Mesh HDR WPAN Resource Allocation Optimization Approaches

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Abstract: *In the multihop IEEE 802.15.5 networks, all the devices compete to the resources of a shared superframe. In order to distribute these resources in a fair and satisfactory manner among the competing devices, we propose a distributed optimization framework for resource allocation scheme in an IEEE 802.15.5 hop-1. For this purpose, we introduce in this paper a suite of optimization problems for the hop-1 IEEE 802.15.5 resource allocation to optimize fairness and satisfaction without exceeding the superframe size and respecting the demanded channel time size sent by the requesting devices. Simulation results studied and compared the satisfaction factor and fairness index of the different proposed optimization problems. Consequently, a trade-off between satisfaction and fairness should be conducted for choosing the optimal solution.*

Keywords: *IEEE 802.15.5; resource allocation; optimization; fairness; NUM.*

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1. Introduction

An optimization problem is based on an objective function which undergoes one or several constraints. For resource allocation optimization, the limited resources form the constraints of the optimization problem.

Lee *et al.* [4] provides the architectural framework enabling Wireless Personal Area Network (WPAN) devices to promote interoperable, stable, and scalable wireless mesh networking. This standard is composed of low-rate and high-rate WPAN mesh networks. In this work, we adopt the high-rate WPAN mesh. Figure 1 shows a two-hop IEEE 802.15.5 mesh network composed of Mesh Piconet Coordinators (MPNCs) and Mesh DEVices (MDEVs). The MPNCs share the time resources in a superframe (Table 1) in form of Time Units (TUs). Many TUs form a channel time allocation (CTA) which are part of the channel time allocation period (CTAP) of the superframe.

The superframe size is limited to 65535 µs [1]. The shared superframemultihop nature of wireless WPANs poses fundamental challenges to the design of effective and optimal resource allocation algorithms with respect to resource utilization and fairness across different network devices. The primary objective of this study is to fully utilize the superframe resources (i.e., channel time) while maintaining a certain "fairness" in the allocation among different devices.

In this paper, we present an overview of the resource allocation in the literature in section 2. In section 3, the resource allocation mechanism is presented. Additionally, we spot the light in section 4 on thedifferent optimization approaches especially on the Network Utility Maximization (NUM) framework [3] which is applied for the first time for resource allocation optimization in the IEEE 802.15.5.

Moreover, we propose a satisfaction maximization approach. Section 5 presents the simulation results. At the end, section 6 includes the conclusion.

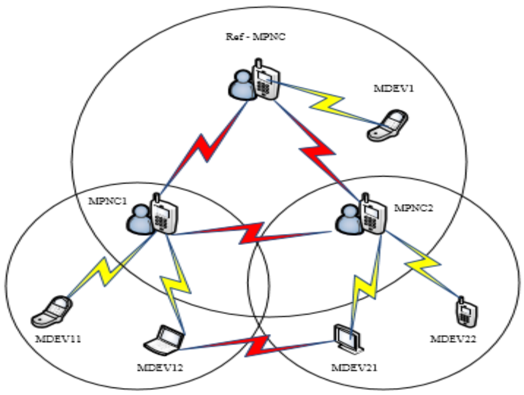

Figure 1. Two-hop IEEE 802.15.5 mesh network.

Table 1. IEEE 802.15.5 Superframe.

Beacon Period			Shared CAP	CTAP			
B1	B2	….	CAP	CTA	TU	TU	….

2. Related Work

The problem of designing distributed access control for attaining fair rates in wireless networks has been partially addressed. Tassiulas and Sarkar [10] propose a centralized algorithm for attaining max–min fairness in certain classes of networks. However, centralized strategies cannot be used in large, dynamic ad-hoc networks.

In another line of work, Nandagopal *et al.* [5] and Ozugur *et al.*[6] propose decentralized heuristic medium access strategies that try to achieve some fairness objectives, but the authors do not prove the fairness properties of these approaches. In this context, researchers have shown that globally fair rates can be attained via distributed approaches based on convex programming.

