systems will allow Device to Device (D2D) communication as an underlay of a cellular network. [11] In D2D communication underlying a cellular network, the network needs to determine whether communications between two devices that are close to each other should take place via the direct D2D link (D2D mode) or via the base station (cellular mode). Doppler et al. in [2] proposed a mode selection method for D2D communications. This method, however, uses a fixed subchannel allocation and fixes the transmission powers of the base station (BS) and user equipment (UE) in each subchannel without considering frequency selective fading. Consequently, its resource allocation does not take advantage of the multiuser diversity in OFDMA networks. To utilize the multiuser diversity gain in different subchannels, the network has to consider a scheme for sharing resources between cellular users and D2D users. Such a scheme poses challenges. One type of scheme dedicates a certain amount of resources to D2D users. In particular, Oeng et al. [3] presented a joint mode selection and resource allocation algorithm for cellular controlled short-range communication in OFDMA networks where D2D users share an orthogonal resource with cellular users. This scheme assigns dedicated resources to D2D users. Although there is no possibility of interference in it, it effectively requires more resources to accommodate D2D users and limits the system throughput. The other type of scheme enables D2D users to reuse the resources of cellular communications. It, however, faces the problem of interference, and it needs to maintain the target performance level of the cellular network. This resource reuse problem is addressed in [4] and [5], but both studies are limited to one D2D pair reusing all of the subchannels allocated to one or more cellular users. Marco et al. [6] proposed a more flexible resource reuse scheme incorporating mode selection and power allocation. It minimizes the overall power consumption, but not maximizes the system throughput. To the best of our knowledge, the prior studies do not deal with joint mode selection and resource allocation by which D2D communications reuse cellular resources flexibly while maximizing the system throughput. We undertook such a study, and here, we present a mode selection and resource allocation scheme based on particle swarm optimization (PSO□MSRA) to maximize the system throughput while guaranteeing the minimum rate requirements of all users.

The organizational framework of this study divides the research work in the different sections. The System model for resource allocation is presented in section 2. Further, in section 3 shown Concept of Resource allocation and Methodology is discussed in section 4 and In section 5, Simulation Results work is shown. Conclusion and future work are presented by last sections 6.

II. System Model And Problem Formulation

Let us consider the downlink transmission of a D2D underlay OFDMA network in a single cell having N sub channels and a set C of cellular users and a set D of D2D pairs uniformly labelled with k = 1, 2, .. " K , where K equals |C| + |D|. The system model is illustrated in Fig. 1, where D2D communications reuse the downlink resources of cellular network. We assume that each device is equipped with another transmitter module and that the BS can get knowledge about the channel states information of all the involved links in order to select a suitable mode and allocate resources flexibly to maximize the network throughput.

According to the underlying D2D infrastructure, there are two possible transmission modes, i.e., q = 0 (cellular mode), where a given user communicates with the serving BS, and q = I (D2D mode), where a D2D pair communicates via the direct D2D link. Obviously, for cellular users, q is by definition always 0, while for D2D pairs, q = 0 or q = 1. Let us define the binary variable xk:$_{n}^{q}$ as the mode selection and sub channel assignment indicator, with the value I if user k is assigned sub channel n with mode q and 0 otherwise.

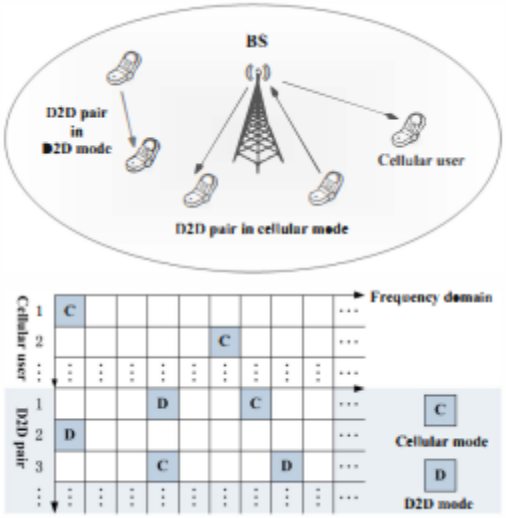

Fig.1: System Model

If a D2D pair chooses D2D mode, it can either get an exclusive assignment of sub channels or reuse sub channels assigned to users in cellular mode (which will cause interference). Let I k, n be the interference experienced at cellular user k or the receiver of the D2D pair k in sub channel n, and 1 BSn be the received interference power in sub channel n at the BS. If a sub channel is assigned to a D2D pair in D2D mode and a cellular user, the interference from the D2D transmitter on the cellular user and from BS on the D2D receiver will be reduced. When D2D pair k in D2D mode reuses subchannel n assigned to another D2D pair in cellular mode, the receiver of D2D pair k may suffer interference from the BS or the transmitter of the D2D pair in cellular mode.

Here Ik, n takes the maximum of the above two possible interference levels.

Denoting the transmission power allocated to user k in sub channel n at the BS by Pk. of the transmitter of D2D pair k in sub channel n by P::n , the transmission rate of D2D pair k in mode I in sub channel n can be expressed as

$$r_{k,n}^{(1)} = B\log(1+P_{k,n}^{D}G_{k,n}^{D}/(P_n+I_{k,n})) \qquad k \in \mathbf{D}$$

III. System Model

The system in this work is a wireless video network operating with a TDMA (Time-Division Multiple-Access) MAC (Medium Access Control) protocol. This is a common multiple access approach employed in various wireless protocols (e.g. IEEE 802.16e, 802.11e and 802.15.3c) in order to achieve the required QoS of low-latency, high data rate applications. A central entity controls medium access allocating time-slots based on device requests. Due to the individual time-slot allocation, a device has sole access to the medium to transmit its data thus avoiding contention from competing devices in the vicinity. Interference caused by simultaneous transmission can therefore be neglected. Each device in our wireless network has a video to transmit to one other device in the network. The resource allocation algorithm runs at the central point of the network, which we will refer to as the Access Point (AP). Each device transmits its video sequence parameters (θ, R0, D0) to the AP, the algorithm is executed and a rate allocation for each transmitting device is produced. Based on this rate, the AP assigns a portion of the available MAC super frame to each transmitting device and broadcasts this allocation. The device then compresses the video at the advised rate for transmission in the allocated time slot. It is assumed that the wireless devices in the network have the resource required to encode the stored video prior to transmission. It is further assumed that the system experiences ”ideal” network conditions such that there is no channel loss.

IV. Methodology

PSO is a stochastic, population-based optimization algorithm, which has good performance, low computational cost and easy implementation. In PSO, a number of individuals (particles) in a swarm move around in the search space and look for the optima. The position of each particle represents a candidate solution to an optimization problem, and a fitness function is defined to evaluate the quality of the solutions. Every particle memorizes the historical personal best position and global best position discovered so far in order to guide them to the best solution after several iterations.

