Fairness Issues in Resource Allocation Schemes for Wireless Visual Sensor Networks

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ABSTRACT

This work addresses the problem of fairness and efficiency evaluation of various resource allocation schemes for wireless visual sensor networks (VSNs). These schemes are used to optimally allocate the source coding rates, channel coding rates, and power levels among the nodes of a wireless direct sequence code division multiple access (DS–CDMA) VSN. All of the considered schemes optimize a function of the video qualities of the nodes. However, there is no a single scheme that maximizes the video quality of each node simultaneously. In fact, all presented schemes are able to provide a Pareto–optimal solution, meaning that there is no other solution that is simultaneously preferred by all nodes. Thus, it is not clear which scheme results in the best resource allocation for the whole network. To handle the resulting tradeoffs, in this study we examine four metrics that investigate fairness and efficiency under different perspectives. Specifically, we apply a metric that considers both fairness and performance issues, and another metric, which measures the equality of a resource allocation (equal utilities for the nodes). Another metric computes the total system utility, and even the last metric computes the total power consumption of the nodes. Ideally, a desirable scheme could achieve high total utility, while being equally fair to all nodes, and requiring low amounts of power.

Keywords: Fairness issues, Jain's index, performance to fairness, power consumption, resource allocation, total utility.

1. INTRODUCTION

Many modern applications in communication networks and computer systems involve a number of agents which have to collaborate or compete with each other in order to exploit the usually limited network resources. Although the general feeling tends to associate fairness with equality, researchers disagree as to what should be equalized. Sometimes, it is desirable to achieve similar utilities for all nodes of the network, while some other times the goal is an equal utility penalty for all nodes relative to the maximum achievable utility. Additionally, there are times where the challenge is a high total utility allocation, cumulatively for the nodes, considering the available network resources, channel conditions, participating nodes and video content characteristics.

In previous works,[1–3] we confronted the challenge of optimal resource allocation among the nodes of a wireless *direct sequence code division multiple access* (DS–CDMA) *visual sensor network* (VSN), using a centralized topology and a cross–layer design. Each sensor node had a bit rate that could be used for both source coding and channel coding, while it also had an amount of power necessary for sensing, processing, and transmission of the captured data. Hence, the source coding rate, channel coding rate and power level were the transmission parameters of each node. Since our primary concern was the maximization of the video quality that reached the end–user, a dynamic adjustment of sensor nodes' transmission parameters was required.

The source coding rate determines the bit rate used for the compression of a video sequence, while the channel coding rate defines the relative protection of the transmitted video sequence from channel errors. Under a total bit rate constraint, a higher source coding rate will result in less strong channel coding, thus requiring a higher transmission power in order to maintain reliable communications. Aiming at the achievement of high video quality, the transmission power should be adequately high to permit reliable data transmission and maintain the quality of the video reception. On the other hand, given that sensor nodes are battery–operated systems, it needs to be low enough to prolong battery lifetime. Moreover, since DS–CDMA allows all nodes to transmit over

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the same channel, transmissions of one node cause interference to the transmissions of the other nodes. This is another reason for keeping the transmission power to low levels.

All explored criteria in our previously published works dealt with the same problem of optimal resource allocation, having to solve a different objective function at each time. In Ref. 1, the optimization problem involved the minimization of the average and maximum video distortion among all nodes of the network, using the *minimum average distortion* (MAD) and *minimum maximum distortion* (MMD) criteria. In Refs. 2 and 3, the *Nash bargaining solution* (NBS) and the *Kalai–Smorodinsky bargaining solution* (KSBS) were applied, respectively, to find fair and efficient resource distribution assignments.

A work that applies the NBS to the problem of fair and optimal bandwidth allocation among multiple collaborative users is presented in Ref. 4. In that work, two assumptions were made for the assignment of the bargaining powers to each user. It is worth mentioning that the *bargaining power* for a user declares how advantaged is that user in the resource allocation problem. Specifically, the higher the bargaining power for a user, the more advantaged the user is, and vice versa. According to the first scenario of Ref. 4, all users were assigned equal bargaining powers, while according to the second scenario, different bargaining powers were assigned to each of the users. The different bargaining powers were determined using an algorithm that aimed to similar quality levels for each user, at the cost of the overall system performance (i.e., the weighted sum of utilities).