Qiu *et al.* [7] developed an efficient distributed method to solve resource allocation problem in hyper-dense small cell networks. For reducing the computational complexity for small cell networks, the resource allocation scheme in [1] divided the original optimization problem into two subproblems, and low complexity algorithms were developed. The authors in [11] proposed an optimization scheme for cooperative routing and scheduling together with channel assignment to establish a network path for each request in wireless mesh networks. Several approaches are used for the resource allocation optimization, but no approach is applied to the IEEE 802.15.5.

3. Resource Allocation Mechanism

In the overloaded condition, it is not economical for the network provider to provide the admitted devices a full Quality of Service (QoS) by rejecting excessive devices. However, a degradation of QoS must have a limitation. Otherwise, even with a large amount of admitted devices, too much unsatisfactory QoS could also harm the welfare of the network provider. So we consider several optimization solutions to allocate the resource efficiently in the overloaded network. In the sequel, we propose a generic hop-1 resource allocation mechanism (Figure 2) based on the proposed optimization solutions.

This mechanism can be divided into three stages as follows:

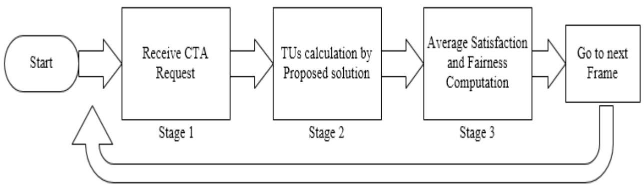

Figure 2. Hop-1 resource allocation optimization algorithm.

Stage 1 is about Initialization and receiving channel time requests: At the initial stage, the minimum and maximum superframe sizes ($size_{min}$ and $size_{max}$) are set. Additionally, the reference MPNC (ref-MPNC) receives the channel time requests (CTRqs) sent by the hop-1 devices. In this paper, we also adopt the concept of bulk CTRqs (BCTRqs) introduced in [11]. Therefore, if the device sending the CTRq is an MPNC, then its request is a BCTRq which is equal to the aggregate of the channel time requests sent by its hop-2 devices. To guarantee that the values of the minimum number of time units (TUs) (min_TU_k) and the desired number of TUs (des_TU_k), which are identified in the CTRq of a device k, are in function of the requested channel time (r_k), we propose to introduce two new parameters. These parameters are denoted by "a" and "b" such that:

$$min\_TU_k = a * r_k \text{ and } des\_TU_k = b * r_k \quad (1)$$

Where a and b values are less than or equal to 1. Actually, these parameters represent the lower and the upper limits of the range used for calculating the granted resources x_k.

Stage 2 is about Hop-1 channel time calculation by Optimization problem: At this stage, the ref-MPNC applies one of the proposed optimization problems for calculating the optimal value x_k^* to be assigned to each of the requesting devices.

Stage 3 is about Hop-1 average satisfaction and fairness calculation: After calculating x_k^* at stage (2), the satisfaction factor (s_k) for device k is calculated at this stage. This factor can be expressed as:

$$s_k = \frac{P(r_k)}{r_k} \quad (2)$$

Where the function *P(.)* represents the optimization problem that is used to allocate the channel time for the requesting devices. The output of $P(r_k$) represents the assigned channel time (x_k^*) to each device k. Then, the average satisfaction factor for the devices with accepted requests, is computed as:

$$s_{av} = \frac{\sum_k s_k}{N_a} \quad (3)$$

Where N_a represents the total number of devices with allocated resources as presented in [9].

The index used for fairness measurement is the Jain's Fairness index[2], and it is defined as:

$$F\big(P(r_k)\big) = \frac{(\sum_k s_k)^2}{N \sum_k (s_k)^2} \quad (4)$$

Where N represents the number of all devices. While the satisfaction factor is related to the devices with granted resources, the fairness index is considered as a more global indicator of the system performance.

4. System Model and Problem Formulation

In this section, we apply two conventional approaches for resource allocation in an IEEE 802.15.5 hop-1 system model (Figure 3), namely the proportional fairness and the uniform allocation. Additionally, we familiarize the NUM problem [3] to be applied on our scheme and propose a satisfaction maximization approach.

