Ecology-Inspired Coexistence of Heterogeneous Wireless Networks

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Abstract—A number of wireless standards (e.g., IEEE 802.11af and IEEE 802.22) have been developed or are currently being developed for enabling opportunistic access in white space. When heterogeneous wireless networks that are based on different wireless standards operate in the same spectrum, coexistence issues can potentially cause major problems. Enabling collaborative coexistence via direct coordination between heterogeneous wireless networks is very challenging due to incompatible MAC/PHY designs of coexisting networks. Moreover, the direct coordination would require competing networks or service providers to exchange sensitive control information that may raise conflict of interest issues and customer privacy concerns. In this paper, we present an architecture for enabling collaborative coexistence of heterogeneous wireless networks over white space, called Symbiotic Heterogeneous coexistence ARchitectuRE (SHARE). By mimicking the symbiotic relationships (i.e., the interspecific competition process) between heterogeneous organisms in a stable ecosystem, SHARE establishes an indirect coordination mechanism for spectrum sharing between heterogeneous wireless networks via a mediator system, which avoids the drawbacks of direct coordination. Analytical and simulation results show that SHARE allocates spectrum among coexisting networks in a weighted-fair manner without any inter-network direct coordination.

I. INTRODUCTION

Industry and research stakeholders have initialized standardization efforts to enable wireless networks’ utilization of “white space” (WS). These efforts include IEEE 802.22 Wireless Regional Area Networks (WRAN) [8], IEEE 802.11af (WiFi over WS) [6], ECMA 392 (WPAN over WS) [2], etc. When heterogeneous wireless networks that are based on different wireless standards operate in the same WS spectrum band, coexistence issues can potentially cause major problems. In this paper, we focus on the heterogeneous coexistence between wireless networks that employ different wireless technologies.

The coexistence schemes for wireless networks can be broadly classified into two categories. A non-collaborative coexistence scheme is the only feasible approach when there are no means of coordination between the coexisting networks, such as the coexistence of WiFi and ZigBee networks [5], [15]. A collaborative coexistence scheme can be employed when coexisting networks can directly coordinate their operations, such as the self-coexistence schemes for 802.22 networks [1], [9].

Existing coexistence schemes fail to adequately address the heterogeneous coexistence problem for a number of technical and policy reasons. Non-collaborative schemes cannot handle the coexistence among heterogeneous networks due to their incompatible MAC strategies. Collaborative strategies may require the exchange of potentially sensitive information (e.g., traffic load, bandwidth requirements) across different networks to negotiate the spectrum partitioning, which could raise conflict-of-interest issues and customer privacy concerns for competing wireless networks or service providers. Moreover, it is difficult to find a third party that can serve as a global or centralized decision maker that supervise all heterogeneous networks and allocate spectrum to them.

In this paper, we propose a coexistence framework, called the Symbiotic Heterogeneous coexistence ARchitectuRE (SHARE), that employs an indirect coordination method for enabling collaborative coexistence among heterogeneous wireless networks. As its name implies, the proposed framework was inspired by the inter-species relations that exist in biological ecosystems. A symbiotic relation is a term used in biology to describe the coexistence of different species that form relations via indirect coordination. SHARE exploits a mediator system that forwards sanitized data to establish the indirect coordination mechanism between coexisting networks. SHARE employs an ecology-inspired spectrum sharing algorithm inspired by an interspecific resource competition model that enables each network to autonomously determine the amount of spectrum that it should appropriate without direct negotiation with competing networks. Our analytical and simulation results show that SHARE guarantees weighted-fairness in partitioning spectrum and improves spectrum utilization.

The rest of this paper is organized as follows. We provide background knowledge of the mediator system and theoretical ecology in Section II. In Section III, we give an overview of SHARE. We present the SHARE algorithm and provide analytical results in Section IV. In Section V, we evaluate the performance of SHARE using simulations. We conclude the paper in Section VI.

II. TECHNICAL BACKGROUND

As stated previously, SHARE employs a mediator system to establish an indirect coordination mechanism between wireless networks. Note that the mediator is not a global decision
The mediator helps address conflict-of-interest issues and customer privacy concerns, which may arise when coexisting networks operated by competing service providers are required to exchange sensitive traffic information in order to carry out coexistence mechanisms. The mediator sanitizes the sensitive information received from the coexisting networks and then returns the sanitized information back to them. The coexisting networks autonomously execute their coordinated coexistence mechanisms using the sanitized data.

