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Autonomous and adaptive resource allocation among multiple nodes andmultiple applications in heterogeneous wireless networks

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Abstract:

A variety of wireless communication methods, including cellular, Wi-Fi, WiMAX, and DSRC, will be accessible to mobile users and apps in the near future. More and more people and applications will be able to be accommodated in mobile environments as wireless communication and mobile devices continue to advance. We need an adaptive method that allows mobile users and apps to share the available network resources while meeting each application's quality of service needs. This is necessary since there are limited wireless resources, and the communication quality of different applications might vary over time. We provide an adaptive resource allocation technique in this study that allows each node to decide for itself how much wireless network resource to allocate to each of the networked apps that run on it. We use an attractor composition model—inspired by the self-organising and ever-changing behaviour of living systems—to achieve this goal. We validated our mechanism's ability to stably and adaptively distribute wireless network resources to applications by doing numerical analyses. This process took into account the applications' QoS needs and ensured that network resources were shared equitably across nodes. Our technique is also shown to be better than one in which a node allocates resources by solving an optimisation issue.

1. Introduction

There will be a plethora of wireless communication options for mobile users and life-improving apps popping up all over the place in the near future, thanks to the expansion of wireless network technology. In terms of cost, connection, latency, capacity, and availability, wireless communications come in a wide variety of forms, including cellular, Wi-Fi, WiMAX, and DSRC (Dedicated Short Range Communication). The unpredictability of wireless communication and the rivalry between users and apps for the limited resources of wireless networks also cause most characteristics to vary over time. Depending on the quality of service (QoS) requirements of the networked application, such as low latency for voice over IP (VoIP), low cost for electronic mail (e-mail), or high bandwidth for video streaming, a wireless network may be more or less appropriate. In light of the current state of wireless networks and the quality of service (QoS) needs of individual applications, it is imperative that nodes—i.e., equipment executing networked applications—make dynamic resource allocation decisions. For interactive communication, a one-way end-to-end latency of less than 150 ms is required, for instance, by a VoIP app that runs on a smartphone [1]. Consequently, VoIP applications benefit from being assigned to cellular or DSRC networks, which provide connections with little latency and jitter. Even when there is a lot of traffic, an email software can handle delays. Consequently, an e-mail app would do well on a Wi-Fi or WiMAX network as these types of networks provide a high-speed connection at a cheaper price than cellular networks.
Researchers and developers have been drawn to cognitive networking in recent years as a means to efficiently and effectively use existing wireless networks. One definition of a cognitive network is the technology that can detect the state of wireless networks and choose the best network to make the most of the resources available on those networks [2-6]. An cognitive network's wireless network resource is a channel, spectrum, or network that is defined by its frequency, coding scheme, MAC protocol, or other wireless network-related characteristics. Adaptive resource allocation in a diverse wireless network environment is a good use of current approaches, however most of them focus on allocating resources between nodes or across applications on a single node. To illustrate the issue of allocating resources among several nodes, Kassar et al. presented an automated network selection method in [4]. They

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came up with a thorough method for the node to use multi-attribute decision-making techniques to help it choose the best possible network. Taking rule-based multi-attribute decision making into account, they examine networks with more than 10 characteristics. But they didn't think about how to make efficient and effective use of several networks; their method just takes one into account. We require a method to assign each application on each node the best wireless network based on its quality of service requirements and the characteristics of the available heterogeneous networks in an environment where multiple nodes are running different applications. After knowing the state of the accessible wireless networks and the quality of service needs of all applications, this kind of resource allocation may be expressed as an optimisation problem with the goal of maximising the degree of satisfaction per node and per application. An access point or other central node must exchange messages aggressively and often with other nodes in the vicinity to keep the information up-to-date in order for this optimisation to take place. To stay up-to-date on the state of other nodes' applications, nodes still need to communicate with each other often, even if they are each assigned the responsibility of determining the best way to allocate resources. In the next-generation network setting, where numerous networked applications have access to a variety of wireless networks, such mechanisms are completely impractical due to the energy and bandwidth consumed during message exchanges and other dynamic characteristics of wireless networks.

