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Channel Time Allocation PSO for Gigabit Multimedia Wireless Networks

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Abstract—This article introduces a resource allocation solution capable of handling mixed media applications within the constraints of a 60 GHz wireless network. The challenges of multimedia wireless transmission include high bandwidth requirements, delay intolerance and wireless channel availability. A new Channel Time Allocation Particle Swarm Optimization (CTA-PSO) is proposed to solve the network utility maximization (NUM) resource allocation problem. CTA-PSO optimizes the time allocated to each device in the network in order to maximize the Quality of Service (QoS) experienced by each user. CTA-PSO introduces network-linked swarm size, an increased diversity function and a learning method based on the personal best, Pbest, results of the swarm. These additional developments to the PSO produce improved convergence speed with respect to Adaptive PSO while maintaining the QoS improvement of the NUM. Specifically, CTA-PSO supports applications described by both convex and non-convex utility functions. The multimedia resource allocation solution presented in this article provides a practical solution for real-time wireless networks.

Index Terms—Particle Swarm Optimization, Resource Allocation, Multimedia, Wireless Personal Area Networks.

I. INTRODUCTION

A RECURRENT theme in recent industry reports [1], [2] is the identification of high volumes of video traffic in both fixed and mobile networks and the projection of further growth in this trend. Two specific statistics from [1] highlight the importance of gigabit multimedia systems: (1) The sum of all forms of video is projected to be approximately 86% of global consumer traffic by 2016 and (2) High Definition Internet Video will comprise 79% of Video-on-Demand by 2016.

A problem therefore arises with respect to resource allocation particularly in the context of future wireless networks. The increasing bandwidth demand conflicts with the limited bandwidth available in wireless networks. The problem analyzed in this work is the issue of allocation of wireless resource within a multi-user, mixed application network. A well established approach to the allocation of wireless resource within a multi-user network is network utility maximization (NUM). With NUM, a utility function represents how a specific application perceives quality according to the amount of allocated resource.

In the study of NUM and resource allocation solutions, the focus has predominantly been on the presentation of traffic types as convex functions such that convex optimization techniques can be applied. However, multimedia applications such as Video-on-Demand (VoD), Voice over Internet Protocol (VoIP) and Internet Protocol Television (IPTV) have different traffic profiles as presented by Shenker [3]. As such the multimedia resource allocation problem is a non-convex problem.

This research is motivated by the gap in existing studies for a mixed multimedia resource allocation method capable of supporting applications described by non-convex utility functions and suitable for implementation in a practical wireless network. This latter requirement is driven by the fact that the time dedicated to resource allocation detracts from the data transmission time. This is particularly significant for larger network sizes. It is notable that much of the existing research considers small networks of 2-10 devices for which computation time is low and solutions can be efficiently obtained. With larger network sizes, the convergence speed of the algorithm becomes a greater issue due to a high number of required computations. The frequency or interval of the algorithm execution is dictated by the convergence time but also affects the resource allocation as dynamic changes to application or network resource requirements necessitate execution of the optimization algorithm.

Particle Swarm Optimization (PSO) was introduced by Kennedy and Eberhart in 1995 for solving global optimization problems [4]. PSO belongs to a range of evolutionary techniques developed in the past 40 years, which can be employed to solve non-convex problems.

Of the evolutionary algorithms PSO has the appeal of simplicity and evidence of good performance in a variety of application domains. It has been demonstrated to be more computationally efficient than the Genetic Algorithm [5]. In addition, when the benchmark function results of a comparative study of evolutionary algorithms [6] are compared with the same function results of an Adaptive PSO (APSO) [7], it is identified that the solution quality is similar with APSO achieving the best convergence speed. Based on these analyses, PSO is the resource allocation method selected in this work.

A number of contributions are made in this work. The first is the presentation of Channel Time Allocation Particle Swarm Optimization (CTA-PSO). This resource allocation method supports the accurate description of real-time traffic as a non-convex function. Secondly, the method supports simultaneous resource allocation across multiple applications, which removes the constraint of allocating fixed bandwidth to individual services or arbitrary priority setting for particular

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applications. As a result, pre-planning of network resources is not required with CTA-PSO.

CTA-PSO is a cross-layer approach accounting for the Application (APP), MAC and PHY layer requirements/conditions. A comprehensive study of the key elements of the PSO: swarm size, max. velocity setting, penalty function value and stopping criterion has been carried out to find the optimum CTA-PSO settings. The conventional PSO algorithm has been further extended to include two specific algorithms. *Increased Diversity* introduces diversity to the swarm over the course of the PSO in order to avoid convergence at a local maximum. Consideration of the application type has led to introduction of a *Pbest Learning Method*, which reduces the PSO convergence time. The CTA for each device also accounts for the transmission rate on the wireless link ensuring a fair allocation between devices within the optimization.

In order to demonstrate the performance of CTA-PSO, a practical wireless network has been simulated. High Definition video traces are used to present realistic traffic to the system. CTA-PSO is tested on a series of network sizes up to 40 devices challenging the implementation based on the requirement for a fast algorithm execution time.

In Section II, a literature review is provided. The channel time allocation problem is introduced in Section III and the CTA-PSO solution is presented in Section IV. Two new algorithms, which define CTA-PSO are described in Section V. Performance results are presented in Section VI and conclusions are drawn in Section VII.