In this scheme, let r_k represents the requested channel time resources of a device k, and x_k be the channel time resources to be assigned by the ref-MPNC. Let N denotes the set of hop-1 devices and C denotes the capacity of the superframe.

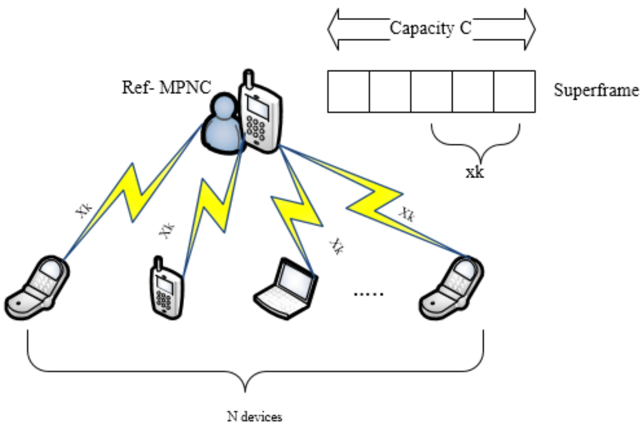

Figure 3. IEEE 802.15.5 hop-1 system model.

4.1. Proportional Fairness Resource Allocation Approach

Proportional fairness claims that resources should be shared so as to maximize an objective function describing the overall utility of the contending stations. We propose and analyze a proportional share resource allocation scheme that balances the trade-off between superframe capacity and fairness for realizing channel time allocation in time-shared superframe.

Further, we associate a weight with each device, which determines the relative share of the resource that a device should receive. Each device is assigned a share of the superframe. In this subsection, x_k is defined as the multiplication of a weight w_k and the total superframe capacity C. w_k is defined as a ratio of the device's *k* requested resources divided by the sum of the total requested resources of all the devices as:

$$w_k = \frac{r_k}{\sum_r^N r_k} \qquad \text{for k=1, 2, …, N} \qquad (5)$$

Then, the problem for calculating x_k can be expressed as:

$$x_k^* = w_k * C \qquad \text{for k=1, 2, …, N}$$
$$\sum_{k=1}^{N} w_k = 1 \qquad (6)$$

The satisfaction factor s_k for a device *k* refers to a uniform device satisfaction irrespective of the device's requested channel time. This factor is then computed as

$$s_k = \frac{x_k^*}{r_k} = \frac{r_k/\sum_r r_k}{r_k} * C = \frac{C}{\sum_r r_k}$$

4.2. Uniform Resource Allocation Approach

The uniform resource allocation goal is to spread a given workload evenly to all the parties, where rates have to be allocated to available devices as evenly as possible. Then, the optimal device rate x_k^* for a device k is expressed as: $x_k^* = \frac{C}{N}$, where the optimal resources to be allocated for the hop-1 devices are constant and refer to equal distribution of superframe resources with capacity C divided by N devices. Therefore, the obtained device satisfaction is: $s_k = \frac{x_k^*}{r_k} = \frac{C}{N * r_k}$

4.3. NUM Convex Optimization Approach

Convex programming is an important tool for the optimization approach; in particular, Lagrange duality is a key tool in decomposing the otherwise complex optimization problem into easily solvable components. Convexification in time or frequency enables dual algorithms to reach the global optimum of the overall network optimization problem efficiently.

For this problem, we assume that each device k is associated with a utility functionU_k, which reflects the "utility" of the device.$U_k$represents the degree of satisfaction of its corresponding device, where (.) is strictly concave, non-decreasing and continuously differentiable. The use of such utility functions is common in the literature to model fairness, since with different utility functions, the rate allocation$x_k$that maximizes the total system utility can be mapped to a range of fairness objectives. The objective is to find the device rate$x_k$vector that maximizes the sum of the utilities of all devices. This objective is subject to the constraint that the sum of the total granted resources of the hop-1 devices does not exceed the maximum superframe capacity.