Our proposed approach for autonomously allocating network resources across various nodes and applications is completely distributed and flexible. Each node in our system chooses its own wireless network based on its own needs. Before doing anything else, a node must determine the state of the wireless networks that are accessible to it. The app then checks to see whether the assigned networks meet the needs of the apps. The next step is for it to decide which wireless network each application will use. We use an attractor composition model, a nonlinear mathematical framework for the dynamical and adaptive behaviour of biological systems, to achieve stable and adaptive resource allocation in a constantly changing environment [7]. As a noise-driven metaheuristic, the attractor composition model adaptively finds a stable solution to an optimisation issue. The potential of the solution space is influenced by the quality of the present solution, and possible solutions are defined as attractor points of a dynamical system. A deep basin of attractor matching to the solution in solution space becomes visible and the system's state remains statically there when the present solution is adequate. When an existing solution is no longer suitable for a given situation, the state undergoes random changes and the basin of attractor grows shallow until a suitable replacement is discovered. An autonomous node may determine the best resource allocation solution for the present state of wireless networks and application quality of service needs by using its own level of satisfaction as an indication of the allocation's goodness. As a result of nodes' indirect interactions with one another and the fact that resource allocation at other nodes affects the state of wireless networks, nodes ultimately distribute the available network resources fairly.

Below is the outline for the remainder of the article. In Section 2, we provide the attractor composition model. Section 3 then presents a new approach to resource allocation in heterogeneous wireless networks, one that can handle several nodes and applications. Section 4 then compares the outcomes with a technique that uses per-node optimisation and presents numerical evaluation findings. In Section 5, we wrap up the paper and go over some potential next steps.

Attractor composition model and its application to resource allocation

Since the attractor composition model is an extension of the attractor selection model, we first briefly introduce the attractor selection model and then explain the attractor composition model in this section.

1.1. Attractor selection model

Adapting to changing conditions is the goal of the attractor selection model, a metaheuristic for optimisation issues [8]. A symbiotic relationship is the result of the model's development from the adaptive behaviour of biological systems. The two nutrients A and B are essential for the growth of mutant E. coli cells, which are engineered in biological experiments. The production of one nutrient interferes with the production of another, a phenomenon known as a mutually inhibiting connection in nutrient synthesis. The degree of gene expression of the related messenger RNA regulates nutrient synthesis.

The dynamics of mRNA concentrations are defined by the following time-dependent differential equations:

$$\frac{dm_1}{dt} = \frac{s(\alpha)}{1 + m_2^2} - d(\alpha) \times m_1 + \eta_1, \tag{1}$$

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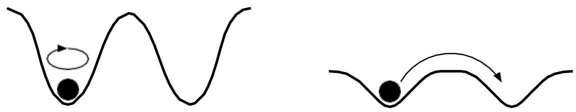

(a) High activity (b) Low activity

Fig. 1. Potential space with two attractors.

$$\frac{dm_2}{dt} = \frac{s(\alpha)}{1 + m_1^2} - d(\alpha) \times m_2 + \eta_2, \tag{2}$$

The mRNA concentrations for nutrients A and B are denoted as m1 and m2, respectively. The cell's state is determined by a pair of m1 and m2, denoted as (m1, m2). α, where α ranges from 0 to 1, is an activity parameter that represents the present state of a cell, such as its growth rate, which depends on both the cell's state and the nutritional conditions in its surroundings. The synthesis of nutrients is carried out by s(α) while their breakdown is done by d(α). In [8], for instance, s(α) = 6α and d(α) = α. White Gaussian noise, denoted by η1 and η2, represents the internal and external noise that is intrinsic to biological systems. The two stable states, or attractors, of a dynamical system defined by the aforementioned equations are m1 and m2. To rephrase, as seen in Figure 1(a), the dynamical system's potential space contains two basins of attractors. It is assumed that a cell remains attracted and produces nutrition A, denoted as m1 m2. The cell may develop effectively and exhibit high activity when both nutrients are present in suitable amounts in the environment, i.e. the culture medium. Consequently, there is a high entrainment force and deep basins of attraction. Therefore, the cell statically remains at the attractor, even while the noise factors impact the mRNA concentrations. Consider for a moment a scenario where vitamin B is unavailable in the environment and the nutritional situation is subject to periodic variations. The cell cannot expand due to a lack of vitamin B since it produces nutrient A. The result is a reduction in the cell's activity. As a result, attraction basins become shallower. Concurrently, the words representing noise start to have a greater impact on the state (m1, m2). The cell is propelled towards the attractor as indicated in Fig. 1(b) because it synthesises more nutrient B than nutrient A, thus m1 < m2. This kind of nutrient synthesis is more advantageous under the present nutritional conditions, thus the cell starts to expand and become more active. Because of the uptick in activity, the basins of attractor sink farther, and the state becomes entangled with a different attractor at m1 m2. At some point, the cell starts to statically synthesise vitamin B. This is how cells are able to effectively adjust their nutrient synthesis to respond to constantly changing nutritional conditions in their surroundings.