II. RELATED WORK

Solutions to convex optimization NUM problems are the focus of much research. However, a much smaller area of research is devoted to non-convex optimization problems. In this Section we introduce related work linked to both NUM in which non-convex utility functions are studied, and to PSO-based wireless resource allocation solutions. Predominantly, the limitation with existing work as compared to our solution is the inability to support applications such as real-time video transmission described by non-convex functions. This is coupled with the practical implementation issues of proposed solutions such as long algorithm execution time beyond a small network size (e.g. 2-10 devices).

One of the earliest works to consider inelastic flows is a distributed subgradient method presented by Chiang et al. in [8]. Two alternatives are provided for a mixed flow network. A pricing-based admission control option leads to a long convergence time while the rate allocation alternative requires a limit to be placed on the link capacity allocated to flows of a certain group. Setting a limit on the link capacity allocated to groups of flows requires awareness of the number of flows in a group and the number of groups in the network, all of which changes dynamically. If the allocation to individual groups is not appropriate, it is possible that the network throughput will be sub-optimal. The options in [8] are not considered to be practical for a real-time implementation.

A Nash Bargaining Solution (NBS) is described in [9], in which players cooperate to reach a fair allocation of resources.

Two solution methods are proposed for the NBS using the lagrangian method and semi-definite programming. Although elastic and rate/delay adaptive (inelastic) applications are considered in the study, the sigmoid rate/delay adaptive function is converted to a concave function for the study. Similarly, in [10], [11], the NBS solution is applied to the multimedia resource allocation problem but the use of the Distortion-Rate model [12] presents a convex optimization problem.

In [13], a sum-of-squares method is introduced. This approach has received little consideration in the literature due to its centralized approach. While this is not a drawback for the centralized network implementation of this work, the approach is complex and involves, for example, manipulation of the sigmoid function to produce a polynomial for inclusion in the solution. The direct use of the sigmoid function in CTA-PSO removes this requirement to generate a set of polynomials.

A unified resource allocation and traffic management approach is presented in [14]. For the resource allocation algorithm, independent subproblems are generated from the non-convex problem using the dual decomposition approach. These subproblems are solved using a hybrid PSO-SQP (sequential quadratic programming) method. With the method in [14], an improvement is identified over the standard distributed subgradient algorithm presented in [8]. The main issue with [8], [14] is that although the functions used follow the established elastic, rate-sensitive and delay-sensitive flow classifications, the parameters used in the functions bear no apparent relationship to the described traffic e.g. for elastic traffic $U_i(x_i) = \log(a_i x_i + h_i)$ with $a_i = 15$ and $h_i = 0.6$. No explanation is provided for the settings a_i, h_i .

The PSO method has been applied to resource allocation in wireless networks in a limited capacity [15]–[19]. In [15], a distributed PSO algorithm for video communication in a wireless mesh network is presented. Information is exchanged between local PSO modules introducing control overhead, which absorbs valuable data transmission time and removes the centralized nature of the algorithm. Although the method in [15] describes video transmission, the results are limited by the fact that the application and network parameters are not linked to real system data such as video traffic/traces.

The focus in [16] is joint power and rate allocation. An improved adaptive PSO is introduced based on dynamic velocity updates, improved constraint handling, and distributed stopping criteria. The authors identify a faster convergence to the optimum solution than the original APSO (Adaptive PSO) presented in [7]. However, the utility function for the sources in the network is \log rate, which is generally representative of traditional data services [3] and not multimedia. The traffic characteristics are not considered in the solution.

In [17], PSO is applied to the mixed-integer problem of resource management in a wireless visual sensor network. A basic PSO is implemented with a large number of iterations indicating that the convergence speed of the algorithm has not been considered. PSO is proposed as a solution to video streaming in a wireless network in [18]. The optimization based on minimum queue size and packet delay produces up to 1 dB video quality improvement compared with rate-distortion optimization. However, only 3 devices are considered, which

limits the analysis both with respect to competition for resource and in terms of PSO performance.

PSO is used in [19] to maximize the weighted Quality of Experience (QoE) of competing video sources. QoE is defined in terms of allocated bandwidth and packet error probability. The PSO solution presents improved performance over a congestion optimization approach (bandwidth allocated to optimize network congestion). However, the description of the algorithm execution time is based on 2 competing network devices. As will be illustrated in this work, the larger the network, the longer the convergence time of the PSO algorithm. A further difference between [19] and this work is the CBR traffic used for simulation based on the assumption of non-live video streaming. Non-live video streaming enables on-demand rate adaptation/traffic-shaping to be performed without concern for the time absorbed by such processes.

Each of the works presented in this Section tackle *individual* elements of the wireless multimedia resource allocation problem. In contrast, CTA-PSO, provides a cross-layer solution for allocation of wireless resource within a multi-user, mixed application network.

III. CHANNEL TIME ALLOCATION PROBLEM

The multimedia channel time allocation problem is presented here. The resource allocation problem involves optimizing the time allocated to each network device in order to maximize the Quality of Service (QoS) experienced by each user in the network. Two applications are presented. The first is VoD in which on-demand streams are stored on a server with content transmitted upon request. The second is real-time IPTV for which the video streams are only available at one particular time i.e. when the event is occurring in real time.