B. Ecology-inspired Spectrum Allocation

As mentioned before, spectrum allocation among the coexisting networks through direct coordination may not be possible (due to a lack of infrastructure), may be too costly, or may be shunned by the competing network operators because they
do not want to provide their sensitive information. Instead of
direct coordination, the SHARE framework adopts an indirect
coordination mechanism, which is inspired by an interspecific
competition model from theoretical ecology.

**Design objective.** In a spectrum sharing process, a network
has to figure out how much spectrum it can appropriate
given its bandwidth requirement. Suppose a time-spectrum
block is the minimum unit amount of spectrum allocation.
Let \( S_i \) denote the number of time-spectrum blocks allocated
to network \( i \in K \) during a period. We refer to \( S_i \) as the
spectrum share of network \( i \).

Our objective is that the spectrum sharing process will
eventually reach a state of equilibrium, where the number of
allocated blocks to each network is proportional to its reported
bandwidth requirement.

**Inspiration from ecology.** In ecology, the population dy-
namics of a species in the interspecific resource competition
process can be captured by the L-V competition model. In the
context of network coexistence, we build a weighted com-
petition model to help a network to determine the dynamics of
its allocated spectrum, given its bandwidth requirement.

**Information exchange between the mediator and a
network.** The mediator exchanges two types of control in-
formation with every network:

1) **Upload of local report.** Network \( i \) reports the current
value of \( S_i \) to the mediator;
2) **Download of sanitized data.** The mediator replies back
to network \( i \) with the sanitized data, i.e., sum of numbers
time-spectrum blocks of all other coexisting networks,
\( \sum_{j \neq i,j \in K} S_j \).

**C. Problem Formulation**

Suppose that \( K \) denotes a set of \( n \) co-located networks
that have individual bandwidth requirements \( R_1, R_2, ..., R_n \),
and operate over the same spectrum. The first objective for
coexisting networks is to split the available spectrum into \( n \) pieces that are proportional to their individual bandwidth
requirements, without sharing individual bandwidth require-
ments with each other.

Let \( S(K) = [S_1, S_2, ..., S_n] \) denote the spectrum share
vector for \( K \).

We define the fairness index, \( F(S(K)) \), for networks in \( K \) as follows:

\[
F(S(K)) = \frac{(\sum_{i \in K} S_i)^2}{\sum_{i \in K} R_i \cdot \left(\frac{S_i}{R_i}\right)^2}.
\]

The maximum value of \( F(S(K)) \) is one (the best or weighted-
earth case), where the allocated spectrum share value of a
network is proportional to its bandwidth requirement.

Let \( \mathcal{I}_i \) denote the set of shared control information known
by network \( i \), and it is easy to see that \( R_i \in \mathcal{I}_i \). However, we
assume that \( R_j \notin \mathcal{I}_i \) —i.e., co-located networks, \( i \) and
\( j \), do not know each other’s bandwidth requirements.

We formulate a weighted-fair spectrum allocation problem
where heterogeneous networks dynamically determine their
spectrum share values.

\[^1\text{The vector is a row vector or a } 1 \times n \text{ matrix.}\]

### TABLE I

A mapping between biological and wireless network ecosystems.

<table>
<thead>
<tr>
<th>Biological ecosystem</th>
<th>Wireless network system</th>
</tr>
</thead>
<tbody>
<tr>
<td>A species</td>
<td>A network</td>
</tr>
<tr>
<td>Population of a species</td>
<td>Spectrum share of a network</td>
</tr>
<tr>
<td>Population dynamics (growth or decline)</td>
<td>Dynamics of spectrum share</td>
</tr>
</tbody>
</table>

**Problem 1:** Given a set of \( n \) co-located networks, \( K \), operating over \( N \) channels, one has to solve the following problem
to find the spectrum share vector for \( K \):

Maximize \( F(S(K)) \)

subject to \( \frac{S_i}{S_j} = \frac{R_i}{R_j} \), and \( R_j \notin \mathcal{I}_i, \forall i, j \in K \).

The first constraint \( \frac{S_i}{S_j} = \frac{R_i}{R_j} \) guarantees the weighted fairness.