In Ref. 2, we grouped the nodes into two clusters, based on the amount of motion in the scenes they record. In that work, we applied a version of the NBS, the n.NBS, where we assumed that the bargaining powers assigned to each class of nodes were proportional to the number of nodes in each class. In the present paper, we propose a variation of the NBS presented in Ref. 2, the so called c.NBS, which also assumes a node clustering into two groups. The differences is that equal bargaining powers are assigned to each class of nodes, irrespective of the cardinality of each class. Additionally, in this work we apply two other schemes that aim both at the maximization of the total system utility achieved by all the nodes of the network. The first scheme calculates an unweighted version of the total system utility and is called the *maximize total utility* (MTU) and the second one calculates a weighted version of the total system utility and is called the *weighted maximize total utility* (w.MTU). The w.MTU assumes weights for each class of nodes that are proportional to the cardinality of the class.

Both MTU and w.MTU have been used in the literature to solve similar resource sharing problems. The work presented in Ref. 5 solves the resource allocation problem of maximizing the sum of transmitter utilities subject to a minimum and maximum data rate constraint per link and peak power constraints per node in a wireless multihop network. In Ref. 6, the objective is to schedule uplink transmissions in order to maximize the overall system utility, under explicit fairness constraints. Moreover, in Ref. 7 the scheduling and resource allocation problem for the downlink in a CDMA–based wireless network is considered. This problem reduces to maximizing the weighted throughput over the state–dependent downlink capacity region, while taking into account the system–wide and individual user constraints. Also, in Ref. 8 an optimal feedback allocation policy for cellular uplink systems is proposed, where the base station has a limited feedback budget. The optimal allocation policy of that paper involves solving a weighted sum–rate maximization problem at every scheduling instant.

All of the schemes presented in this paper, i.e., the MAD, MMD, n.NBS, c.NBS, KSBS, MTU and w.MTU are able to provide Pareto–optimal solutions. A solution is *Pareto–optimal* when there is no other solution that is simultaneously preferred by all nodes.[9] Therefore, since all of the considered schemes offer Pareto–optimal solutions, there is no a single scheme that would be selected by all nodes to be the best. Figure 1 graphically depicts the Pareto–optimal solutions achieved by each of the considered schemes assuming a node clustering into two motion classes. Specifically, in this case, 70 nodes image scenes with high levels of motion and 30 nodes image scenes with low levels of motion.

Considering the tradeoffs between video quality and power consumption that result after using a specific scheme, we engaged in an effort to evaluate each examined scheme under different fairness aspects. Various fairness metrics have been proposed in the literature to weigh the video quality impact of using different resource allocation policies.[10–12] Each metric studies performance and efficiency from a different point of view, considering

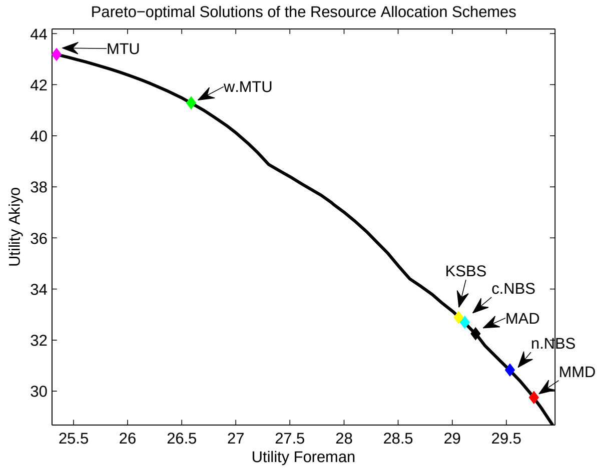

Figure 1: Pareto–optimality of the solutions.

different kinds of fairness for the nodes. In Ref. 10, different resource allocation policies are used to determine a quality–fair resource allocation for decoding tasks sharing a single resource constrained processor. In the same work, a metric that captures the quality requirements for each task is used to compare these policies. Specifically, a factor of 0 indicates that a task achieves its minimum desired quality and a factor of 100 indicates that a task achieves its maximum desired quality. A negative value for this factor indicates that a task achieves below its minimum required quality, while a positive value indicates that the task achieves higher quality than the minimum.

In Ref. 11, different resource management strategies are compared in terms of the maximum quality drop, while the optimal strategy minimizes this drop. A metric defined as the ratio of the largest quality drop among wireless stations in the network using each considered scheme to the quality drop incurred by the KSBS for the wireless stations is proposed in that paper. For the KSBS, the quality drop is the same for all wireless stations. Also, in Ref. 12, the metrics of average, minimum and standard deviation of channel capacity, the Kalai–Smorodinsky solution score and the NBS score are used to investigate the spectrum allocation achieved by the bargaining solutions. Furthermore, in the same paper, the bargaining solutions are compared with the allocation that maximizes the sum of channel capacities.