A. IPTV Utility Function

In [3] Shenker describes audio/video applications as delay-adaptive and [20] introduces a utility function for IPTV described by the logistic model, as presented in (1).

$$U_i^{iptv}(R_i) = \frac{1}{1 + \left(\frac{1}{\epsilon} - 1\right) e^{xR_i}}, \quad x = \frac{2 \log \left[\frac{1}{\epsilon} - 1\right]}{RH_i} \quad (1)$$

In (1), ϵ denotes the tiny IPTV user utility when allocated bandwidth is at the lower limit, RL_i . The upper and lower limits (RH_i, RL_i respectively) are determined by the application requirements. For example, the lower limit is set by the minimum acceptable quality of the IPTV application and the upper limit is set by the maximum required quality. The IPTV utility function (1) is normalized against the maximum data rate requirement, RH_i , such that the utility lies in the range [0,1]. By normalizing each utility contribution, each device (VoD/IPTV) has an equal weight in the NUM problem.

B. VoD Utility Function

The Distortion Rate (DR) model proposed in [12] describes video transmission. It is widely used in the research community based on the accuracy of the model in approximating the DR performance of the video encoder. It is described in (2).

$$D(R) = \frac{\theta}{R - R_0} + D_0, \quad R \geq R_0, \quad D_0 \geq 0, \quad \theta > 0, \quad (2)$$

where D is the distortion of the video sequence, measured as the Mean Square Error, and R is the data rate for the sequence. θ , R_0 , and D_0 are model parameters related to the characteristics of the individual video sequence.

In order to solve the resource allocation problem for the multimedia network, the video DR model is presented in PSNR form for the maximization problem. The utility function for Video-on-Demand is given in (3).

$$U_i^{vod}(R_i) = 10 \log_{10} \left(\frac{255^2 (R_i - R_0)}{D_0 (R_i - R_0) + \theta} \right) \quad (3)$$

By normalizing (3), the utility range is the same [0,1] for both the IPTV and the VoD application. The VoD utility value is normalized, $NU_i^{vod}(R_i)$, using the formula in (4).

$$NU_i^{vod}(R_i) = \frac{U_i^{vod}(R_i) - U_i^{vod}(RL_i)}{U_i^{vod}(RH_i) - U_i^{vod}(RL_i)} \quad (4)$$

C. Channel Time Allocation NUM Problem

The NUM problem can be described as:

$$\begin{aligned} \text{Maximize} \quad & \sum_{i=1}^{nv} NU_i^{vod}(R_i) + \sum_{j=1}^{nt} U_j^{iptv}(R_j) \\ \text{Subject to} \quad & \sum_{k=1}^N R_k \leq C \quad N = nv + nt \\ & RL_k \leq R_k \leq RH_k \quad \forall k = 1, 2, \dots, N \end{aligned} \quad (5)$$

where N is the total number of devices, nv is the number of VoD devices and nt is the number of IPTV devices. C is the sum capacity of the network.

The NUM problem presented in (5) is a rate allocation problem. This is converted to a channel time allocation problem to enable calculation of the resource allocation at the MAC layer where $CTAP$ is the Channel Time Allocation Period and CL and CH are the lower and upper CTA requirements, respectively. This is representative of a 60 GHz wireless network e.g. IEEE 802.15.3c. It is achieved by introducing the superframe duration and distinguishing between the physical transmission rate on each wireless link based on channel condition. The relationship between the data rate and the CTA is:

$$R_i = \frac{CTA_i * R_{mac_i}}{sf} \quad (6)$$

where sf is the superframe duration and R_{mac_i} is generated based on goodput on the transmission link.

$$R_{mac_i} = \frac{l_{data}(1 - per_i)}{\frac{l_{data}}{C_i} + \frac{l_{ack}}{R_b} + 2\left(\frac{l_{oh}}{R_b} + t_{sifs}\right)} \quad (7)$$

where l_{data} is the frame payload size, per_i is the packet error rate generated from the signal-to-noise ratio (snr_i) on the

link and C_i is the capacity of the mm-Wave channel considering shadow fading in an indoor environment as per [21]. l_{ack} is the acknowledgment frame size, R_b is the basic/control data rate, l_{oh} is the frame overhead and t_{sifs} is the short interframe space duration. The denominator in (7) represents the time to transmit a frame based on the channel capacity and the PHY and MAC layer packetization overhead.

The channel capacity, C_i , is determined from a standard link budget analysis as described in (8-12).

$$C_i = B \log_2[1 + snr_i] \quad (8)$$

$$snr_i = P_R - L_I - N_0 \quad (9)$$

$$N_0 = -174 + 10 \log_{10}[B] + F \quad (10)$$

$$P_R = P_T + G_T + G_R - PL \quad (11)$$

$$PL = A + 20 \log_{10}[f] + 10n \log_{10}[d] \quad (12)$$

where B is the system bandwidth and snr_i is the signal-to-noise ratio (SNR). The SNR is derived from the receive signal power, P_R , the transceiver implementation loss, L_I , and the thermal noise level, N_0 , at a standard temperature of 17°C with the bandwidth B in Hz and the noise figure F . P_T is the transmission power and G_R and G_T are the antenna gain of the receiver and the transmitter respectively. PL is the path loss model for the 60 GHz indoor environment considering shadow fading [21] where f is the carrier frequency in GHz and d is the distance between the transmitter and receiver in metres. A is the attenuation value and n is the path loss exponent.