To account for M dimensions, we expanded the model in [9] as

$$\frac{dm_i}{dt} = \frac{s(\alpha)}{1 + (\max_{1 \le j \le M} m_j)^2 - m_i^2} - d(\alpha) \times m_i + \eta_i \tag{3}$$

where $1 \le i \le M$ and

$$s(\alpha) = \alpha \times \left[\beta \alpha^{\gamma} + \frac{1}{\sqrt{2}}\right], \tag{4}$$

$$d(\alpha) = \alpha. \tag{5}$$

state values are the values mi where 1 ≤ i ≤ M. M attractors are present in the model, where mi mj is defined as 1 ≤ j < M, j i. The parameters β and γ have positive real values. The stability of attractors is enhanced when the basins of attraction get deeper with larger β. The state value increases at a lower pace as γ becomes larger. Consequently, convergence slows down and entrainment strength decreases.

To maximise performance in a constantly changing environment, adaptive control might use the attractor selection paradigm, which defines activity as control goodness (e.g., performance) and attractors as control alternatives. The approach has found use, for instance, in MANET routing [11] and overlay multipath routing [10]. Attractors in MANET routing represent the selection of neighbour nodes, and route length determines the activity, with M being the number of neighbours. When sending a packet, each node along the route considers the attractor selection model and selects a neighbour node that will result in the shortest path. It was shown that, in a dynamically changing environment, attractor selection-based routing outperforms traditional routing.

Attractor composition model

Now consider the general model of attractor selection, which is formulated as,

$$\frac{dm_i}{dt} = f(m_i) \times \alpha_i + \eta_i, \quad 1 \le i \le N. \tag{6}$$

m_i is a vector of state values of entity i, e.g. a cell and a node, and α_i is the activity of entity i. $f()$ is a function defining attractors. η_i is a vector of white Gaussian noise to introduce the effect of noise to each of state values. N is the number of

entities. According to what was said before, the attractor selection model allows every part of the system, i, to decide on its own how to behave, mi, which results in a high level of activity, αi. The system achieves a globally excellent state where all entities have high activity and peacefully live via mutual interactions among themselves since they share the same environment. This is despite the fact that their decisions are independent of each other. One way in which cellular synthesis affects nutrient concentrations in culture medium is via the process of membrane penetration. Hence, other cells are affected by a cell's adaptive behaviour.
Accelerating global optimisation, the attractor composition model clearly formulates interaction among entities [7]. A model for the attractor's composition is described as

$$\frac{dm_i}{dt} = f(m_i) \times \alpha + \eta_i, \quad 1 \leq i \leq N. \tag{7}$$

Take note that the action is now a system-wide metric for the system's quality. Consequently, the model's global activity may be maximised by each system constituent acting independently and adaptively.
The cross-layer optimisation in a wireless sensor network is approached using the attractor composition model in [7]. This network is structured with an overlay network for periodic data collection over a physical sensor network. Each sensor node adjusts its operating frequency in response to changes in the network architecture, as shown in Eq. (7). Autonomous and adaptive control at multiple tiers work together to achieve the overarching aim of minimising the data collecting latency by doing the same action.