Since an ideal scheme offers high amounts of total utility cumulatively for all nodes, behaves equally fairly to all of them assigning similar utilities and also consumes low amounts of power also cumulatively for all nodes, for the results evaluation obtained from all presented schemes, in this work we investigate four different fairness notions. Firstly, we apply a metric[13] that captures both performance and fairness issues, assuming that the total utility varies per scheme. Secondly, we compute the Jain's fairness index[14] in order to investigate the equality of the resource allocations achieved by each considered scheme. Thirdly, we calculate the overall gained utility cumulatively for both motion classes and fourthly, we measure the total power required by both motion classes of each considered scheme.

The rest of the paper is organized as follows: Section 2 describes the system setup as well as it presents the model used in order to calculate the expected video distortion. The applied resource allocation schemes are summarized in Section 3, and Section 4 includes all examined fairness metrics that are used to evaluate the fairness and efficiency of each scheme. Section 5 cites and interprets the experimental results, while in Section 6 conclusions are drawn.

2. SYSTEM SETUP

This work considers a DS–CDMA VSN, where the battery–operated nodes survey scenes with various motion levels. A centralized control unit communicates with the nodes in order to request changes to their transmission parameters, considering their needs for both compression and error protection during transmissions. High–motion scenes have to be compressed with more bits than scenes with lower motion levels. Then, given a bit rate constraint R_k, a lower bit rate may be thus used for channel coding, since $R_k = R_{\mathrm{s},k}/R_{\mathrm{c},k}$, where $R_{\mathrm{s},k}$ is the source coding rate and $R_{\mathrm{c},k}$ the channel coding rate.

For the channel coding, we assume *rate compatible punctured convolutional* (RCPC) codes,[15] which allow the use of Viterbi's upper bounds on the bit error probability P_b. Assuming *binary phase shift keying* (BPSK) as the employed modulation scheme, P_b satisfies the inequality:

$$P_\mathrm{b} \leqslant \frac{1}{P} \sum_{d=d_\mathrm{free}}^{\infty} c_d P_d, \quad \text{where} \quad P_d = \frac{1}{2}\,\mathrm{erfc}\left(\sqrt{\frac{dR_\mathrm{c}E_k}{I_0}}\right). \tag{1}$$

The parameter P is the period of the code, d_free is the free distance of the code and c_d is the information error weight. The complementary error function is denoted as erfc(), while R_c is the channel coding rate and E_k/I_0 the energy per bit to *multiple access interference* (MAI) ratio. The index k denotes the corresponding node of the network.

The power level, S_k, for each node k, is given by $S_k = E_k\, R_k$, and is measured in Watts (W). In our investigation, we assume that the interference can be approximated by *additive white Gaussian noise* (AWGN) and that thermal and background noise can also be modeled as AWGN. In this case, the energy per bit to MAI and noise ratio, $E_k/(I_0 + N_0)$, should be used for the calculation of P_b instead of E_k/I_0:

$$\frac{E_k}{I_0 + N_0} = \frac{S_k/R_k}{\sum\limits_{j \neq k}^{K} S_j/W_t + N_0}, \qquad k = 1, 2, \ldots, K, \tag{2}$$

where $I_0/2$ is the two–sided noise power spectral density due to MAI and $N_0/2$ is the power spectral density of the thermal and background noise, measured in Watts/Hertz (W/Hz). The amount W_t is the bandwidth, measured in Hz. The index k refers to the corresponding node, and j to each interfering node. Clearly, when a node increases its power level, its energy per bit to MAI and noise ratio also increases. This means that the video quality of this node is also increased at the cost of increased interference to the other nodes.

In this work, *universal rate distortion characteristics* (URDCs) were used[1–3] in order to calculate the expected video distortion, $E[D_{\mathrm{s+c},k}]$. They relate $E[D_{\mathrm{s+c},k}]$ with the bit error probability P_b with the equation:

$$E[D_{\mathrm{s+c},k}] = \alpha \left[\log_{10}\left(\frac{1}{P_\mathrm{b}}\right)\right]^{-\beta}. \tag{3}$$

The parameters α and β are positive, and they are determined through a mean squared error optimization procedure, using a number of ($E[D_{\mathrm{s+c},k}]$, P_b) pairs, experimentally obtained for specific bit error rates.[1–3] By substituting Eqs. (1) and (2) into Eq. (3), we observe that the expected distortion, $E[D_{\mathrm{s+c},k}]$, for node k, is a function of the source coding rate for node k, the channel coding rate for node k, and the power levels of all nodes.