**IV. AN ECOLOGY-INSPIRED SPECTRUM ALLOCATION
ALGORITHM**

**A. A Weighted-fair Spectrum Competition Model**

1) **The stable equilibrium of the L-V competition model:**
The L-V competition model provides a method for defining a
state of “stable equilibrium” and finding the sufficient
conditions for achieving it. If one considers the interspecific
competition process described by equation (1), when \( K_i = K_j \)
and \( \alpha_{ij} = \alpha_{ji} \) for any two species \( i \) and \( j \), then the sufficient
condition for stable equilibrium is \( \alpha_{ij} < 1 \).

2) **The basic spectrum competition model:** In Table I , we
identify a number of analogies between a biological ecosys-
tem and a network system. Based on equation (1) and the
analogy, we can easily obtain the following basic spectrum
competition model:

\[
\frac{dS_i}{dt} = rS_i \left(1 - \frac{S_i + \alpha \sum_{j \neq i} S_j}{C}\right),
\]

where \( S_i \) is the spectrum share for network \( i \), and \( r \) is an
intrinsic rate of increase. In equation (3), the carrying
capacity is equal to the number of time-spectrum blocks in
a period given \( N \) channels. A competition coefficient \( \alpha < 1 \)
will guarantee a stable equilibrium—i.e., all the competing
networks will have the same spectrum share value.

Next, we will show how to extend the basic competi-
tion model to a weighted-fair spectrum competition model
that complies with the weighted-fairness requirement (i.e.,
\( \frac{S_i}{S_j} = \frac{R_i}{R_j} \) for any two networks \( i \) and \( j \) in a state of stable
equilibrium.

3) **The weighted-fair spectrum competition model:** The
basic spectrum competition model guarantees a stable equilib-
rium where all the competing networks have the same spec-
trum share value. However, solutions to Problem 1 must satisfy
the requirement of weighted fairness, which implies that the
competing networks’ spectrum share values are proportional
to their bandwidth requirements. For example, if network \( i \) has
a bandwidth requirement that is twice that of network \( j \), then
network \( i \)’s allocated spectrum share should also be twice the
allocated spectrum share of network \( j \).
The concept of network sub-species. To support the weighted-fairness in spectrum share allocation, we construct a weighted-fair spectrum competition model by introducing the concept of “sub-species”. A network with a higher bandwidth requirement would have a greater number of sub-species than a network with a lower bandwidth requirement. We use the bandwidth requirement \( R_i \) as the number of sub-species of network \( i \).

Let \( S_{i,k} \) denote the spectrum share allocated to the sub-species \( k \) of network \( i \), where \( k \in [1, R_i] \). In the weighted competition model, every sub-species \( k \) of network \( i \) calculates the change in its spectrum share according to the following equation:

\[
\delta_{i,k} = \frac{dS_{i,k}}{dt} = rS_{i,k} \left( 1 - \frac{S_{i,k} + \alpha \sum_{k \neq k} S_{i,k} + \alpha \sum_{j \neq i} S_j}{C} \right).
\]

Then, network \( i \) obtains its spectrum share value by combining the spectrum share values of all of its sub-species, i.e., \( S_i = \sum_k S_{i,k} \).

In SHARE, every network \( i \) periodically sends its spectrum share value \( S_i \) to the mediator, and then the mediator sends back the sanitized data \( \beta_i = \sum_{j \neq i} S_j \) to network \( i \). The spectrum share allocation process terminates when \( \delta_{i,k} = 0 \) for all \( i \) and \( k \). Note that the sanitized data \( \beta_i \) is used (instead of actual bandwidth requirement information) to mitigate conflict of interest and privacy issues that may arise between competing networks. The use of sanitized data coincides with the second condition of Problem 1. We show the pseudo code in Algorithm 1 and describe the procedure of SHARE as below.