We adopt the basic NUM problem [1] to be applied for distributed resource allocation in the IEEE 802.15.5 network. We investigate the problem of optimal channel allocation in the sense of maximizing the aggregated utility function $\sum_k U_k(x_k)$, over the channel time resource x_k of a device k, subject to the linear superframe resources constraints $\sum_k x_k \leq C$for all devices. Now, we can formulate an optimal problem for maximizing the total utilities over all devices as follows:

$$\text{P1:} \quad \underset{x_k}{\text{Maximize}} \sum_k U_k(x_k)$$
$$\text{Subject to } \sum_{k=1}^{N} x_k \leq C \qquad (7)$$
$$x_k \geq 0 \quad , k \in N$$

We also consider that the utility function for each device k is logarithmic, which is the most used utility in the resource allocation problems. This function is defined as:

$$U_k(x_k) = \rho \log x_k, \;\; \rho \geq 1 \qquad (8)$$

Where ρ is a constant indicating the scale of the utility function. We introduceρinto the utility function in order to differentiate between the aggressivity of different classes of devices. In our scenario, we consider that all the devices belong to the same class with equal ρ.

The objective function in (7) maximizes the aggregated utility of all devices. The constraint of the optimization problem (P1) is the resource constraint on the shared superframe. By optimizing toward such an objective, both optimal resource allocation and fair resource allocations may be achieved among channel time requests of devices at hop-1 and this will be shown later by results. For solving the problem (7), we first form the Lagrangian as:

$$L(x,\lambda) = \sum_k \rho \log x_k \; + \lambda\left(C \; - \sum_k x_k\right) \qquad (9)$$

Where $\lambda \geq 0$ is the Lagrange multiplier associated with the linear constraint of the CTRq sent to the ref-MPNC. Then, we apply the Lagrangian dual decomposing on (9). In dual decomposition methods, the master problem sets the price for the resources, and each subproblem has to decide the amount of resources to be used depending on the price (Figure 4). The role of the master problem is then to obtain the best pricing strategy. The additivity of total utility and linearity of flow constraints leads to a Lagrangian dual decomposition into individual devices terms as follows:

$$L(x,\lambda) = \sum_k [\,\rho \log x_k - \lambda^k x_k] + C\lambda = \sum_k L_k(x_k, \lambda^k) + C\lambda \quad (10)$$

Where λ^k is the price associated with the channel time request sent by device k to the ref-MPNC. This 'net utility' maximization can be obviously conducted distributively by each device, as long as λ is the feedback to device k, where k maximizes (, λ_k) over x_k for a given λ^k thus solving:

$$x_k^*(\lambda^k) = \underset{x_k \geq 0}{\operatorname{argmax}}[\rho \log x_k - \lambda^k x_k], \quad \forall\, k \qquad (11)$$

Which is unique due to the strict concavity of (x_k) and $x^*(\lambda\;)$ is a Lagrangian maximizer. $x_k^*(\lambda^k)$ is the optimal channel time that maximizes the net benefit of device k, and the price per unit request is equal to λ^k.

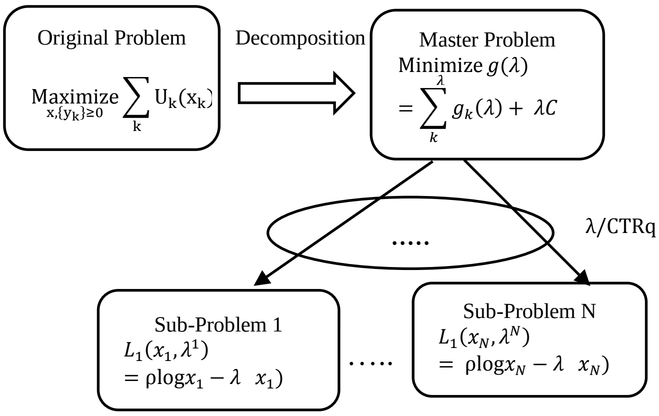

Figure 4. Proposed NUM optimization problem decomposition.