This determination of the physical layer link quality is used to ensure fair allocation between devices within the optimization i.e. a device transmitting at a lower data rate due to a weaker link will require a longer CTA to achieve the same QoS as that of a device using a better link. Furthermore, it presents a model representative of a typical mm-Wave radio link. The CTA NUM is in (13) with CL_k and CH_k calculated from (6).

$$\begin{aligned} \text{Maximize} \quad & \sum_{i=1}^{nv} NU_i^{vod}(CTA_i) + \sum_{j=1}^{nt} U_j^{iptv}(CTA_j) \\ \text{Subject to} \quad & \sum_{k=1}^N CTA_k \leq CTAP \quad N = nv + nt \\ & CL_k \leq CTA_k \leq CH_k \\ & \forall k = 1, 2, \dots, N \end{aligned} \quad (13)$$

IV. CHANNEL TIME ALLOCATION PARTICLE SWARM OPTIMIZATION (CTA-PSO)

CTA-NUM (13) is a nonconvex optimization problem, which will be solved using PSO. In the application of PSO to the resource allocation problem, the n dimensions of the search space are the number of devices in the wireless network. Each swarm particle is therefore represented by a vector of CTAs, the size of which is equal to the number of transmitting devices in the network. At each iteration, each particle's velocity, V_i , and position, X_i (where X_i is the CTA vector), is updated according to the following equations:

$$V_i^{t+1} = \omega V_i^t + c_1 r_1 (Pbest_i^t - X_i^t) + c_2 r_2 (Gbest_i^t - X_i^t) \quad (14)$$

$$X_i^{t+1} = X_i^t + V_i^{t+1} \quad (15)$$

where t is the iteration number, ω is inertia weight factor, c_1 and c_2 are acceleration constants, and r_1 and r_2 are uniform random numbers. The inertia weight, ω , controls the contribution of the previous velocity to the velocity update. c_1 and c_2 represent the weight of memory of a particle's best position towards the memory of the swarm best position. $Pbest$ 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, F . In the resource allocation problem (13), F is the utility function to be maximized.

The PSO fitness function, F , for the CTA problem is described in (16).

$$\begin{aligned} F &= \sum_{i=1}^N U_i(CTA_i) \quad \text{if } \sum_{i=1}^N CTA_i \leq CTAP, \\ F &= \sum_{i=1}^N U_i(CTA_i) + \gamma \left(CTAP - \sum_{i=1}^N CTA_i \right) \\ & \quad \text{otherwise,} \end{aligned} \quad (16)$$

where the penalty value, $\gamma > 0$. The penalty value accommodates the constraint that the sum time allocated must not exceed the available resource i.e. the $CTAP$.

For the resource allocation problem, PSO has a centralized implementation. A population of n particles is initialized to random positions satisfying the constraints of the CTA bounds on each device. The fitness value of each particle is determined and $Pbest_i$ and $Gbest$ are set. The velocity and position of each particle are iteratively updated until an agreed stopping criteria is met. The channel time allocations are then distributed to the devices in the network.

The main criticism of PSO as compared with other optimization techniques is the length of time required to converge to the optimal solution. This was illustrated in [22]. In order to produce a solution suitable for practical implementation in a wireless network, the convergence time must be reduced while ensuring that the global optimum is reached rather than a local optimum as can happen with premature convergence. To achieve this, $Pbest_i$ and $Gbest$ can be used to control exploration and exploitation in the search space. Exploration refers to the ability of the swarm to explore different regions of the search space in order to locate the global optimum. Exploitation refers to the ability of the particles to concentrate the search around a promising area of the search space in order to refine a potential solution. In order to reach the optimal solution within a reasonable time, the right balance must be achieved between exploring the solution space and refining potential solutions. The parameters of ω , c_1 and c_2 in (15) can also be tuned to aid this process. A number of works have

explored the impact of adapting these PSO parameters [7], [16], [23], [24].

In a comparison of several PSO techniques, Adaptive Particle Swarm Optimization (APSO) [7] emerged as exhibiting superior convergence and utility maximization performance with the fastest execution time. CTA-PSO therefore takes APSO as a basis for further development. A comprehensive study of the key elements of the PSO such as swarm size, maximum velocity setting, penalty function value and stopping criterion has been carried out to determine the optimum settings for CTA-PSO. Due to space limitations, only the results are highlighted here.

1) *Swarm Size*: Swarm population size influences convergence speed of the algorithm based on its contribution to the number of function evaluations required to reach the optimum solution; $FunctionEvaluations = SwarmSize * No.ofIterations$. In the evaluation of a range of swarm sizes (20 – 100 based on analysis of similar problems in the literature) for each network size, it was identified that a network-linked swarm size optimizes the sum utility. The values are proposed in Table I.