1.2. Application of attractor composition model to resource allocation

There are two possible ways to apply the attractor composition model to the problem of resource allocation between nodes and applications, and they vary in how they understand the global activity that all entities participate in. Entity i is associated with a node where activity α is defined as the efficiency of resource allocation in a certain area with numerous nodes. For this kind of system to work, either every node or a hub node has to know how satisfied every other node is in order to determine the activity. It seems like it would be impractical and costly in terms of bandwidth and energy.
Alternatively, it is more practical and practicable to define the activity α per node. Here, entities that are in a race for

applications are matched with resources. By plugging the values of N and M into Eq. (7), application i on a node may independently choose a wireless network to utilise, given that there are M network resources available. The activity α that all apps on a node share is determined by how satisfied they are with each other.

cooperate such that the node's level of satisfaction is maximised. The sharing of network resources is another way in which nodes operate cooperatively via indirect connection with one another. Following this analysis, we lay out our suggestion in full in the section that follows.

2. Autonomous and adaptive resource allocation mechanism

As explained in the previous section, we adopt the attractor composition model to achieve autonomous and adaptive resource allocation among multiple nodes and multiple applications in the environment where heterogeneous wireless networks are available to nodes. In this section, we first explain a scenario considered in the paper and then describe our resource allocation mechanism.

2.1. Target network and application

Here, we take it as read that nodes have access to a variety of wireless networks. Assuming that cellular, Wi-Fi, WiMAX, and DSRC networks are all accessible and that a node assigns one of these networks to each application, we conduct numerical tests. Nonetheless, these are not the only target networks that our plan encompasses. In addition, as long as their characteristics can be collected at that level of granularity, resource allocation may be done at any level of granularity from a network that is characterised by its technologies, channels, spectrum, and waveform. Access area size, wireless bandwidth, connection setup and communication latency, connection dependability, communication stability, and cost are some of the ways in which these networks vary from one another. For instance, in most metropolitan areas, cellular networks are accessible, with the exception of subterranean areas. Having said that, the actual bandwidth is much lower than the capacity, which is only about 7.2 or 14.4 Mbps. Additionally, communication is expensive and there is a limit to the amount of concurrent connections in a cell. In contrast, nodes in a Wi-Fi network may use a low-cost, high-speed connection (up to 54 Mbps) without breaking the bank. Nevertheless, Wi-Fi networks have very limited reach, with an area of coverage that is no more than a few meters around an access point.
Any kind of portable electronic equipment, whether a car, laptop, or smartphone, is represented by a node. Various apps that rely on wireless networks are operating on each node. Several applications, each with its own unique quality-of-service (QoS) needs, are running in a vehicle, including navigation, reporting on the car's status, video streaming, voice over IP, email, and web surfing [12,13]. When it comes to bandwidth, several applications have different needs. Video streaming apps, for instance, demand a lot of

it, whereas voice over IP apps prefer a connection with little latency and jitter. It is also thought that a module or a

program, which is responsible for allocation of resources to applications. In the case of a car, an OBU (On Board Unit) is equipped with multiple wireless network interfaces to provide applications with access to wireless networks. A node in this case corresponds to a car or more specifically an OBU of a car.

2.2. *Overview of our mechanism*

Application requirements for quality of service (QoS)—including, but not limited to, necessary bandwidth, acceptable delay jitter, and reasonable transmission cost—are declared to the node at regular control intervals. Simultaneously, a node may, using cognitive radio technology, learn about the present state of accessible wireless networks, including things like available bandwidth, delay jitter, and transmission cost [14–16]. The next step is for the node to assess how well the assigned network meets the quality of service criteria of each application. The next step is to determine the activity of the node by calculating its degree of satisfaction from the degree of application satisfaction. Each application's state value vector is modified by the attractor composition model based on the activity. It all comes down to assigning each program a wireless network with the highest state value. While activity is high and resource allocation remains unchanged, this is because the present allocation can fulfil the quality of service needs of applications. If not, the activity shrinks and the noise term determines how resources are distributed, leading to inefficient allocation.

2.3. *Resource allocation based on state vector*

For attractor composition-based resource allocation, a node maintains a set of N state vectors, where N is the number of applications. State vector $\boldsymbol{m}_i$ of application i $(1 \leq i \leq N)$ is defined as,

$$\boldsymbol{m}_i = (m_{i,1}, \ldots, m_{i,j}, \ldots, m_{i,M}), \tag{8}$$

where M is the number of wireless networks available to a node. We assume that wireless networks are indexed, but the order of indexes does not affect resource allocation.