We can thus define a price-based rate allocation function for each device, also denoted as x_k^*, that maps λ^k into a maximizer of the partial Lagrangian L_k. Collecting such functions for all the devices, we write the Lagrangian maximizer vector as $x^*(\lambda\;)$ where the argument is the channel time price. Now, we seek a decentralized solution where the knowledge of the utility functions of all requests is not needed. The key to decentralization is to investigate its dual problem and to decompose the problem via pricing. The master Lagrange dual problem of (7) can be written as:

$$\underset{\lambda}{\text{Minimize}}\; g(\lambda) = \sum_k g_k(\lambda) + \lambda C \qquad (12)$$

$$\text{Subject to} \qquad \lambda \geq 0$$

Where $g_k(\lambda) = L_k(x_k^*(\lambda^k), \lambda^k)$. Since the solution in (11) is unique, it follows that the dual function g(λ) is differentiableand the following gradient method can be used

$$\lambda\;(t+1) = \left[\lambda\;(t) - \theta\left(C \;- \textstyle\sum_k x_k^*\;\left(\lambda^k(t)\right)\right)\right]^+ \qquad (13)$$

Where $C \; - \sum_k x_k^* \;\left(\lambda^k(t)\right)$ is the component of a gradient vector of g(λ), t is the iteration number, and $\theta > 0$ are sufficiently small positive step sizes and$[\;\;]^+$denotes the projection onto the nonnegative orthant.

Certain choices of step sizes, such as $\theta = \beta/t$, $\beta > 0$, guarantee that the sequence of dual variables (t) converges to the dual optimal λ^* as $t \rightarrow \infty$ since the duality gap of (7) is zero. It can be shown that the primal variable $x^*(\lambda(t))$ also converges to the primal optimal variable $x*$. For a primal problem that is a convex optimization, the convergence is towards a global optimum. Furthermore, since the problem (7) is a convex optimization and the problem (11) has a unique solution, x^* and λ^* are the globally optimal primal solutions of (7). Using the NUM problem presented in (7) for our network optimization scenario, a new constraint on the optimal channel time size has to be added.

This is in the aim of adapting the NUM problem to become coherent to the IEEE 802.15.5. Moreover, the addition of this constraint guarantees that the allocated resources for each device are within the minimum and the desired requested TUs as identified in the CTRq sent by a device to the ref-MPNC. Now the problem (7) can be redefined as follows:

$$\text{P1:} \quad \underset{x,\{y_k\}\geq 0}{\text{Maximize}} \sum_k U_k(x_k)$$

$$\text{Subject to } \; x_k \leq y_k \qquad (14)$$

$$\sum_{k=1}^{N} y_k \leq C$$

$$\min\_TU_k \leq y_k \leq \text{des}\_TU_k, \quad \forall\, k \in N$$

We apply the dual decomposition approach on (14) by relaxing the flow constraints, thus the latter problem can be now written as:

$$\underset{x,\{y_k\}\geq 0}{\text{Maximize}} \sum_k [\,U_k(x_k) - \lambda^{(k)} x_k] + \sum_k \lambda^{(k)} y_k$$

$$\text{Subjectto} \sum_{k=1}^{N} y_k \leq C \qquad (15)$$

$$\min\_TU_k \leq y_k \leq \text{des}\_TU_k \quad, \forall\, k \in N$$

This problem decomposes into one maximization for each device, as (1) in the basic NUM, with the following additional resource-bounding maximization to obtain the y_k :

$$\underset{\{y^{(k)}\}\geq 0}{\text{Maximize}} \sum_k \lambda^{(k)} y_k \tag{16}$$

$$\text{Subject to } \sum_{k=1}^{N} y_k \leq C$$

$$\min\_TU_k \leq y_k \leq \text{des}\_TU_k, \ \forall\, k \in N$$

The basic problem in (7) can be solved centrally by the ref-MPNC as a way to distribute the super frame resources among the devices, according to the prices given by the Lagrangian multipliers (k), which are different for each device. With this choice, the Lagrange multipliers are computed using a sequential algorithm which, at each step, updates them based on the value of the local subgradient in (17) similar to (11). Then the maximization in (17) is solved independently by each device. At each time iteration *t*, a new subgradient has to be computed. Thus the updating rules for each multiplier at time t +1 are:

$$\lambda^{(k)}\ (t+1) = [\lambda^{(k)}(t) - \theta(y_k(t) \ - x_k^*(\lambda^k(t)))]^+, \forall\, k \in N \tag{17}$$