TABLE I
ADAPTIVE SWARM SIZE VALUES

Network Devices	Swarm Size	Network Devices	Swarm Size
2 - 10	40	21 - 30	80
11 - 20	60	31 - 40	100

2) *Maximum Velocity*: A V_{max} setting of 10 – 20% of the dynamic range of the variable on each dimension is proposed in [25]. In the CTA problem, V_{max} is linked to the maximum and minimum CTA required; CTA_{max}^d and CTA_{min}^d respectively. The V_{max} value is described by (17). The optimum σ setting is 0.1 or 10%.

$$V_{max}^d = \sigma(CTA_{max}^d - CTA_{min}^d) \quad (17)$$

3) *Penalty Function*: The penalty function setting in CTA-PSO is critical to ensure that the CTAP constraint is never violated. In CTA-NUM, the penalty factor (γ in (16)) is linked to the CTAP sum capacity constraint and the individual CTA limits, CTA_{min} , CTA_{max} . A range of values were tested based on the CTA range [0ms, 15ms]. The penalty factor, $\gamma = 5$ produces the optimum sum utility across a range of CTA-NUM tests.

4) *Stopping Criterion*: The results of a performance comparison of four distribution-based stopping criteria techniques applied to the CTA-NUM problem are presented in Table II. The distribution-based methods use distance measurements to determine the spread of the swarm across the search space. The utility improvement is compared with Δ PSNR results for a fixed limit stopping criterion of 1000 iterations. The value of 1000 has been selected based on the minimal utility improvement observed beyond that point.

The threshold in each method is set to 0.001, which is a conservative value based on analysis of the problem to

TABLE II
STOPPING CRITERIA PERFORMANCE ON CTA-NUM

Method	Mean Utility Improvement	Mean Δ PSNR (dB)	Mean Iterations
<i>StdDev</i>	0.95	0.05	836
<i>StdDevQuick</i> (Best 50%)	0.65	-0.08	465
<i>StdDevQuick</i> (Best 75%)	0.95	0.05	813
<i>MaxDist</i>	0.95	0.05	926
<i>MaxDistQuick</i> (Best 50%)	0.75	0.005	688
<i>MaxDistQuick</i> (Best 75%)	0.83	0.007	831
Fixed Limit	0.96	0.05	1000

ensure that the threshold is not triggered based on convergence around a local maximum. The results in Table II identify that *StdDevQuick* using the best 75% particles in the calculation is the most effective stopping criterion. It maintains the mean Δ PSNR improvement but with the lowest number of iterations.

CTA-PSO is a centralized algorithm executed at the piconet controller (PNC) in the 60 GHz network. To run an application (e.g. video), each device transmits a CTA request to the PNC. The PNC receives the CTA requests and uses the application information (e.g. video DR parameters) along with the physical link data rate to generate CTA bounds for the device. With this information, the max. velocity and penalty function for CTA-PSO are calculated at the PNC. The swarm size is selected from a look-up table in the PNC based on the number of connected devices. The *StdDevQuick* algorithm executes in each iteration of CTA-PSO.

V. CTA-PSO DEVELOPMENT

The objective in this work to produce a solution to the CTA-NUM problem for practical implementation in a wireless network means that even for larger network sizes such as 30/40 devices, the solution must be reached within a tight time-scale to support dynamic resource allocation.

As a result, further developments in addition to the PSO parameter settings presented in the previous Section are introduced to generate the complete CTA-PSO solution. Two specific algorithms are defined; the first, *Increased Diversity*, introduces diversity to the swarm over the course of the PSO in order to avoid convergence at a local maximum; the second, *Pbest Learning Method* exploits learning linked to the traffic in the wireless network in order to reduce the convergence time of the PSO. A network of 40 devices with 50% VoD traffic and 50% IPTV traffic is simulated for the analysis.

A. Increased Diversity

An analysis of APSO in terms of sum utility and distribution of the swarm over the course of the PSO highlighted the relationship between swarm distribution and convergence of the PSO to the global maximum. This relationship is exploited here to ensure convergence to the global maximum, which was not achieved by APSO in our analysis.

An additional measurement is introduced to CTA-PSO to observe swarm performance. This is based on the observation that the similarity of particles in the swarm increases over time as particles move towards $Gbest$. Similarity refers to a particle with almost the same value on every dimension as another particle in the swarm. Simple removal of similar swarm particles does not produce a consistent improvement in convergence speed. As an alternative, swarm diversity has been explored.

Diversity describes the difference or variation in particles across the swarm population. A distinction is made here between similarity, which referred to a pair-wise comparison of differences, and diversity, which refers to variety in the full swarm. The average Hamming distance of a particle from all other particles in the swarm is used to quantify the diversity of the swarm. The pair-wise Hamming distance is the most commonly used measure of population diversity in evolutionary algorithm genotypic space; where genotype refers to the actual particle description. If the diversity of the swarm is low, there is a likelihood that the swarm will converge around a local maximum. The Hamming distance between particle a_i and b_j is

$$H(a_i, b_j) = \sum_{k=1}^D |a_{ik} - b_{jk}| \quad (18)$$

where D is the dimension of the particle. The average Hamming distance is calculated as in (19) where $NPar$ is the swarm size.

$$AH = \frac{\sum_{i=1}^{NPar-1} \sum_{j=i+1}^{NPar} H(a_i, b_j)}{\sum_{i=1}^{NPar-1} (NPar - i)} \quad (19)$$

The diversity of the swarm in the 40 device example based on APSO is illustrated in Fig. 1. It can be seen that the diversity of the population starts high, decreases rapidly over the first 100 iterations and remains low thereafter. This is indicative of a local maximum being explored.