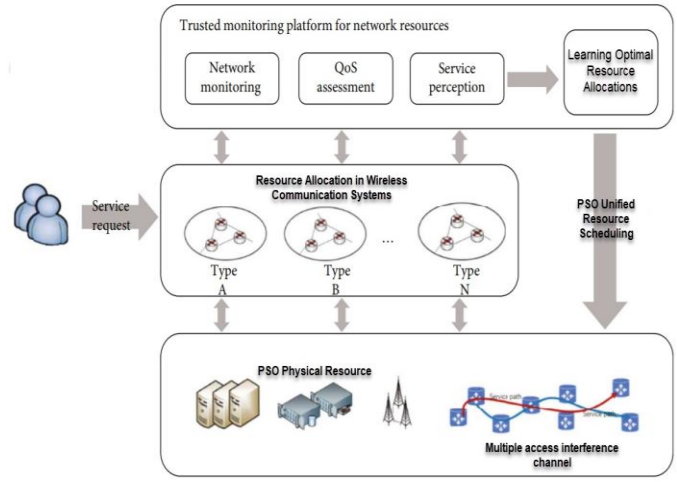

Fig. 2: Proposed Block Diagram

The particle swarm optimization concept is based on the swarm movement of birds and fish, for example when they search for food. In the implementation of PSO, each individual is represented by a volume-less particle in an n-dimensional search space. Each particle moves in the search space with a velocity, which is dynamically adjusted according to its experience and that of its companions.

At each iteration, each particle’s velocity, Vi , and position, Ri , is updated according to the following equations:

$$V_i^{t+1} = \omega V_i^t + c_1 r_1 (Pbest_i^t - R_i^t) + c_2 r_2 (Gbest_i^t - R_i^t)$$
$$R_i^{t+1} = R_i^t + V_i^{t+1}$$

Where t is the iteration number, ω is inertia weight factor, c1 and c2 are acceleration constants, and r1 and r2 are uniform random numbers. P best is the individual best position of a particle. Gbest is the position of the best particle in the search space. A particle keeps track of its coordinates in the search space and aims to reach Gbest. The best solution is determined by the value of the fitness function, which is calculated at each iteration. In the resource allocation problem (5), the fitness function is the utility function to be minimized. To accommodate the constraint of PND i=1 Ri ≤ C, a penalty or cost for violating the capacity constraint is built into the fitness function as follows:

$$F = \begin{cases} \sum_{i=1}^{ND} U_i(R_i) & \text{if} \sum_{i=1}^{ND} R_i \le C, \\ \sum_{i=1}^{ND} U_i(R_i) & \\ \quad -\lambda\left(C - \sum_{i=1}^{ND} R_i\right) & otherwise, \end{cases}$$

where the penalty value, λ > 0. The similarity to the Lagrangian and the use of Lagrangian multipliers/prices [5] can be noted. However, the concept of updating the dual variables to converge to the dual optimal in the Lagrange problem is replaced by use of the swarm in PSO. The solution to the resource allocation PSO is a vector of rates, the size of which is equal to the number of transmitting devices in the

network. The constraint RLi ≤ Ri ≤ RHi is accommodated by bounding the search space in each dimension with the upper and lower rate limits of each device.

A. Setting PSO Parameters for Resource Allocation

One major criticism of PSO is the issue of premature convergence causing the algorithm to reach a local minimum rather than the global minimum objective. An overview of the proposed means to avoid premature convergence is presented in [14]. The methods focus on exploiting individual ability by use of P besti and Gbest and controlling exploration of the swarm in the search space. The parameters in (6) perform this function. c1 and c2 are learning rates representing the weight of memory of a particle's best position towards the memory of the swarm best position. ω is the inertia weight, controlling the contribution of the previous velocity to the velocity update. In [15], an implementation of the Nelder-Mead algorithm as a local search technique around the best solution found by PSO is demonstrated to decrease convergence time of the solution. Experimenting with these methods revealed that the following settings had a positive effect on the performance of the PSO for our resource allocation problem:

Bounding the particles at initialization to meet the capacity constraint in (4). This means that if a random particle is generated, the sum of which dimensions is larger than the capacity of the network, then the particle is rejected and another random particle is generated. • Velocity clamping, which is an alternative to adapting the inertia weight? This limits the speed of movement of the particle with respect to Gbest. • Implementing the Nelder-Mead (NM) method at each iteration of the PSO to improve the current Gbest thus reducing the number of PSO iterations required. NM is a non-linear optimization algorithm for minimizing an objective function in a multi-dimensional space [13]. Due to space Limitations, the steps of the Nelder Mead algorithm are not detailed here. The interested reader is referred to [13].

Based on the results of our experiments, it has been determined to set swarm size = 40, c1 = c2 = 2, ω = 1, [V min, V max]=[−100, 100] and to exploit the Nelder-Mead algorithm to increase the rate of convergence. In the next Section, the results of PSO with NM applied to HD video transmission are discussed.

V. SIMULATION RESULTS

The simulation results simulated using MATLAB 2015b Version.

A. EXISTING SYSTEM

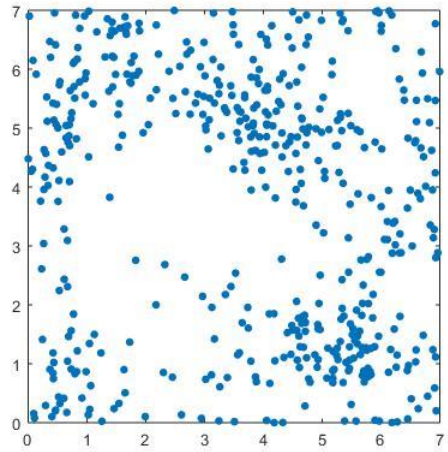

Fig. 3: Showing area Distribution

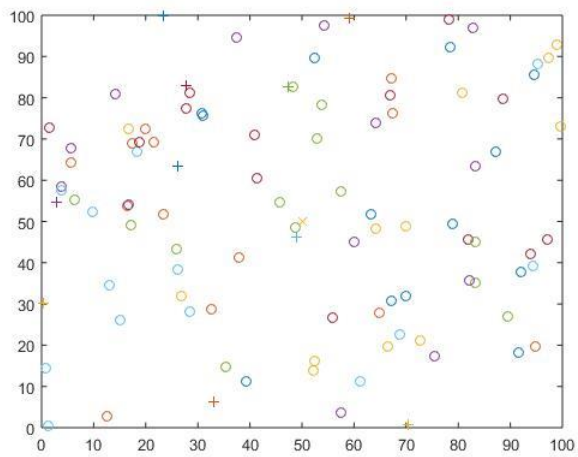

Fig. 4: Achievable data transmission rate for the proposed hybrid block diagonalization model