Additionally, in order to get a solution which converges to a stable value, the step sizeθshould be set to be small constant. Then, the standard dual algorithm to solve (14) is defined as:

1. Each device k needs its utilityU_k. Additionally, the ref-MPNC needs the superframe capacity (maximum capacity is 65535 μs). Initially set t = 0 and (0) = 1.
2. Then, each device locally solves its problem by computing (16) and then broadcasts the solution $x_k^*(\lambda^k(t))$.
3. The ref-MPNC updates its price with the gradient iteration (17) and broadcasts the new price (t+1).
4. Set $t \leftarrow t$+1 and go back to step 2 until satisfying the termination criterion.

Therefore, as mentioned in the above analysis, the optimal resource allocation can be obtained by every device maximizing its own channel time benefit, which is a distributed and parallel computing process. Thus, the computational complication of central control node (ref-MPNC) is significantly alleviated, which makes the scheme easily applied to the real systems. The obtained device *k* satisfaction is: $s_k = \frac{x_k^*}{r_k}$; where x_k^* varies for each device *k* based on its Lagrange maximizer λ^k.

4.4. Satisfaction Maximization-based Approach

To make comparisons with the fairness approach, it is interesting to state an allocation algorithm to maximize the satisfaction. In that perspective, we propose an optimization problem that is derived by maximizing the summation of each device's satisfactory level in the whole network. In this problem, we take the device's satisfactory level to indicate the device's satisfaction and quantify the device's satisfactory level. The summation of each device's satisfactory level is used as the criterion to select the optimal resource allocation. The target problem can be formulated as:

$$\text{P2: Maximize} \sum_{k=1}^{N} \boldsymbol{s_k} = \sum_{k=1}^{N} \frac{x_k}{r_k} \text{Subject to} \quad x_k \geq 0$$

$$\sum_{k=1}^{N} x_k \leq C \tag{18}$$

$$\min\_TU_k \leq x_k \leq \text{des}\_TU_k$$

Where $\sum_{k=1}^{N} s_k$ represents the summation of each device's satisfaction factor. For calculating the optimal resources using (P2), we apply the Lagrange dual decomposition for solving this problem similarly as applied to (P1). Thus, the equations (9) to (17) are applied on (P2), while substituting (x_k) in (P1) by the satisfaction function s_k in (P2).

5. Hop-1 Resource Allocation Mechanism Simulation Results

Several simulations were run to study and compare the performance of the proposed optimization frameworks for different loaded hop-1 IEEE 802.15.5 networks. Without loss of generality, a scenario of a ref-MPNC with 30 hop-1 devices is considered for a two-hour simulation duration. The requests sent by the hop-1 devices (one request per a device) to the ref-MPNC are considered to follow an exponential distribution with mean equals to (μ) μs. The requesting devices are assigned the channel time resources according to the available superframe capacity and the different optimization frameworks. For the utility function, we consider that ρ=1 to indicate normal and equal devices aggressivity.

5.1 Different Optimization Approaches Performance

Figure 5 shows the average device satisfaction with respect to different loaded networks for the different proposed optimization problems. It is shown that all these problems achieve a very high satisfaction (i.e. greater than one) for low-loaded networks where the condition $\sum_{k=1}^{N} r_k < C$is satisfied. Then, this satisfaction factor drops as load increases. It is also shown that the satisfaction factor obtained by each of the uniform and the proportional approaches is less than that of the NUM and the satisfaction maximization approaches. Not surprisingly, it is observed that the satisfaction maximization approach achieves the highest satisfaction among these approaches, but gives the lowest system fairness as shown in Figure 6. Moreover, the proportional approach provides the lowest satisfaction factor but the highest fairness index.

It is also noticed that the satisfaction factor is not enough to reflect the efficiency of these problems since it hides the fact that some devices can have very high satisfaction while some other devices have much low satisfaction. Thus, the fairness index is a better performance indicator since it reflects the satisfaction and the rejection rates.