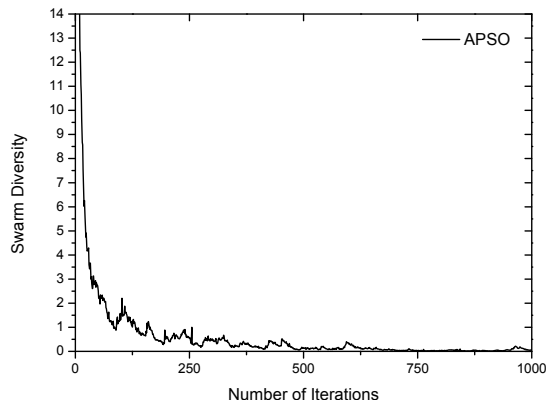


Fig. 1. Swarm Diversity for APSO (40 Devices)

In order to avoid this situation of convergence and stagnation of the swarm at a local maximum, a new function is introduced to the PSO to increase the diversity of the swarm.

At a set interval, the diversity of the swarm is measured using the average Hamming distance measurement (19). To avoid unnecessary computation for this function, the interval (int) is set to 100 iterations. If the diversity in the swarm is below a given threshold, the diversity function is run. Based on experimental observation, the threshold has been set to 1.

The particles are sorted in order of best fitness value based on $Pbest$. The worst 50% of the particles are removed. The reason for keeping the best 50% is to maintain the good knowledge of the swarm. If the swarm is in fact gathering around the global maximum, the convergence progress will not be interrupted. The swarm is then diversified by introducing new particles to make up the 50% that have been removed. These particles are randomly scattered in the search space bounded by the maximum and minimum $Pbest$ fitness values of the original swarm. Constraining the particles to this solution space also takes advantage of the knowledge built up by the swarm in the preceding iterations.

The diversity function is introduced to the 40 device example and the variation in swarm diversity is shown in Fig. 2a. The greater diversity of the population is clear in the earlier iterations with a spike following each implementation of the diversity function. The higher diversity values represent greater exploration by the swarm. With progressive implementations of the function the swarm diversity returns more quickly to the diversity value just prior to the spike. This is apparent in the narrowing of the base of spikes 4 and 5 in Fig. 2a as indicated by the arrows. This represents increasing localization of the swarm exploration and can be considered as confirmation that the global optimum has been found. The swarm then gradually converges, settling to a low diversity value.

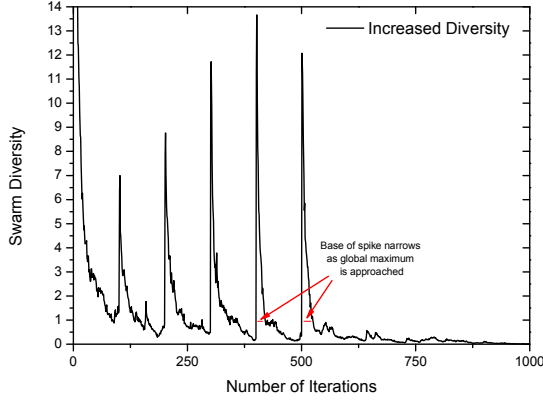
The corresponding utility curve is shown in Fig. 2b illustrating the improvement in sum utility over APSO.

B. $Pbest$ Learning Method

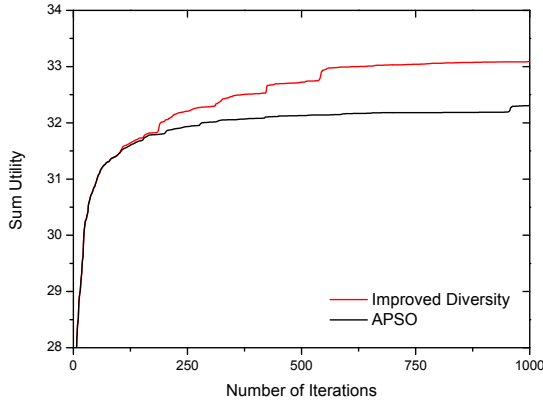
Consideration of the nature of video traffic motivates a further improvement to the PSO. Over the course of a video sequence, the frame size and hence Group of Pictures (GoP) size reflect the nature of the video scene content. For a series of GoPs, it is observed that the GoP size will remain approximately the same until a change in action/sequence/scene in the video occurs. An example is illustrated in Fig. 3 showing the scene change variation in GoP size at a macro scale and the similarity in GoP size across a short sequence.

In the context of the dynamic resource allocation problem, this similarity in GoP size means that the range of the device requirements remains similar for a sequence of GoPs. The device requirements reflect the swarm search space.