3. RESOURCE ALLOCATION STRATEGIES

Before the presentation of the resource allocation schemes used to optimally determine the nodes' transmission parameters, it is necessary to define the utility function. The *utility function*, U_k, constitutes a measure of relative satisfaction for each node k. In our problem, it is defined equivalently to the *peak signal to noise ratio* (PSNR)[2,3] i.e.,

$$U_k = 10 \log_{10} \frac{255^2}{E[D_{\mathrm{s+c},k}]}, \tag{4}$$

and is measured in decibel (dB). The higher the value of the utility function, the better the video quality, and vice versa. The quantity $E[D_{\mathrm{s+c},k}]$ represents the expected distortion given by Eq. (3).

In the following, we summarize all the criteria that we used in order to determine the source coding rate, $R_{s,k}$ for node k, the channel coding rate, $R_{c,k}$ for node k, and the power levels, S, of all nodes, in an effort to achieve the highest possible video quality for each node. The constraint that holds for all presented criteria is that each node can utilize the same total bit rate for both source and channel coding.

- **Minimum Average Distortion** (MAD): This criterion aims at the minimization of the average distortion of all K nodes of the network:

$$\min \frac{1}{K} \sum_{k=1}^{K} E[D_{\mathrm{s+c},k}](R_{\mathrm{s},k}, R_{\mathrm{c},k}, S),\ \ k \in \{1, \ldots, K\}, \tag{5}$$

  while it does not assert fairness among the nodes. Hence, distortion is allowed to vary significantly from node to node as long as the average distortion is kept to minimal levels.

- **Minimum Maximum Distortion** (MMD): This criterion attempts to minimize the maximum distortion among all K nodes:

$$\min \max_{k} E[D_{\mathrm{s+c},k}](R_{\mathrm{s},k}, R_{\mathrm{c},k}, S),\ \ k \in \{1, \ldots, K\}. \tag{6}$$

  The MMD guarantees that all distortions are kept within acceptable ranges.

- **Nash Bargaining Solution with Equal Node Advantage** (n.NBS): This bargaining solution, based on its fairness axioms, which guarantee that it is *feasible*, *Pareto optimal*, *invariant to affine transformations*, and *independent from irrelevant alternatives*,[2] can be determined as:

$$\arg \max_{U \geq dp} \prod_{k=1}^{K} (U_k(R_{\mathrm{s},k}, R_{\mathrm{c},k}, S) - dp_k)^{a_k}, \quad \text{with} \quad \sum_{k=1}^{K} a_k = 1. \tag{7}$$

  The quantity $U = (U_1, U_2, \ldots, U_K)^\top$ is the vector of utilities of all K nodes. The vector $dp = (dp_1, \ldots, dp_K)^\top$ is the *disagreement point*, which includes the minimum utilities that each node expects by joining the game, without cooperating with the other nodes. The amount a_k corresponds to the bargaining power assigned to each node and declares the advantage of each node in the resource allocation game. The higher the value of the bargaining power, the more advantaged the node, and vice versa. In this case, we assumed that *all nodes are equally advantaged*, meaning that $a_k = 1/K$. Thus, given a node clustering into two motion classes based on the amount of motion of the captured scenes, the bargaining powers assigned to each class of nodes are proportional to the number of nodes in each class.

- **Nash Bargaining Solution with Equal Class Advantage** (c.NBS): This solution is a variation of the n.NBS. It has to fulfill the same axioms as the n.NBS,[2] and is also found by maximizing Eq. (7). In this criterion, we consider a different assumption about the bargaining powers. Specifically, having a node clustering into C motion classes, based on the amount of motion of the captured scenes, *each class of nodes is equally advantaged* in the resource allocation game, meaning that $a_k = 1/C$, for the k class of nodes.

- **Kalai–Smorodinsky Bargaining Solution** (KSBS): This bargaining solution also has to fulfill a set of axioms, which guarantee that it is *feasible*, *Pareto optimal*, *invariant to affine transformations*, while it also satisfies the axiom of *individual monotonicity*.[3] The KSBS, $F(\mathbf{U}, dp)$ for the feasible set $\mathbf{U}$ and the disagreement point dp, is found by taking the maximal element of the feasible set on the line connecting the disagreement point and the utopian point. The *utopian point* is the vector of maximum achievable utilities that each node can get by joining the game. The *feasible set* $\mathbf{U}$ is the set of all possible utilities achieved by the nodes, where the utility for each node results from a different combination of the source coding rates, channel coding rates and transmission powers of the nodes.

- **Maximize Total Utility** (MTU): In some cases, all the nodes of the network aspire to maximize the total system utility. Assuming again a node clustering into C motion classes and *equal weights for each class of* *nodes*, we have to maximize the function:

$$\max \sum_{k=1}^{C} U_k^{cl}(R_{\mathrm{s},k}, R_{\mathrm{c},k}, S), \tag{8}$$

where U_k^{cl} corresponds to the utility of class k. This scheme derives a Pareto–optimal solution.