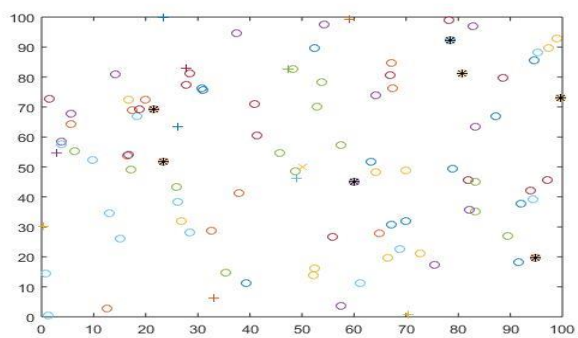

Fig. 5: The simulated Q-value update under learning based D2D matching algorithm over mmWave m-MIMO based 5G mobile wireless networks

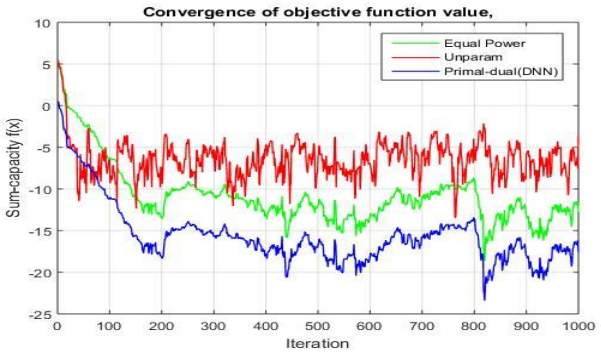

Fig. 6: Convergence of objective function value using DNN method with policy gradients, the exact un parameterized solution, and an equal power allocation amongst users. The DNN parameterization obtains near-optimal performance relative to the exact solution and outperforms the equal power allocation heuristic.

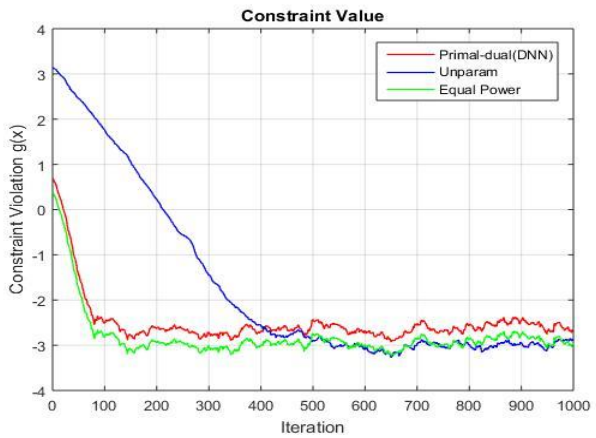

Fig. 7: constraint value using DNN method with policy gradients, the exact un parameterized solution, and an equal power allocation amongst users. The DNN parameterization obtains near-optimal performance relative to the exact solution and outperforms the equal power allocation heuristic.

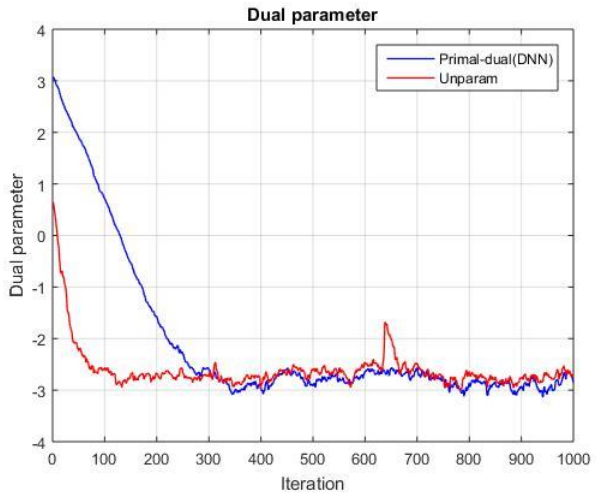

Fig. 8: dual parameter for simple capacity using DNN method with policy gradients, the exact un parameterized solution, and an equal power allocation amongst users. The DNN parameterization obtains near-optimal performance relative to the exact solution and outperforms the equal power allocation heuristic.

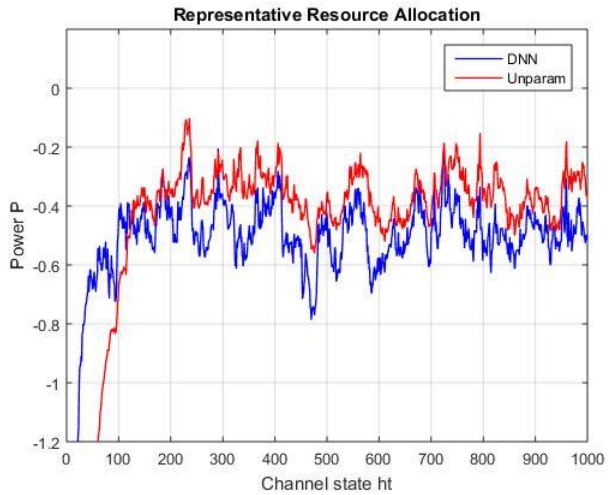

Fig. 9: Example 1 representative resource allocation policy functions found through DNN parameterization and un parameterized solution. Although the policies differ from the analytic solution, many contain similar shapes. Overall, the DNN method learns variations on the optimal policies that nonetheless achieve similar performance.

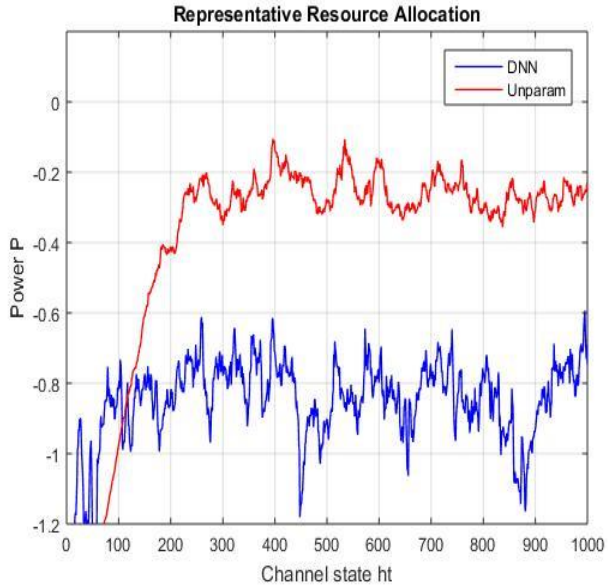

Fig. 10: Example 2 representative resource allocation policy functions found through DNN parameterization and unparameterized solution. Although the policies differ from the analytic solution, many contain similar shapes. Overall, the DNN method learns variations on the optimal policies that nonetheless achieve similar performance