A $Pbest$ learning element called PBL is therefore introduced. Following an initial execution of the algorithm and while the number of devices in the network remains constant, rather than randomizing the swarm particle positions at each execution of the algorithm, knowledge of the previous best particle positions is used. By considering the $Pbest$ positions



(a)



(b)

Fig. 2. Response to Diversity Function (40 Devices) (a) Swarm Diversity and (b) Convergence Behaviour

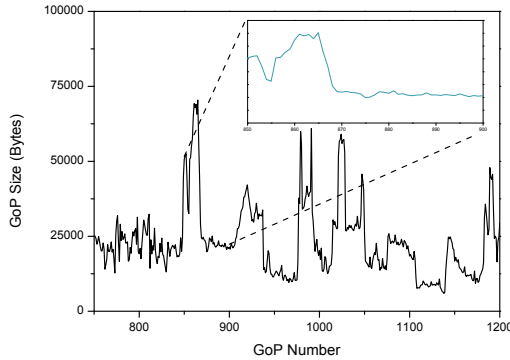


Fig. 3. Group of Picture Size Variation - *The LakeHouse*

of the previous GoP, the convergence time of the current GoP can be improved. This improvement is identified by the mean number of iterations to convergence in Table III.

The percentage of the best (identified by the maximum utility) *Pbest* positions for the PSO initialization is varied for a set of sequences and the mean values presented. In

TABLE III
CTA-PSO CONVERGENCE WITH *Pbest* LEARNING METHOD, PBL

	Random	25% PBL	50% PBL	75% PBL	100% PBL
Mean No. of Iterations	787	726	724	706	729

Table III, it can be seen that the greatest improvement in speed of convergence is achieved with 75% *Pbest* particles and 25% randomly generated particles at initialization. This compromise can be explained as follows. If 100% of the previous GoP *Pbest* particles are selected, low diversity in the swarm can cause the “experienced” particles to search around a previously known and potentially local maximum. In contrast, introducing a proportion of “experienced” particles guides the swarm towards previously known areas of fitness (max. utility) while the random proportion of the swarm encourages exploration of other areas of the search space.

The impact of abrupt variations in device requirements based on multiple simultaneous scene changes and devices entering/leaving the network must be accommodated by the method. To do this, a range variation threshold, *rng*, is set, which if exceeded causes PBL to be suppressed enabling a full random swarm generation. Similarly if the number of devices requesting a CTA, *N*, changes, random swarm generation is employed.

CTA-PSO (Channel Time Allocation PSO) is the combination of the Increased Diversity algorithm, the *Pbest* Learning Method and the settings described in Section IV. CTA-PSO is designed to solve the CTA-NUM problem achieving fully optimized resource allocation in a reduced convergence time as compared to other PSO methods.

The process to ensure full exploration of the search space has been discussed. Following exploration, CTA-PSO demonstrates the ability to reach the maximum sum utility to achieve an optimal resource allocation solution for the network. By means of confirmation of the performance of CTA-PSO, the PSO is continued up to 2000 iterations. The convergence plot is displayed in Fig. 4.

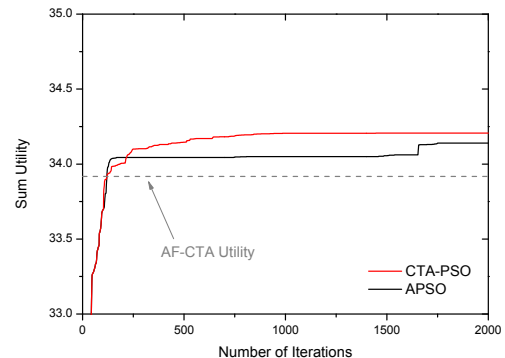


Fig. 4. CTA-PSO vs. APSO Convergence - 2000 Iterations (40 Devices)

With CTA-PSO, the utility is seen to increase gradually but steadily up to approximately 850 iterations from which point a negligible improvement is made. In contrast, without the increased diversity function, the APSO method reaches a local maximum at about 200 iterations only jumping out of it at about 1500 iterations. The Absolute Fairness in CTA (AF-CTA) result is also shown in Fig. 4 to identify the benefit of the NUM approach. With AF-CTA, the channel time is equally allocated amongst all devices unless that allocation would exceed the device requirement. In that case, the extra time is equally divided amongst the remaining devices.

The correlation between the individual device resource allocation at 1000 and 2000 iterations is illustrated in Fig. 5. The negligible variation as identified by the high R^2 value indicates that the optimal allocation has been achieved.

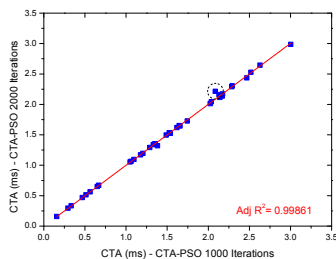


Fig. 5. CTA-PSO individual resource allocation at 1000 and 2000 iterations (40 Devices)

In comparison, the lower R^2 value and scattered results in Fig. 6 indicate that the APSO solution continues to vary between 1000 and 2000 iterations and the final 2000 iterations result also differs from the optimal CTA-PSO result.