- **Maximize Weighted Total Utility** (w.MTU): Inspired by the n.NBS, where each node was considered equally advantaged in the game, we approached the MTU from a different point of view, assuming *weights that are proportional to the cardinality* N_k*, of each class* k. Therefore, the resulting equation was:

$$\max \sum_{k=1}^{C} a_k \, U_k^{cl}(R_{\mathrm{s},k}, R_{\mathrm{c},k}, S), \tag{9}$$

where the weight a_k equals $a_k = N_k/K$.

The presented criteria, i.e., MAD, MMD, n.NBS, c.NBS, MTU, and w.MTU result in global optimization problems that are resolved using the *particle swarm optimization* (PSO) algorithm.[1–3] It belongs to the category of population-based algorithms and is a stochastic algorithm for numerical optimization tasks.[16,17] PSO is an effective and efficient algorithm able to solve the mixed–integer optimization problems resulting from the discrete values of the source and channel coding rates, and the continuous values of the power levels of the nodes. The KSBS was geometrically derived from the graphical representations of the utility sets, as it is explained in detail in Ref. 3.

4. PERFORMANCE AND FAIRNESS EVALUATION

This section presents the metrics we applied in this work in order to evaluate the results obtained from the different resource allocation schemes. Specifically, we used four metrics, each of which investigates fairness under a different point of view, considering different fairness and performance aspects at each time.

1) *Performance to Fairness Metric* (PF)

This metric captures both relative performance and relative fairness issues. It assumes that the total utility achieved by all nodes using a specific scheme is higher under one scheme compared to the utility achieved by all other competing schemes. Also, the PF metric requires that only some nodes achieve higher utilities under the same scheme, and surely not all of them at the same time. This fact implies that the solutions provided by the considered schemes have to be Pareto–optimal, something that is verified by the results of each of the examined schemes. See for example Fig. 1.

Assuming that the criterion that maximizes the unweighted version of the total system utility, namely the MTU, is used as the reference criterion for this metric, we define the performance to fairness metric[13] as:

$$PF(MTU, Cons) = \frac{\sum_{k=1}^{K}(U_k^{MTU}(R_{\mathrm{s},k}, R_{\mathrm{c},k}, S) - U_k^{Cons}(R_{\mathrm{s},k}, R_{\mathrm{c},k}, S))}{\sum_{k=1}^{K}\max(0, U_k^{Cons}(R_{\mathrm{s},k}, R_{\mathrm{c},k}, S) - U_k^{MTU}(R_{\mathrm{s},k}, R_{\mathrm{c},k}, S))}, \tag{10}$$

where $Cons$ refers to each considered scheme. The numerator of Eq. (10) quantifies the total performance gain of using the MTU over $Cons$, while the denominator quantifies the unfairness of using the MTU over $Cons$. Since the MTU criterion was considered as the reference criterion, the PF values for this scheme are not defined.

2) *Jain's Index* (JI)

This index measures how equal is a resource allocation for all nodes constituting the network, while in cases of unequal allocations it measures how far the allocations are from equality. Specifically, it is defined as:[14]

$$JI_{Cons}(U) = \frac{\left|\sum_{k=1}^{K} U_k^{Cons}(R_{\mathrm{s},k}, R_{\mathrm{c},k}, S)\right|^2}{K \cdot \sum_{k=1}^{K}(U_k^{Cons}(R_{\mathrm{s},k}, R_{\mathrm{c},k}, S))^2}, \tag{11}$$

where $Cons$ refers to each considered scheme and U corresponds to the vector of utilities of all K nodes. It takes values between 0 and 1 and this boundedness helps us to understand intuitively the fairness index. The closer the JI value is to the unit, the more equal the resource allocation is for the nodes. For example, if $JI_{Cons}(U) = 0.9$, this means that the considered scheme $Cons$, is unfair to the 10% of the nodes. Therefore, this metric provides a quantitative value to the fairness of the allocation.

3) *Total Utility Metric*

This metric examines the total utility that a scheme will bring cumulatively from all nodes. According to this metric, the most efficient scheme is the scheme that gathers the highest overall system utility, without examining how close are the utilities achieved by each node, but only the sum of all utilities as a whole. Specifically, this metric computes:

$$\sum_{cl=1}^{C} U_{cl}, \tag{12}$$

if we also assume a node clustering into C motion classes.