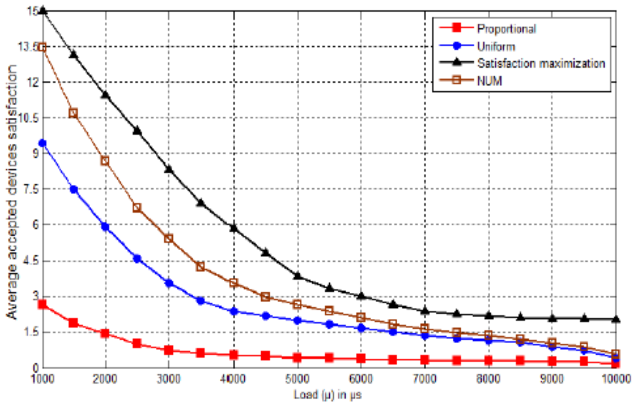

Figure 5. Average satisfaction factor.

Additionally, all these approaches attain a fairness index greater than zero, which reflects the fact that no devices are rejected. The absence of rejection is due to the fact that there exists no situation where the total granted resources exceed the superframe capacity C.

Consequently, it is shown that there is an over-satisfaction for the devices at low load, thus wasting the resources. This is also followed by a rapid degradation in the satisfaction when load increases. Therefore, we propose to introduce a fairness maximization rule into the different approaches.

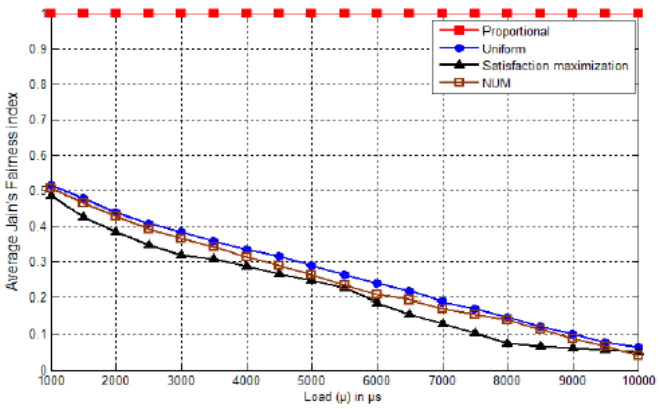

Figure 6. Averaged Jain's Fairness index.

5.2 Fairness Maximization (FM) Rule

Based on the previously obtained results, we propose this rule in aim to optimize the fairness among the contending devices. It is based on the idea of granting resources for a higher number of devices even if with lower satisfaction factor, in order to achieve better overall system fairness. We introduce C' to represent the remaining superframe resources. Then, the FM rule is defined as follows:

1. *Step 1*: Calculate x_k^* using any of the previously defined optimization problems.
2. *Step 2*: Apply the FM rule for each device k such that:
   - If x_k^*< min $\_TU_k$ or x_k^*< 0, then reject the request since its resulting satisfaction factor will be less than the acceptable satisfaction threshold,
   - else if x_k^*>des_TU_k , then set $x_k^*$to the desired number of TUs (des_TU_k) in order to avoid the over-satisfaction and thus the depletion of resources,
   - Then, compute sat_k for each device k.
   - Moreover, in case that sat_k>1, then set sat_k to 1 and $x_k^*$to des_TU_k. This case could be obtained in the proportional and the uniform approaches, whose satisfaction factor is independent of x_k^*.
   - Finally, compute the number of remaining requesting devices as $N = N' - 1$.
3. *Step 3*: Compute the remaining superframe capacity $C' = C - \sum_k^{N-N'} x_k^*$,
4. *Step 4*: Set $N \leftarrow N'$ and $C \leftarrow C'$, then go back to step 1.

The advantages of applying this rule can be described as follows: Firstly, no satisfaction factor with values greater than one is obtained, thus avoiding the wastage of the resources. Secondly, this rule allows more device requests to be accepted but with lower satisfaction factor, whose average remains very convenient and acceptable as shown in Figure 7.