At regular control intervals, the activity α is evaluated and the state vectors are updated accordingly.

$$\frac{dm_{i,j}}{dt} = \frac{s(\alpha)}{1 + (\max_{1\leq k\leq M} m_{i,k})^2 - m_{i,j}^2} - d(\alpha)m_{i,j} + \eta_{i,j}, \tag{9}$$

where $\eta_{i,j}$ is the white Gaussian noise with mean zero and standard deviation σ. For $s()$ and $d()$, we use the same functions in Eq. (4) and Eq. (5), respectively. Then, wireless network indexed as j with the largest state value $m_{i,j}$ in vector $\boldsymbol{m}_i$ is assigned to application i.

2.4. *Activity derivation*

Activity α $(0 \leq \alpha \leq 1)$ indicates the goodness of the current resource allocation. In our proposal, the activity α is derived by the following equation:

$$\alpha = \frac{\sum_{t=0}^{T-1} \alpha_t^*}{T}, \tag{10}$$

where α_0^*, i.e. α_t^* with $t = 0$, is called the current instant activity and α_t^* is the instant activity of t intervals ago. T is a constant defining the window of moving average.

In derivation of the instant activity α_0^*, we use a hysteresis function of the play model [17] to suppress the sensitivity of activity to slight decrease in the degree of satisfaction S of node, which is derived by Eq. (14).

$$\alpha_0^* = \frac{1}{P}\sum_{l=1}^{P} h_l\left(p_l(S)\right), \tag{11}$$

P is the number of play hysterons. p_l $(l = 1, \ldots, P)$ is a play hysteron, which is defined as,

$$p_l(S) = \max\left(\min\left(p_l^-, S + \zeta_l\right), S - \zeta_l\right) \tag{12}$$

where p_l^- is the previous value of p_l and ζ_l is the width of play hysteron p_l. h_l in Eq. (11) is a shape function of p_l, for which we used a sigmoid function as,

$$h_l\left(p_l(S)\right) = \frac{1}{1 + \exp(-g p_l(S))}, \tag{13}$$

g $(g > 0)$ is a gain of a sigmoid function.

Based on preliminary experiments, we found the threshold of activity of a phase transition exists. When the activity is larger than 0.6, a basin of attractor is deep and resource allocation is stable. When the activity becomes smaller than 0.6,

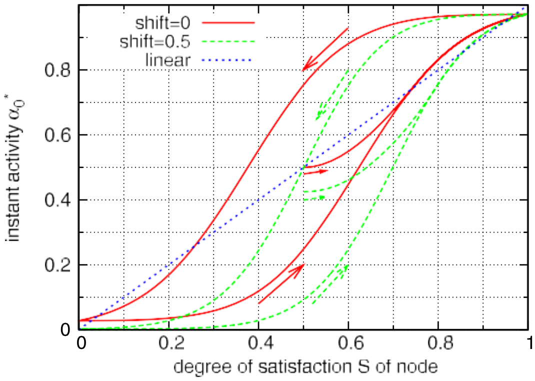

Fig. 2. Hysteresis loop of relationship between the degree of satisfaction of node and the instant activity.

It is at this point that the noise term starts to impact resource allocation. Node behaviour in resource allocation will be negatively affected by sudden changes in wireless network characteristics if we utilise the degree of satisfaction S as the immediate activity, as shown by a linear line in Fig. 2. As a result, resource allocation becomes unstable. The link between the instant activity α0∏ and the degree of satisfaction S of the node is seen in Fig. 2. The hysteresis function causes a solid curve to represent a journey that loops. Whenever a node's level of satisfaction rises from

at first, there is little activity. But once the node's level of satisfaction exceeds a specific threshold, the activity starts to grow at an exponential rate. As a result, nodes will keep trying to find a better way to allocate their resources until their level of satisfaction reaches around 0.67. Once node satisfaction levels are high enough, resource allocation also converges quickly. Alternatively, up to a certain point, activity remains high even while node satisfaction levels are declining. It adds to the problem of resource allocation being insensitive to even a small drop in node satisfaction. Therefore, even if a node's degree of satisfaction drops marginally due to disturbance, it will maintain its existing resource allocation. The hysteresis function, however, prevents the activity from falling below 0.6 until the node's degree of pleasure drops below around 0.43. This means that nodes with satisfaction levels as low as 0.5 will not cause a shift in the present distribution of resources.