4) *Total Power Metric*

This metric investigates the major issue of power consumption by each scheme. Each node of the VSN spends an amount of power in order to assure a reliable video transmission and to maintain the quality of the video reception. On the other hand, it is necessary to keep low amounts of power consumption, since the sensor nodes are battery–operated systems and the prolongation of the battery lifetime is an important issue. Furthermore, in a DS–CDMA system, increased transmission power for a node implies increased interference to the other nodes. Thus, low transmission power is required in order to avoid degradation of the video qualities of the other nodes. Therefore, the Total Power metric calculates the total amount of consumed power required cumulatively for all nodes, grouped into C motion classes:

$$\sum_{cl=1}^{C} S_{cl} \tag{13}$$

where S_{cl} represents the power level of class cl.

5. EXPERIMENTAL RESULTS

For simplicity reasons, in this work, we clustered the $K = 100$ nodes of the network into $C = 2$ motion classes, based on the amount of motion included in the captured scenes. Thus, a high– and a low–motion class of nodes were formed, while the "Foreman" and "Akiyo" video sequences were used to represent each motion class, respectively. The bit rate was 96 kbps and the bandwidth 20 MHz. The source and channel coding rates assumed discrete values, and the power levels assumed continuous values from the set $\mathbf{S} = [5.0, 15.0]$ in Watts. Additionally, the PSNR metric was used for the measurement of the video quality. In all conducted experiments, we assumed that the thermal and background noise can be modeled as AWGN with $N_0 = 10^{-7}$ W/Hz.

Tables 1–5 present the results for all fairness metrics considered in this work. Each of the tables refers to a different node distribution and each line of the tables refers to a specific scheme. The term N_{h} declares the cardinality of the high–motion class of nodes and the N_{l} the cardinality of the low–motion class of nodes. The first column of each table includes the schemes, the second column shows the PF values of each scheme and the third column cites the JI values of the nodes' utilities (expressed in terms of PSNR). The fourth column depicts the total utility achieved by each scheme, and the last column shows the total consumed power for each scheme. Since, a fair and efficient scheme guarantees high amounts of total utility, is equally fair to all nodes and is not demanding in resources (in our case power levels), we use bold type for the lowest PF value, the highest JI value, the highest total utility and the lowest total power among all schemes, for each considered node distribution. Moreover, in Tables 6–10, we present the PSNR of the high–motion class, the PSNR of the low–motion class, the power level of the high–motion class and the power level of the low–motion class, respectively. Of course, each line of the tables refers to a specific scheme, while each of the tables refers to a different node distribution.

Regarding the results from Tables 1–5, one way to interpret the PF values obtained using Eq. (10) is that for every unit of utility lost by a class of nodes using the MTU instead of the considered scheme, there are PF units of utility gained cumulatively for both motion classes using also the MTU instead of the considered scheme. Additionally, the lower the PF value for a scheme, the smaller the discrepancy between the total achieved PSNR by the considered scheme and the MTU. Therefore, if we desire to have a high total utility, the scheme that offers the lowest PF value is the preferred one. However, no specific scheme holds the lowest PF values for all considered node distributions. This always depends on the achieved PSNR values in each case. Moreover, since the MTU criterion was considered as the reference criterion in Eq. (10), the PF values for this scheme are not defined. Additionally, in cases where both motion classes include the same number of nodes, the w.MTU solutions coincide with the solutions of the MTU. Hence, in such a case the PF values are not defined either for the w.MTU. From the JI values, we observe that all schemes promise quite fair utility allocations for both motion classes, since the JI values in all examined cases are greater than 0.93. However, the MMD criterion assures absolutely equal allocations for both motion classes, guaranteeing JI values equal to the unit. This means that the MMD is fair to the 100% of the nodes, as it results from the definition of the Jain's index, and thus it is the most fair scheme among all as it regards the equality of the utility allocations.

Additionally, if we consider that a high–performance scheme provides high amounts of utility cumulatively for both motion classes, the MTU is the scheme that can assure this requirement, as it is declared by its name. Indeed, as we see from the Tables 1–5, this scheme offers the highest total utility in all considered node distributions. Finally, if the system resources are limited (as it is usual in wireless VSNs), it is necessary to have a scheme that is able to optimally allocate the transmission parameters among the nodes, while spending low amounts of power for the video transmission over the network, and guaranteeing adequate levels of viewing quality. In such a case, our choice is the KSBS criterion, since in four out of five node distributions, it assures the lowest power consumption compared to all other schemes.