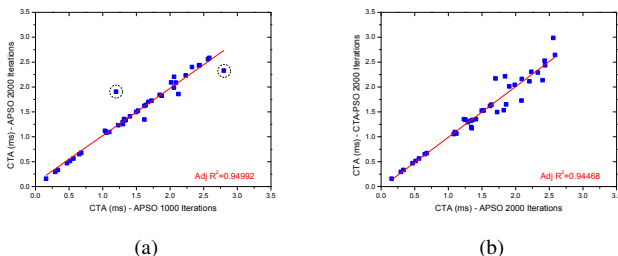


Fig. 6. APSO individual resource allocation (40 Devices) (a) APSO 1000 vs. 2000 iterations and (b) CTA-PSO vs. APSO - 2000 iterations

A variation in CTA represents additional (if the CTA increases)/reduced (if the CTA decreases) time available to individual devices for content transmission in the network. The variation in CTA with APSO as shown in Fig. 6 is likely to represent multiple frames of content. Without reaching an optimal resource allocation, the individual device quality of service can be significantly reduced.

VI. PERFORMANCE RESULTS

The performance of CTA-PSO has been analyzed by simulation. A Mathematica model was developed to represent an IEEE 802.15.3c wireless intra-large vehicle entertainment

system. The parameters used in the simulation are detailed in Table IV. Channel model parameters are as per measurements by Maltsev in [21]. Hardware-related link budget parameters are those studied in [26]. Seven H.264/SVC single-layer HD video traces [27] are used with randomized start point to represent different video at each device.

For the VoD service each device in the network randomly selects a video to display and sends a CTA request message to the PNC. The PNC generates the CTA bounds for the device, as described in Section IV. Each IPTV device also sends a CTA request message to the PNC for a randomly selected video (TV channel). The upper and lower CTA requirements are set based on the Group of Pictures (GoP) requirements with the upper CTA requirement as the time to transmit all the frames of the GoP. The lower CTA requirement is the time to transmit only the I frame of the GoP. The PNC then runs the CTA-PSO algorithm and produces an optimal CTA for each device. The CTA distribution is broadcast in a message from the PNC and each device accesses the channel in its allocated slot to receive the video transmitted from the PNC. The PNC transmits to each individual device in the allocated slot.

TABLE IV
PARAMETERS FOR PERFORMANCE ANALYSIS

Parameter	Value	Parameter	Value
Channel Frequency, f	62.5 GHz	Bandwidth, B	1.782 GHz
Transmit Power, P_T	10 dBm	Noise Figure, F	10 dB
Antenna Gain, G_T, G_R	9 dBi	SIFS, t_{sifs}	2.5 μ s
Implementation loss, L_i	5 dB	Basic Rate, R_b	12.5 Mbps
Attenuation value, A	32.5	PNC Height	2.5 m
Path loss exponent, n	2.0	Seat Pitch/Width	76cm/50cm
MAC payload, l_{data}	1500 bytes	Seat Height	1 m
PHY/MAC header, l_{oh}	34 bytes	ACK pkt, l_{ack}	34 bytes

Performance results for a range of network sizes with 50% VoD and 50% IPTV traffic are presented in Table V. As introduced in Section V, the resource allocation results are compared with AF-CTA. The mean performance values are calculated over 100 intervals (GoPs) in each case. The Δ Utility values in Table V confirm that an improvement in resource allocation based on CTA-PSO as compared to AF-CTA is achieved at all network sizes. The Δ PSNR value measures the actual PSNR improvement achieved in the network when the VoD and IPTV streams are transmitted to the receiving devices based on the PSO CTA.

The PSNR value of each device in each GoP is calculated based on the number of frames of the GoP that it is possible to fully transmit in the allocated channel time. The negative mean Δ PSNR value recorded for the network of 20 devices is explained by the limited marginal utility. A small utility improvement may be generated for a device. However, the corresponding CTA increase may not be sufficient to enable complete transmission of an additional frame so that no PSNR improvement is recorded for the device in that GoP interval. The simultaneous decrease in CTA for a neighbouring device

TABLE V
CONVERGENCE BEHAVIOUR OF CTA-PSO: 50% VoD, 50% IPTV

No. of Devices	10	20
Mean Δ Utility, (σ)	0.009 (0.024)	0.078 (0.047)
Mean Δ PSNR (dB), (σ)	0.022 (0.133)	-0.124 (0.239)
Mean Iterations, (σ)	139 (100)	418 (221)
No. of Devices	30	40
Mean Δ Utility, (σ)	0.487 (0.267)	1.053 (0.653)
Mean Δ PSNR (dB), (σ)	0.066 (0.267)	0.232 (0.375)
Mean Iterations, (σ)	739 (129)	794 (108)

may lead to a lower PSNR for the device. So as a result of the small individual utility variations, which lead to a mean Δ utility improvement as designed by CTA-PSO, the recorded mean PSNR may not outperform the AF-CTA PSNR.

For the larger networks (30/40 devices), the high competition for resource results in a consistent PSNR improvement over AF-CTA.

VII. CONCLUSION

CTA-PSO presents a practical approach for mixed media resource allocation moving beyond current methods of allocation grouped by application type. In this work, we have identified PSO as an appropriate method for multiple application resource allocation. The approach is suitable for practical implementation with applications described directly in terms of their QoS requirements. The results illustrate improvement over a standard resource allocation method of Absolute Fairness in CTA, particularly for larger network sizes. Additionally, CTA-PSO presents an improved convergence speed as compared to APSO while maintaining the QoS improvement of the NUM approach.

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