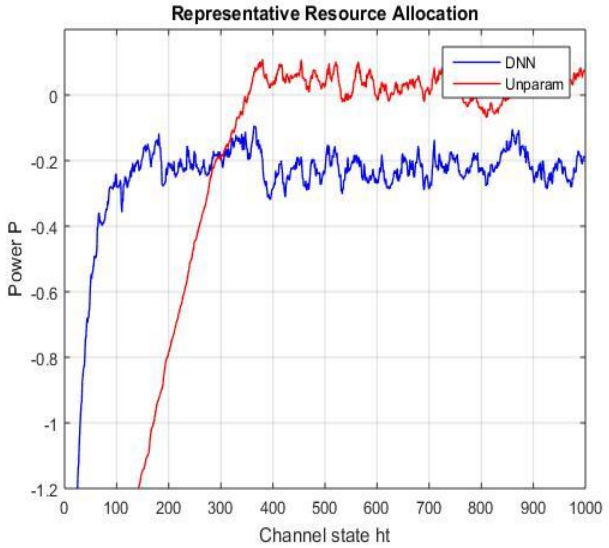

Fig. 11: Example 3 representative resource allocation policy functions found through DNN parameterization and un parameterized solution. Although the policies differ from the analytic solution, many contain similar shapes. Overall, the DNN method learns variations on the optimal policies that nonetheless achieve similar performance

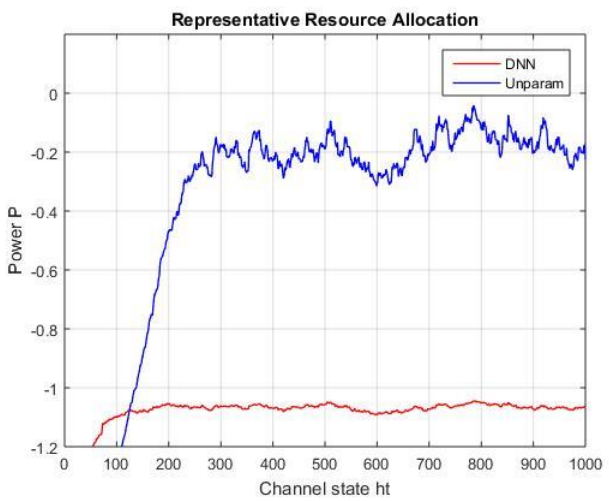

Fig. 12: Example 4 representative resource allocation policy functions found through DNN parameterization and un parameterized solution. Although the policies differ from the analytic solution, many contain similar shapes. Overall, the DNN method learns variations on the optimal policies that nonetheless achieve similar performance.

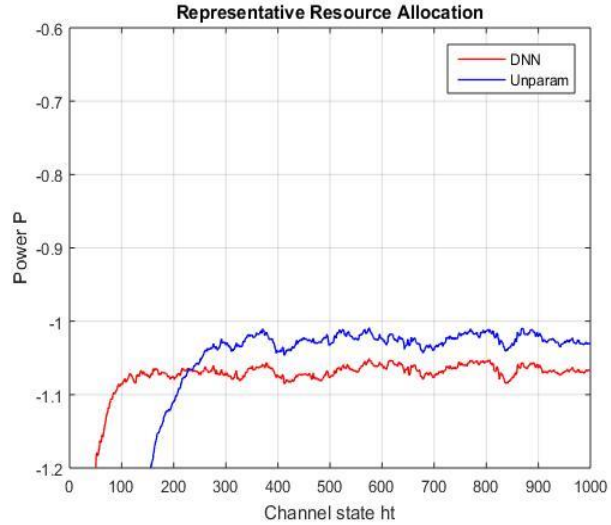

Fig. 13: Example 5 representative resource allocation policy functions found through DNN parameterization and un parameterized solution. Although the policies differ from the analytic solution, many contain similar shapes. Overall, the DNN method learns variations on the optimal policies that nonetheless achieve similar performance

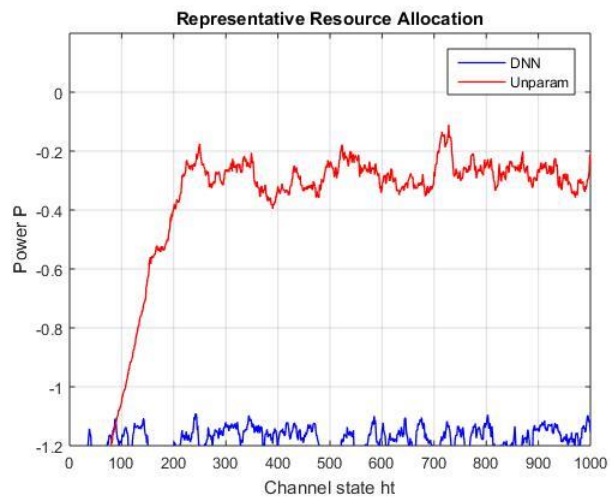

Fig. 14: Example 6 representative resource allocation policy functions found through DNN parameterization and un parameterized solution. Although the policies differ from the analytic solution, many contain similar shapes. Overall, the DNN method learns variations on the optimal policies that nonetheless achieve similar performance.

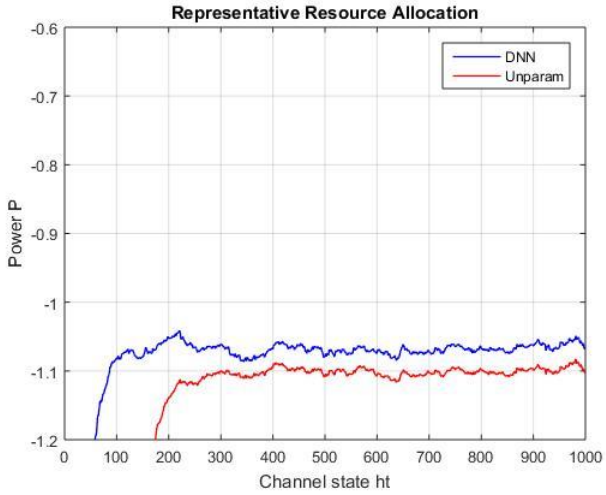

Fig. 15: Example 7 representative resource allocation policy functions found through DNN parameterization and un parameterized solution. Although the policies differ from the analytic solution, many contain similar shapes. Overall, the DNN method learns variations on the optimal policies that nonetheless achieve similar performance