Generalizing, no scheme holds all desired characteristics of achieving the highest total utility, while assigning similar utilities to all nodes, and spending the lowest overall power, at the same time. Clearly, such a scheme would be a preferable scheme. Each proposed metric investigates fairness under a different perspective and it is rather impossible for a single metric to gather all aspects of fairness, at the same time. Specifically, if we are interested in a scheme that gathers the highest amounts of utility compared to all other schemes, our choice would be the MTU criterion. Although the MTU assures the highest levels of utility, it is an unfair scheme if we consider the amounts of consumed power as well as the high discrepancy that is often observed between the PSNR values of the motion classes. The PF values indicate the scheme that approaches in performance the MTU. However, no specific scheme keeps the lowest PF values in all considered node distributions. From another point of view, if our priority is a scheme that assigns as close utilities as possible to both motion classes, surely the MMD criterion would be our selection. However, the total utility gained by the MMD is quite low relative with the total utility gained by the MTU. From another aspect, we would select the KSBS criterion, if we were looking for a scheme that consumes low amounts of power, while guaranteeing adequate levels of video viewing quality, at the same time. Nevertheless, this criterion fails to gather high amounts of total utility compared to the MTU, and even there is a large discrepancy between the utilities of the two motion classes, up to approximately 4 dB.

Scheme	PF	JI	Total Utility	Total Power
MAD	7.9258	0.9974	59.5422	22.6210
MMD	9.0271	**1.0000**	56.7578	20.7257
n.NBS	8.7280	0.9998	57.4630	21.1023
c.NBS	7.7732	0.9965	59.9914	23.0548
KSBS	7.7895	0.9965	60.0059	**18.0000**
MTU	–	0.9392	**71.6932**	20.0000
w.MTU	**5.5677**	0.9736	66.2998	28.6537

Table 1: Fairness metrics for the case of $N_{\mathrm{h}} = 90 - N_{\mathrm{l}} = 10$.

Scheme	PF	JI	Total Utility	Total Power
MAD	1.8301	0.9976	61.4641	22.6110
MMD	2.0510	**1.0000**	59.5078	20.5814
n.NBS	1.9553	0.9995	60.3613	21.3135
c.NBS	1.7870	0.9967	61.8099	23.1208
KSBS	1.7772	0.9962	61.9463	**14.8000**
MTU	–	0.9365	**68.5241**	20.0000
w.MTU	**0.5281**	0.9552	67.8748	23.3521

Table 2: Fairness metrics for the case of $N_{\mathrm{h}} = 70 - N_{\mathrm{l}} = 30$.

Scheme	PF	JI	Total Utility	Total Power
MAD	**0.5027**	0.9991	63.7608	22.0445
MMD	0.5450	**1.0000**	63.1836	20.7300
n.NBS	0.5035	0.9992	63.7292	21.9364
c.NBS	0.5035	0.9992	63.7292	21.9364
KSBS	0.5229	0.9975	63.9489	**15.1000**
MTU	–	0.9548	**66.2700**	23.1044
w.MTU	–	0.9548	**66.2700**	23.1044

Table 3: Fairness metrics for the case of $N_{\mathrm{h}} = 50 - N_{\mathrm{l}} = 50$.

Scheme	PF	JI	Total Utility	Total Power
MAD	0.1749	0.9968	66.4491	23.7092
MMD	0.0331	**1.0000**	66.7706	20.9121
n.NBS	0.1632	0.9963	66.4476	23.9106
c.NBS	**0.0165**	0.9999	66.7746	20.7968
KSBS	0.3109	0.9988	66.4190	**14.7000**
MTU	–	0.9999	**66.7758**	20.6893
w.MTU	0.3611	0.9548	64.5780	22.9236

Table 4: Fairness metrics for the case of $N_{\mathrm{h}} = 30 - N_{\mathrm{l}} = 70$.

Scheme	PF	JI	Total Utility	Total Power
MAD	1.3567	0.9970	69.6722	23.4148
MMD	**0.7140**	**1.0000**	71.3714	20.6298
n.NBS	1.5201	0.9956	69.1898	24.1006
c.NBS	0.8418	0.9999	71.4211	21.9862
KSBS	0.8659	0.9998	71.0125	21.3000
MTU	–	0.9998	**71.6638**	**20.0000**
w.MTU	2.9907	0.9552	62.8391	22.7983

Table 5: Fairness metrics for the case of $N_{\mathrm{h}} = 10 - N_{\mathrm{l}} = 90$.