1) A network \( i \) starts its spectrum share allocation process by creating a number of \( R_i \) sub-species.
2) At the beginning of every frame, every sub-species calculates the change rate of its spectrum share (i.e., \( \frac{dS_{i,k}}{dt} \)) using the sanitized data \( \beta_i \) obtained from the mediator.
3) If the change rate of the spectrum share is positive (or negative), a sub-species increases (or decreases) its spectrum share by randomly selecting a number of time-spectrum blocks to access (or releasing/freeing a number of occupied time-spectrum blocks).
4) At the end of every iteration, every network \( i \) calculates its new spectrum share value by \( S_i = \sum_k S_{i,k} \), and sends \( S_i \) to the mediator. Meanwhile, the network updates the value of \( \beta_i \) from the mediator.
5) Last three steps are repeated until there is no sub-species with a non-zero change rate of spectrum share; that is \( \frac{dS_{i,k}}{dt} = 0 \) for every sub-species \( k \) of any network \( i \).
6) The allocated spectrum share for network \( i \) is \( \sum_k S_{i,k} \).

**B. Characteristics of the Stable Equilibrium**

**Weighted-fairness.** We first prove that the spectrum share allocation algorithm satisfies the requirement of weighted-fairness defined in Problem 1.

**Lemma 1:** Given \( n \) coexisting networks in \( \mathcal{K} \), when \( \alpha < 1 \), the spectrum share allocation process of Algorithm 1 is weighted-fair in partitioning the spectrum consisting of \( C \) time-spectrum blocks.

**Proof:** Suppose network \( i \in \mathcal{K} \) has a number of \( R_i \) sub-species. The spectrum share allocation problem is equivalent to a problem where all sub-species compete for the resource using the L-V competition model. Since the sufficient condition for the equilibrium in the L-V competition model, \( \alpha < 1 \), is satisfied, the algorithm will terminate after a finite number of iterations, and all sub-species obtain the same spectrum share at the equilibrium point [3], [4], which is equal to \( \frac{C}{\sum_{j \in \mathcal{K}} R_j} \).

Hence, network \( i \) with \( R_i \) sub-species will obtain a spectrum share \( R_i \frac{C}{\sum_{j \in \mathcal{K}} R_j} \), and thus \( S_i = \frac{R_i}{R_{i'}} \), \( \forall i, i' \in \mathcal{K} \).

**Stable equilibrium.** We now show that the equilibrium point achieved by the weighted-fair competition model is stable.

**Theorem 1:** Let \( l = \sum_{i \in \mathcal{K}} R_i \) represent the total number of sub-species in the system. The differential equations (4) describe an \( l \)-dimensional system where the equilibrium when \( S_i = R_i \frac{C}{\sum_{j \in \mathcal{K}} R_j} \) is stable.

**Proof:** Suppose networks in \( \mathcal{K} \) generate a total number of \( l \) sub-species. For the sake of simplicity, we assign every sub-species an index from \{1,...,\( l \}\}. Let \( S^* = [s^*_1, ..., s^*_l] \) be the spectrum share vector at the equilibrium point for all sub-species in the system, where \( s^*_i \) is the allocated spectrum share of sub-species \( i \) at the equilibrium point.

By Lemma 1, we have \( s^*_i = \frac{C}{l} \), where \( i \in [1, l] \). Equation (4) is equivalent to

\[
\frac{dS^*_i}{dt} = rS^*_i \left( 1 - \frac{s^*_i + \alpha \sum_{j \neq i, j \in [1, l]} s^*_j}{C} \right) = 0.
\]

That is, \( s^*_i + \alpha \sum_{j \neq i, j \in [1, l]} s^*_j = C \).

We will prove the equilibrium \( S^* \) is stable by linearizing the system equations at this equilibrium point. Let \( S = [s_1, ..., s_l] \) be a spectrum share vector for all sub-species at a non-equilibrium point. We denote the differential equation at this point as

**Algorithm 1** The Spectrum Share Allocation Algorithm.

**Input:** competition coefficient \( \alpha \), capacity \( C \), intrinsic rate of increase \( r \), the sanitized data \( \beta_i \).

**Output:** spectrum share, \( S_i \), for network \( i \).

1: Network \( i \) generates a number of \( R_i \) sub-species.
2: Update the value of \( \beta_i \) from the mediator.
3: while \( (\exists k \in [1, R_i], s.t. \delta_{i,k} \neq 0) \) do
4: \hspace{1em} for \( k = 1 \) to \( R_i \) do
5: \hspace{2em} if \( \delta_{k,i} \neq 0 \) then
6: \hspace{3em} \( S_{i,k} = S_{i,k} + \delta_{i,k} \).
7: \hspace{2em} end if
8: \hspace{1em} end for
9: \hspace{1em} Send \( S_i = \sum_k S_{i,k} \) to the mediator and update the value of \( \beta_i \).
10: \hspace{1em} end while
11: \( S_i = \sum_k S_{i,k} \).
system and the equilibrium eigenvalues are negative. Based on the stability theory, the iterations in Algorithm 1) required for the proposed algorithm to converge to a stable equilibrium.