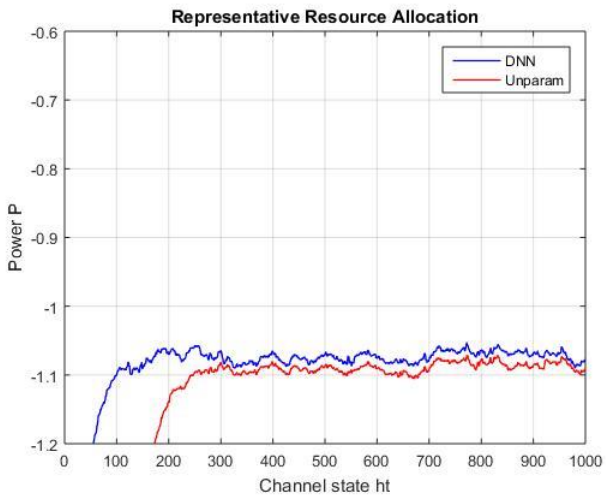

Fig. 16: Example 8 representative resource allocation policy functions found through DNN parameterization and un parameterized solution. Although the policies differ from the analytic solution, many contain similar shapes. Overall, the DNN method learns variations on the optimal policies that nonetheless achieve similar performance

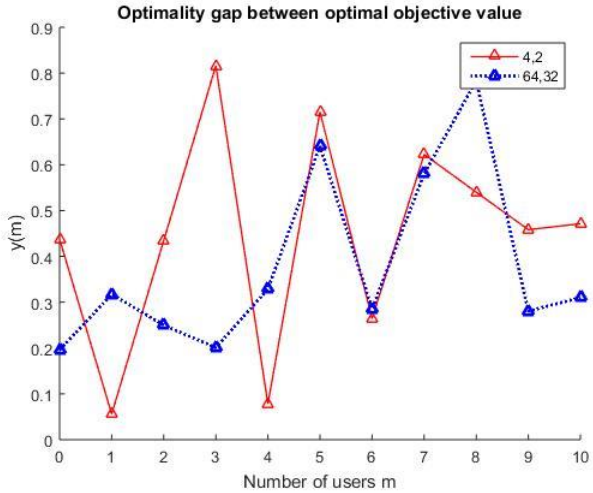

Fig. 17: Optimality gap between optimal objective value and learned policy for the simple capacity problem for different number of users m and DNN architectures. The results are obtained across 10 randomly initialized simulations. The mean is plotted as the solid lines, while the one standard deviation above and below the mean is show with error bars.

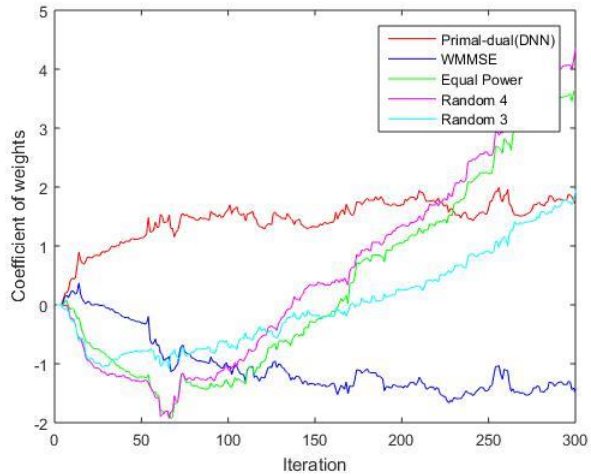

Fig. 18: Convergence of objective function value for interference capacity problem using DNN method, WMMSE, and simple model free heuristic power allocation strategies m = 20 users. The DNN-based primal dual method learns a policy that achieves close performance to WMMSE, better performance than the other model free heuristics, and moreover converges to a feasible solution.

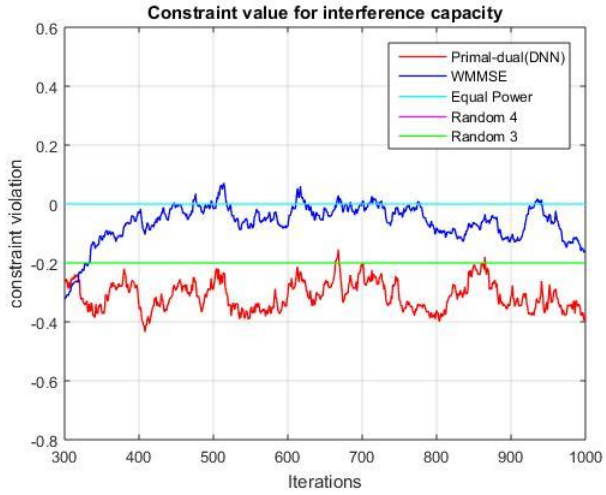

Fig. 19: constraint value for interference capacity problem using DNN method, WMMSE, and simple model free heuristic power allocation strategies m = 20 users. The DNN-based primal dual method learns a policy that achieves close performance to WMMSE, better performance than the other model free heuristics, and moreover converges to a feasible solution.

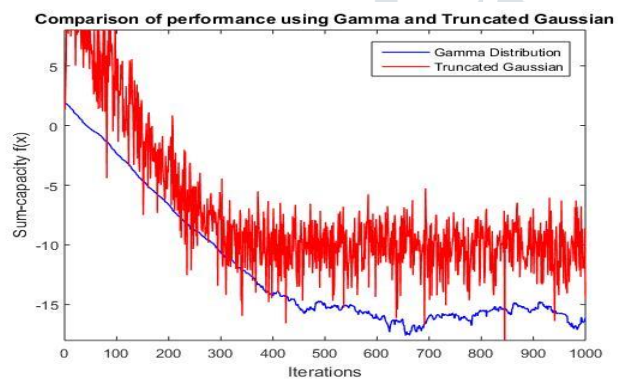

Fig. 20: Comparison of performance using Gamma and truncated Gaussian distributions in output layer of a DNN.