Consequently, the fairness is significantly increased in the different approaches (see Figure 8) compared with that obtained without applying this algorithm.

Figures 7, 8, and 9 show that the uniform approach provides high satisfaction factor with no rejection, but with the lowest fairness index. The proportional approach shows high fairness but with the lowest satisfaction factor and with rejection that appears at lower loads compared to the other approaches. The NUM and the satisfaction maximization approaches provide approximately similar results in terms of fairness, satisfaction and rejection. While the satisfaction maximization approach offers higher satisfaction than NUM, the latter provides better fairness and lower rejection rates at high loads.

Figure shows that fairness degrades quickly at high loads for the proportional, NUM and satisfaction maximization approaches. This is because the rejection ratio increases rapidly at high loads (Figure 9).

Therefore, choosing between these approaches is related to a compromise between the devices' satisfaction and the system's fairness and this is to be decided by the operator.

6. Conclusions

In this paper, we presented a hop-1 resource allocation mechanism based on a distributed optimization framework for fair resource allocation in an IEEE 802.15.5 wireless network. Under the umbrella of this optimization framework, we proposed a suite of problem formulations for the hop-1 IEEE 802.15.5 devices showing different high satisfaction and fairness indexes among these different problems. Consequently, a trade-off between satisfaction and fairness should be conducted for choosing the optimal problem.

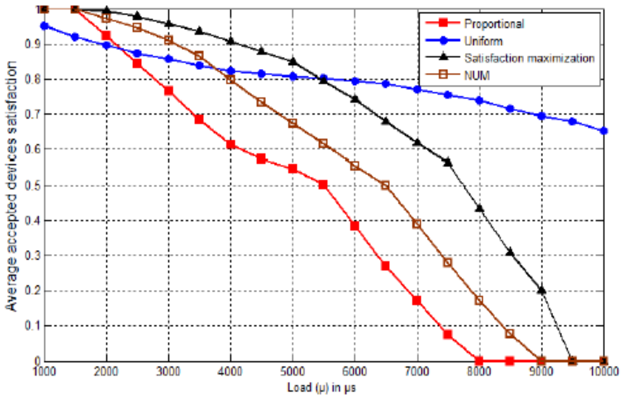

Figure 7. Average satisfaction factor with FM rule.

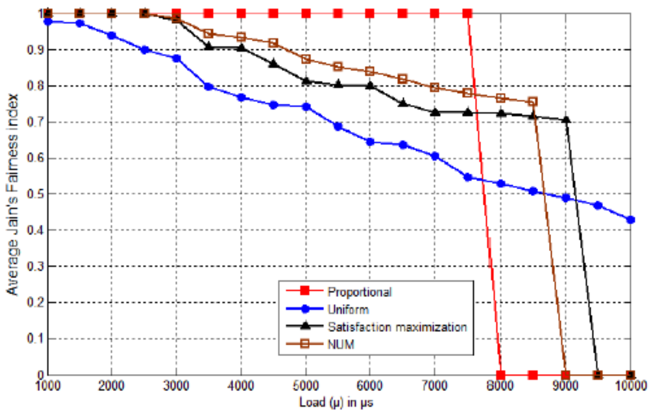

Figure 8. Average Jain's Fairness index with FM rule.

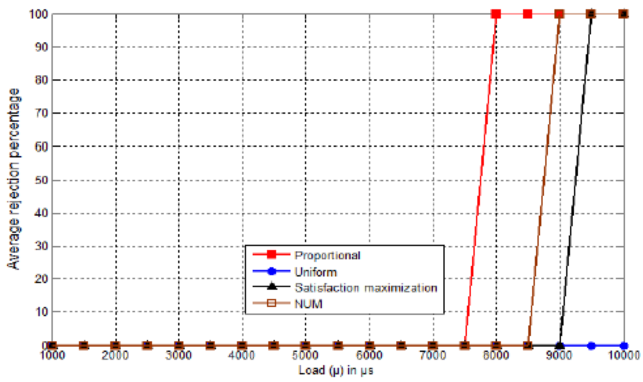

Figure 9. Average rejection rate percentage with FM rule.

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