By integrating Equation (8), we obtain

\[ \Delta s_i = s_i - s_i^* \]

Let \( \Delta s_i = s_i - s_i^* \). By linearizing equation (6) at the equilibrium point, we obtain

\[
G_i(S) = G_i(s_1^*, ..., s_l^*) + \sum_{i \in [1, l]} \left( \frac{\partial G_i(S)}{\partial s_i} \right)_{s_i^*, ..., s_l^*} \Delta s_i
\]

\[ = - \left( \frac{r}{T} \right) \Delta s_i - \frac{r \alpha}{T} \sum_{j \neq i, j \in [1, l]} \Delta s_j. \]

We derive the l by l Jacobian matrix for the above equation (7) as follows

\[
A = \begin{bmatrix}
-\frac{r}{T} & -\frac{r \alpha}{T} & -\frac{r \alpha}{T} & \cdots & -\frac{r \alpha}{T} \\
-\frac{r \alpha}{T} & -\frac{r}{T} & -\frac{r \alpha}{T} & \cdots & -\frac{r \alpha}{T} \\
& & & \ddots & \\
& & & & -\frac{r \alpha}{T} \end{bmatrix}
\]

which is a symmetric matrix. This matrix has two eigenvalues \( \lambda = -\frac{r}{T} - \frac{(l-1) \alpha r}{T} \) and \( \frac{r \alpha}{T} \). Since \( 0 < \alpha < 1 \), the two eigenvalues are negative. Based on the stability theory, the system is stable if all eigenvalues are negative. Hence, the differential equations shown by (4) describe an l-dimensional system and the equilibrium \( S^* = \{s_1^*, ..., s_l^*\} \) is stable.

Convergence time. Next, we analyze the time (number of iterations in Algorithm 1) required for the proposed algorithm to converge to a stable equilibrium.

Theorem 2: Consider \( N \) networks that compete for the same spectrum. In this case, the SHARE’s time-to-convergence until an equilibrium is reached is \( T_e = O(\ln(C/l)) \).

Proof: Similar to the proof of Theorem 1, there are a total of \( l \) sub-species. Let \( A = \sum_{j \neq i, j \in [1, l]} s_j \). Then Equation (5) can be rewritten as

\[
\frac{ds_i}{dt} = rs_i \left( 1 - \frac{s_i + \alpha A}{C} \right) = 0.
\]

By integrating Equation (8), we obtain

\[
s_i(t) = \frac{s_0 e^{rt(1-\frac{A}{C})}}{s_0(r^{rt(1-\frac{A}{C})} - 1) + (C - \alpha A)},
\]

where \( s_0 \) is a small positive constant representing the initial spectrum share value for a network.

To calculate the time-to-convergence, we consider the time which is required to increase the spectrum share for network \( i \) from \( s_0 \) to \( s_i(t) \). Using Equation (9), we obtain the following value for \( T_e \):

\[
T_e = \frac{C}{r(C - \alpha A)} \ln \left( \frac{s_i(t)(s_i(t) - (C - \alpha A))}{s_0(C - \alpha A - s_0)} \right).
\]

Since \( s_i(t) = C/l \) at the equilibrium, the time of convergence of SHARE is \( O(\ln(C/l)) \).

V. PERFORMANCE EVALUATION

A. The Stable Equilibrium

We first look into the the stable equilibrium achieved by the weighted-fair spectrum share allocation scheme. We simulate a number of \( n \) coexisting networks in a block of spectrum that is divided into 10 channels. The period contains eight super-frames, and each super-frame has 32 frames. At the end of every super frame, every coexisting network is required to exchange information with the mediator system. We first set \( n = 2 \), and fix the bandwidth requirements of the two networks as \( R_1 = 2 \) and \( R_2 = 3 \), which implies that network 1 has two sub-species and network 2 has three in the spectrum allocation process. In the L-V competition model, the competition coefficient \( \alpha < 1 \) and the intrinsic rate of increase \( r < 2 \) [11]. The discussions on how to choose appropriate parameter values to achieve fast convergence to an equilibrium can be found in [3], [11]. In this set of simulations we used \( \alpha = 0.9 \) and \( r = 1.95 \). Next, we show that the coexisting networks under SHARE achieve an equilibrium, where the spectrum share of each network is proportional to its bandwidth requirement.