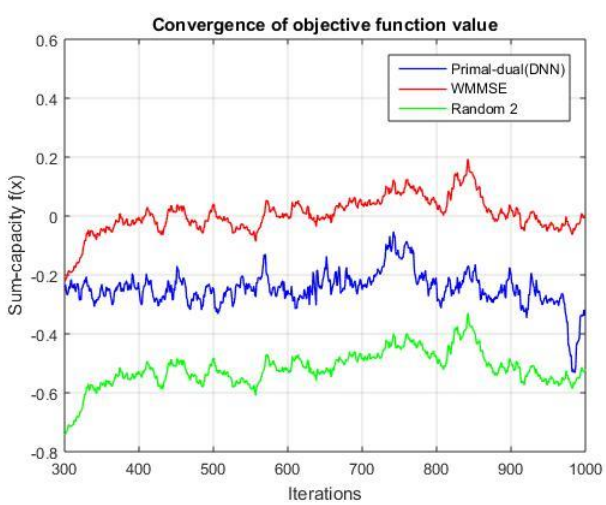

Fig.21: Converegence of objective function value verses sum-capacity

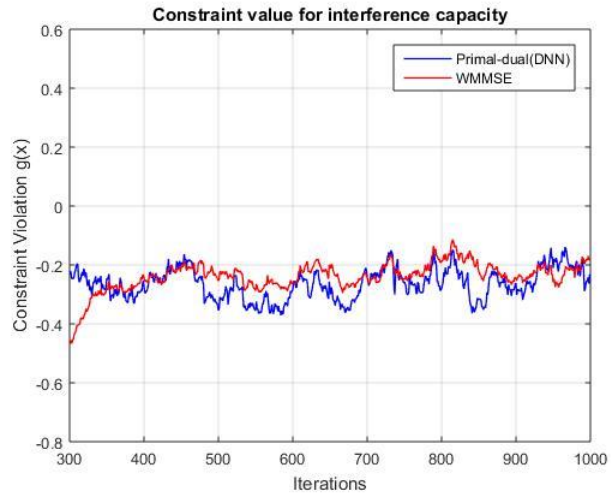

Fig.22: Constraint value for interference capcity and constraint validation

B. PROPOSED SYSTEM

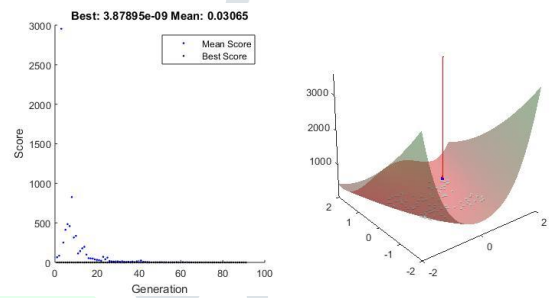

Fig. 23: Area distribution based PSO technology

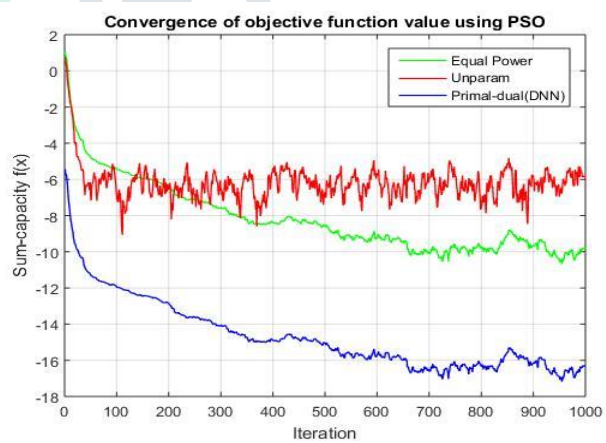

Fig. 24: Based on PSO method Convergence of objective function value using DNN method with policy gradients, the exact un parameterized solution, and an equal power allocation amongst users

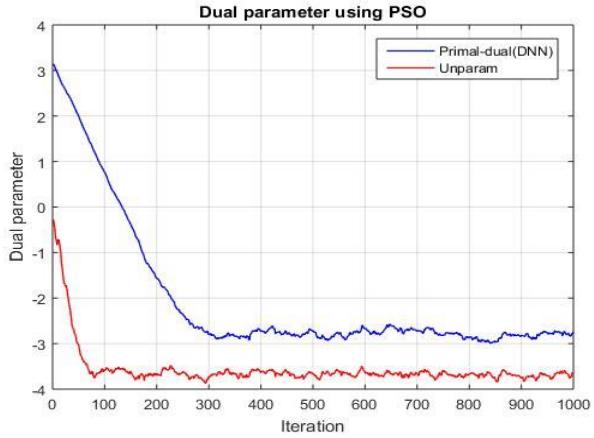

Fig. 25: Using PSO dual parameter for simple capacity on DNN method with policy gradients, the exact un parameterized solution, and an equal power allocation amongst users. The DNN parameterization obtains near-optimal performance relative to the exact solution and outperforms the equal power allocation heuristic.

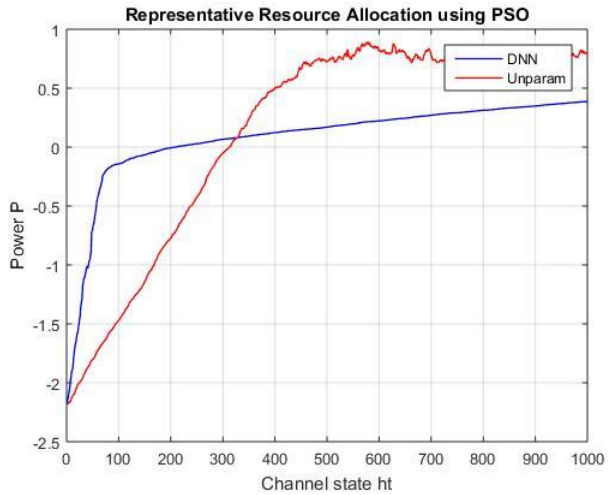

Fig. 27: Example 2 based on PSO representative resource allocation policy functions found through DNN parameterization and un parameterized solution. Although the policies differ from the analytic solution, many contain similar shapes. Overall, the DNN method learns variations on the optimal policies that nonetheless achieve similar performance.

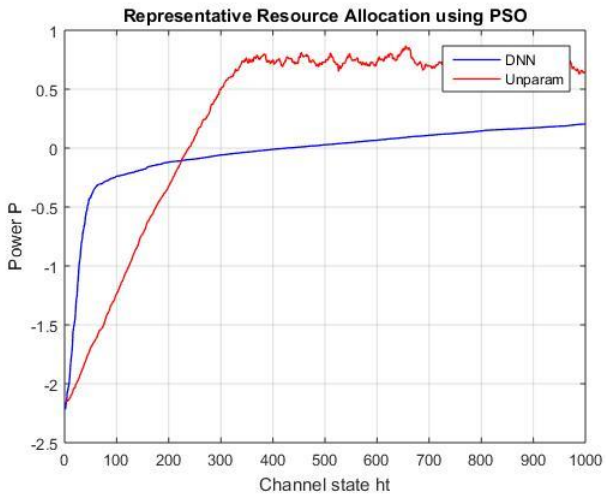

Fig. 26: example 1 based on PSO representative resource allocation policy functions found through DNN parameterization and un parameterized solution. Although the policies differ from the analytic solution, many contain similar shapes. Overall, the DNN method learns variations on the optimal policies that nonetheless achieve similar performance.