Scheme	PSNR	Power
MAD	$[28.2575, 31.2847]$	$[15.0000, 7.6210]$
MMD	$[28.3789, 28.3789]$	$[15.0000, 5.7257]$
n.NBS	$[28.3548, 29.1082]$	$[15.0000, 6.1023]$
c.NBS	$[28.2298, 31.7616]$	$[15.0000, 8.0548]$
KSBS	$[28.2248, 31.7811]$	$[11.7000, 6.3000]$
MTU	$[26.7244, 44.9688]$	$[5.0000, 15.0000]$
w.MTU	$[27.6931, 38.6067]$	$[13.6537, 15.0000]$

Table 6: PSNR values and power level values for the case of $N_{\mathrm{h}} = 90 - N_{\mathrm{l}} = 10$.

Scheme	PSNR	Power
MAD	$[29.2156, 32.2485]$	$[15.0000, 7.6110]$
MMD	$[29.7539, 29.7539]$	$[15.0000, 5.5814]$
n.NBS	$[29.5326, 30.8287]$	$[15.0000, 6.3135]$
c.NBS	$[29.1152, 32.6947]$	$[15.0000, 8.1208]$
KSBS	$[29.0590, 32.8873]$	$[9.5000, 5.3000]$
MTU	$[25.3434, 43.1807]$	$[5.0000, 15.0000]$
w.MTU	$[26.5873, 41.2875]$	$[8.3521, 15.0000]$

Table 7: PSNR values and power level values for the case of $N_{\mathrm{h}} = 70 - N_{\mathrm{l}} = 30$.

Scheme	PSNR	Power
MAD	$[30.9207, 32.8401]$	[15.0000, 7.0445]
MMD	$[31.5918, 31.5918]$	[15.0000, 5.7300]
n.NBS	$[30.9757, 32.7535]$	[15.0000, 6.9364]
c.NBS	$[30.9757, 32.7535]$	[15.0000, 6.9364]
KSBS	$[30.3679, 33.5810]$	[9.8000, 5.3000]
MTU	$[25.9290, 40.3410]$	[8.1044, 15.0000]
w.MTU	$[25.9290, 40.3410]$	[8.1044, 15.0000]

Table 8: PSNR values and power level values for the case of $N_{\mathrm{h}} = 50 - N_{\mathrm{l}} = 50$.

Scheme	PSNR	Power
MAD	$[31.3549, 35.0942]$	[15.0000, 8.7092]
MMD	$[33.3853, 33.3853]$	[15.0000, 5.9121]
n.NBS	$[31.2109, 35.2367]$	[15.0000, 8.9106]
c.NBS	$[33.4708, 33.3038]$	[15.0000, 5.7968]
KSBS	$[32.0458, 34.3732]$	[9.7000, 5.0000]
MTU	$[33.5506, 33.2252]$	[15.0000, 5.6893]
w.MTU	$[25.2666, 39.3114]$	[7.9236, 15.0000]

Table 9: PSNR values and power level values for the case of $N_{\mathrm{h}} = 30 - N_{\mathrm{l}} = 70$.

Scheme	PSNR	Power
MAD	$[32.9280, 36.7442]$	[15.0000, 8.4148]
MMD	$[35.6857, 35.6857]$	[15.0000, 5.6298]
n.NBS	$[32.2861, 36.9037]$	[15.0000, 9.1006]
c.NBS	$[35.8566, 35.5645]$	[15.0000, 6.9862]
KSBS	$[34.9841, 36.0284]$	[15.0000, 6.3000]
MTU	$[36.3876, 35.2762]$	[15.0000, 5.0000]
w.MTU	$[24.6122, 38.2269]$	[7.7983, 15.0000]

Table 10: PSNR values and power level values for the case of $N_{\mathrm{h}} = 10 - N_{\mathrm{l}} = 90$.

6. CONCLUSIONS

This paper studies the behavior modeling and analysis of various resource allocation schemes. These schemes aim at the optimal determination of the source and channel coding rates, and power levels of the nodes in a wireless DS–CDMA VSN. The ultimate goal is the amelioration of the video quality, assuming a centralized topology and a cross–layer design. The novelty of this work focuses on the exploration of performance and fairness of each examined scheme. Specifically, in this work we studied four metrics that examine fairness under a different point of view: i) the PF metric which quantifies the relationship between fairness and performance, ii) the Jain's index which measures how equal is an allocation for all users, using the same scheme, iii) the utility gained cumulatively by all nodes of the same scheme and iv) the total consumed power by all nodes, also under the same scheme. All the solutions provided by the schemes examined in this work, are Pareto–optimal solutions and thus, the choice about the most fair and efficient scheme is not evident. There is no scheme that holds all desired characteristics of achieving the highest total utility, while being equally fair to all nodes (equal utility allocations for the nodes), and spending the lowest total power, at the same time. Therefore, the selection of the appropriate scheme depends on the particular application in combination with the users' desires.

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