Convergence to an equilibrium. From Figure 2, we observe the dynamics of the spectrum share value of each network and each sub-species within a network. “Sub-species \((i,j)\)” in the figure legend represents sub-species \( j \) within network \( i \). The system converges to an equilibrium state in finite time where all sub-species of every network are allocated the same spectrum share value. The aggregate spectrum share value allocated to a network is proportional to its bandwidth requirement.

Stability of the equilibrium. To test the stability of the equilibrium point, we introduce two types of disturbance in bandwidth requirement by: 1) silencing the sub-species (2, 3)
for a short time period (from the 120th to 140th iteration), and 2) deleting the sub-species (2, 3) at the 360th iteration. Figure 3 shows the dynamics of spectrum share values when the disturbance is introduced. As can be seen in the figure, the disturbance causes the system to deviate away from equilibrium, but the coexisting networks quickly converge to a new equilibrium point where the allocated spectrum share values are proportional to the new values of bandwidth requirements.

B. Weighted Fairness

We vary the number of coexisting networks, and in each simulation run, the bandwidth requirement, $R_i$, of each network $i$ is randomly chosen from the range $[1, 5]$. We compare SHARE with an “un-coordinate” allocation scheme where every coexisting network determines its spectrum share value without coordinating with others. This is equivalent to splitting the available spectrum “randomly” to $n$ pieces and allocates them to $n$ coexisting networks. We measure the fairness values using the fairness index defined in Equation (2). Figure 4 clearly shows that SHARE allocates spectrum in a weighted-fair manner, whereas the un-coordinate allocation scheme does not.

![Fig. 5. System satisfaction when: (a) coexisting networks have the identical bandwidth requirement given sufficient spectrum; and (b) coexisting networks have random values of bandwidth requirements given insufficient spectrum.](image)

C. System Satisfaction

In an uncoordinated allocation scheme, every network randomly determines its allocated spectrum share. It is possible that a network with a smaller bandwidth requirement may occupy a larger portion of spectrum than the network with a greater bandwidth requirement, which breaks the rule of spectrum allocation in a weighted-fair manner. We define the satisfaction of network $i$ as the ratio between its allocated spectrum share to its bandwidth requirement, $f_i = \min \{1, \frac{C_i}{R_i} \}$. Then, the system satisfaction is defined as the minimum satisfaction value among all coexisting networks, such as $\Phi = \min_{i \in K} \{f_i\}$.

We vary the number of networks, $n$, and observe the system satisfaction in two cases: in Case 1, the bandwidth requirement value of every network is set as $C/n$; and in Case 2, the bandwidth requirement value of each network is randomly chosen from the range $[1, C]$, where $C$ is the total number of time-spectrum blocks that can be allocated in a period. In Case 1, the available spectrum is sufficient to satisfy all networks’ requirements; and in Case 2, the bandwidth requirements of all networks may exceed the number of available time-spectrum blocks in a period. From Figure 5, we can observe that in both cases, SHARE’s system satisfaction is superior to that of the uncoordinated scheme. In Case 2, as $n$ increases, the system satisfaction value for both schemes decreases because the amount of available spectrum cannot satisfy the bandwidth requirements of all networks.

VI. CONCLUSIONS

Inspired by symbiotic coexistence in ecology, in this paper we presented a framework called Symbiotic Heterogeneous coexistence ARchitecturE (SHARE), which enables collaborative coexistence among heterogeneous networks over white space. SHARE enables two heterogeneous wireless networks to coexist in the same spectrum band through a mediator-based indirect coordination mechanism between them, which avoids the drawbacks of direct coordination mechanisms. The SHARE framework adopts an ecology-inspired spectrum sharing algorithm that is executed by each coexisting network to autonomously and dynamically determine its spectrum share that is proportional to its bandwidth requirement. Analytical and simulation results show that SHARE enables the networks’ spectrum allocation to converge to a stable equilibrium, and that in this allocation, weighted-fairness is ensured and a high system satisfaction value is guaranteed.

REFERENCES