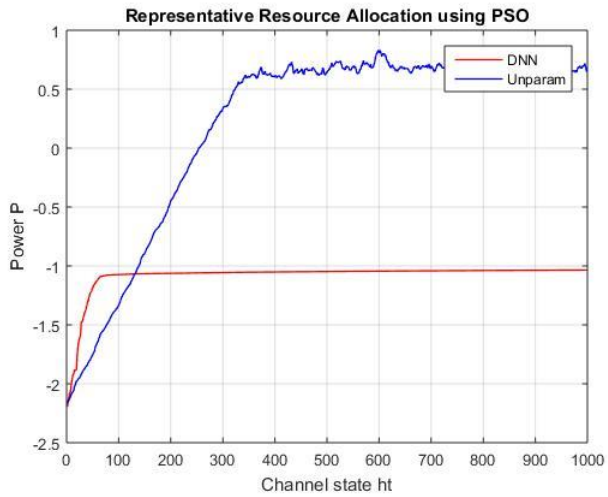

Fig. 28: Example 3 based on PSO representative resource allocation policy functions found through DNN parameterization and un parameterized solution. Although the policies differ from the analytic solution, many contain similar shapes. Overall, the DNN method learns variations on the optimal policies that nonetheless achieve similar performance.

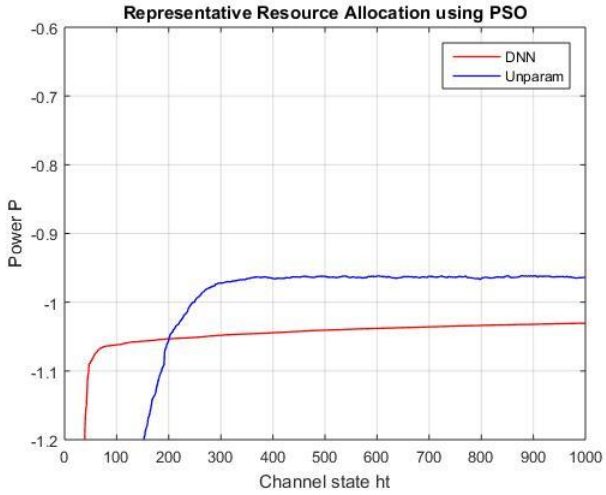

Fig.29: Example 4 based on PSO representative resource allocation policy functions found through DNN parameterization and un parameterized solution. Although the policies differ from the analytic solution, many contain similar shapes. Overall, the DNN method learns variations on the optimal policies that nonetheless achieve similar performance

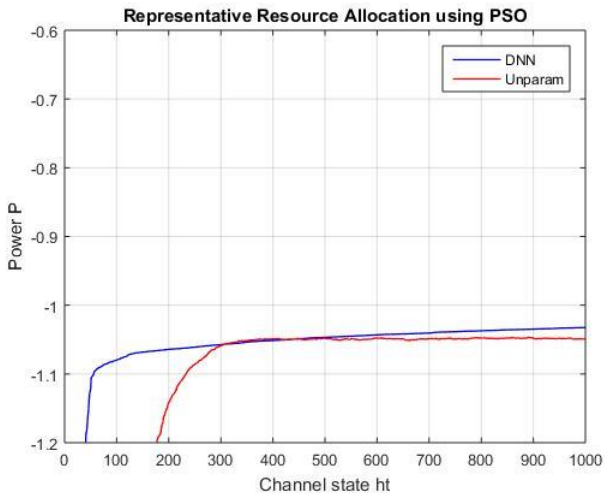

Fig. 30: Example 5 based on PSO representative resource allocation policy functions found through DNN parameterization and un parameterized solution. Although the policies differ from the analytic solution, many contain similar shapes. Overall, the DNN method learns variations on the optimal policies that nonetheless achieve similar performance

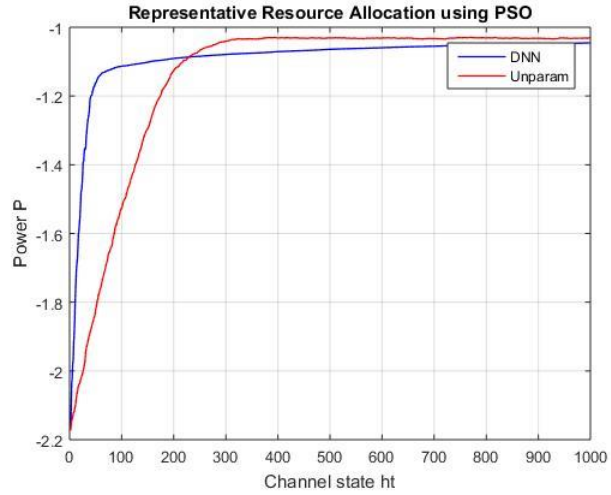

Fig. 31: Example 2 based on PSO representative resource allocation policy functions found through DNN parameterization and un parameterized solution. Although the policies differ from the analytic solution, many contain similar shapes. Overall, the DNN method learns variations on the optimal policies that nonetheless achieve similar performance

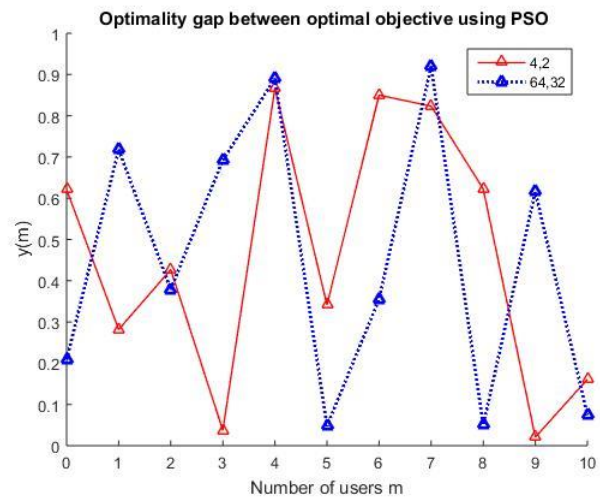

Fig. 32: using PSO Optimality gap between optimal objective value and learned policy for the simple capacity problem for different number of users m and DNN architectures. The results are obtained across 10 randomly initialized simulations. The mean is plotted as the solid lines, while the one standard deviation above and below the mean is show with error bars.

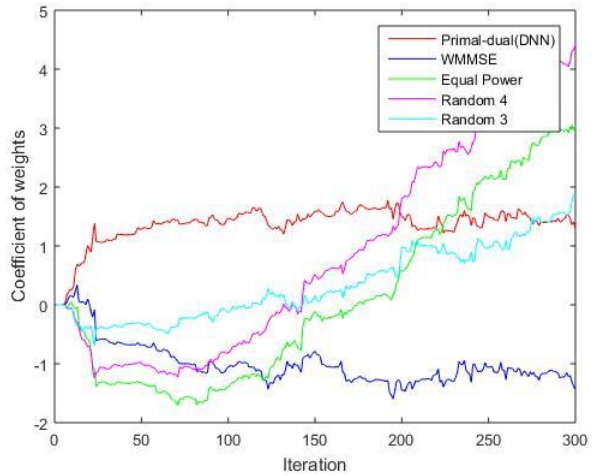

Fig .33: Convergence of objective function value for interference capacity problem using DNN method, WMMSE, and simple model free heuristic power allocation strategies m = 20 users. The PSO based primal dual method learns a policy that achieves close performance to WMMSE, better performance than the other model free heuristics, and moreover converges to a feasible solution.

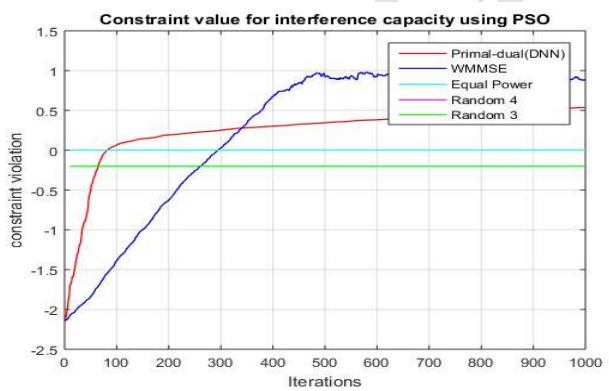

Fig. 34: constraint value for interference capacity problem using DNN method, WMMSE, and simple model free heuristic power allocation strategies m = 20 users. The PSO-based primal dual method learns a policy that achieves close performance to WMMSE, better performance than the other model free heuristics, and moreover converges to a feasible solution.

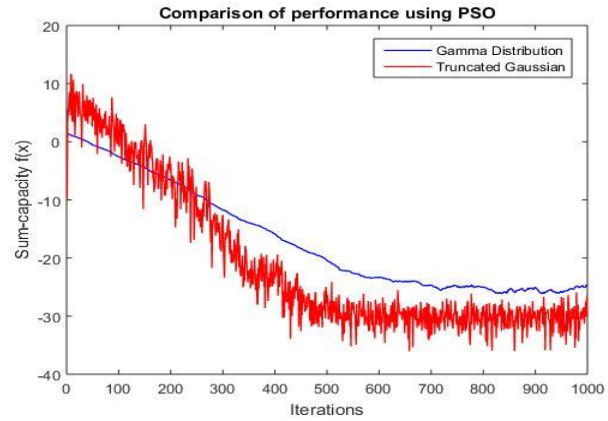

Fig. 35: Comparison of performance using Gamma and truncated Gaussian distributions in output layer using PSO

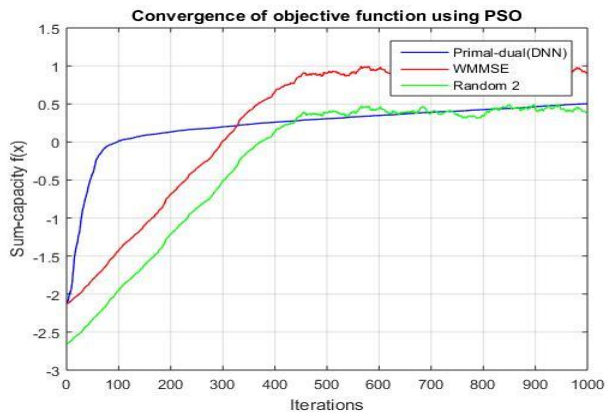

Fig. 36: Convergence of objective function value for interference capacity

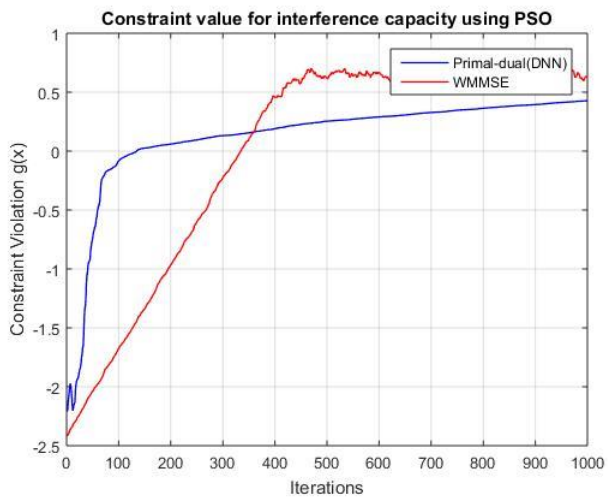

Fig. 37: constraint value for interference capacity using PSO

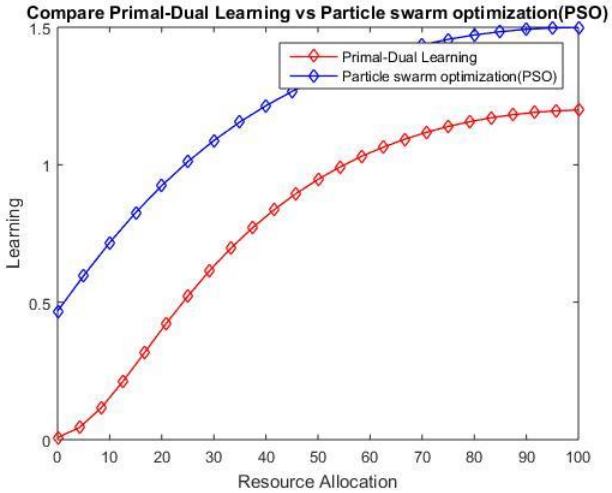

Fig. 38: Compare primal –Dual Learning Vs PSO

VI. CONCLUSION

In this paper we have studied the implementation of particle swarm optimization for solution of the resource allocation problem in multimedia wireless networks. It has been shown that the PSO method can be enhanced in this scenario by introducing the Novel algorithm as a local optimizer at each iteration of the PSO.

The PSO maximizes the system throughput under a minimum required rate guarantee for D2D communication underlay of cellular networks in which the D2D communications can reuse resources of cellular communications flexibly. The method uses a particle representation to map solutions onto particles and establishes a fitness function after handling constraints using penalty function. Simulation results show that PSO outperforms other schemes in terms of throughput and minimum required rate guarantee.

Future Scope

In future scope Resource allocation can be carried out with imperfect CSI conditions. Multiple cell wireless environments can be considered instead of single cell system. But adjacent channel interference becomes a problem. The interference due to adjacent cells has to be considered. Several scheduling concepts can be combined with resource allocation to improve the performance of the system. Moreover, the bit error rate performances for the single layer and cross layer strategies are demonstrated for the PSO-aided adaptive MCCC technique. Application of the proposed generalized PSO model to other communication techniques and scenarios are subject to further investigation.

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