So, as seen by the dashed curve in Figure 2, we move the loop to the right. By replacing S in equations (11) and (12) with 1.5 0.5, the degree of satisfaction S for each node, which may take values between 0 and 1, is transformed to 0.5 to 1. At the point when the activity is 0.6, the degree of satisfaction of the node is about 0.74 on the right curve and 0.54 on the left curve, respectively, due to the shift.

Degree of satisfaction

The degree of satisfaction S of node is derived from the weighted average and the weighted standard deviation of degree of satisfaction of applications to take into account both of the goodness and fairness of resource allocation.

$$S = \frac{\bar{Q}}{1 + b\sigma_Q}, \tag{14}$$

b $(b \geq 0)$ is a constant. The weighted average $\bar{Q}$ $(0 \leq \bar{Q} \leq 1)$ is derived by the following equation:

$$\bar{Q} = \sum_{i=1}^{N} W_i Q_i, \tag{15}$$

where N is the number of applications. Each application has different level of importance from a viewpoint of a node, which is expressed by the weight W_i $(0 \leq W_i \leq 1)$ of application i and $\sum_{i=1}^{N} W_i = 1$. Q_i is the degree of satisfaction ratio of application i. The weighted standard deviation σ_Q is derived by the following equation:

$$\sigma_Q = \sqrt{\sum_{i=1}^{N} W_i(\bar{Q} - Q_i)^2}. \tag{16}$$

Therefore, the activity becomes high when the degree of satisfaction of application is high and similar among applications.

Each application defines QoS requirements using several QoS criteria, e.g. bandwidth, delay jitter, and cost. The degree of satisfaction of application is derived from the degree that QoS requirements of an application are satisfied with a wireless network allocated to the application. The degree of satisfaction Q_i of application i is derived as follows.

$$Q_i = \bar{q}_i - \sqrt{\sigma_i^2}, \tag{17}$$

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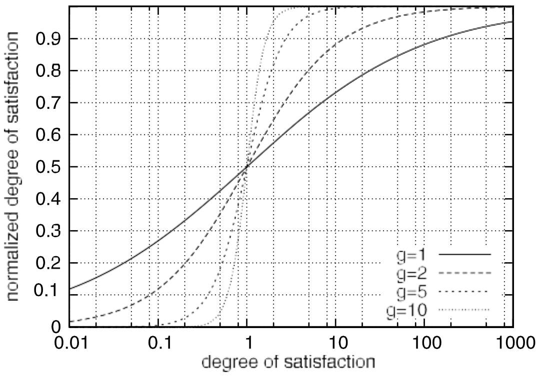

Fig. 3. Slope of sigmoid function used in derivation of degree of satisfaction of QoS on application.

$\bar{q}_i$ and σ_i^2 are the weighted average and weighted variance of degree of satisfaction $q_{i,s}$ of QoS s, respectively:

$$\bar{q}_i = \sum_{s=1}^{K_i} w_{i,s} q_{i,s}, \tag{18}$$

$$\sigma_i^2 = \sum_{s=1}^{K_i} w_{i,s} (q_{i,s} - \bar{q}_i)^2. \tag{19}$$

Here, K_i is the number of QoS criteria specified by application i. In the case that application i uses bandwidth, delay jitter, and cost as QoS criteria, $K_i = 3$ and s is either of the three criteria. $w_{i,s}$ $(0 \le w_{i,s} \le 1, \sum_{s=1}^{K_i} w_{i,s} = 1)$ is the weight of QoS s on application i reflecting the importance of the QoS for the application.

The degree of satisfaction $q_{i,s}$ of QoS s on application i is derived from the QoS satisfaction ratio $x_{i,s}$ as,

$$q_{i,s} = \begin{cases} \dfrac{1}{1+\exp\left(-g_{i,s}\log(x_{i,s})\right)} & (x_{i,s} > 0), \\ 0 & (x_{i,s} = 0), \end{cases} \tag{20}$$

in which the sigmoid function's gain (g > 0) is represented as gi,s. The amount to which each application's QoS need is met by the wireless network provided to it is indicated by the QoS satisfaction ratio xi,s (xi,s ≥ 0) of QoS s. For instance, xi,s represents the bandwidth ratio between the allotted wireless network's available bandwidth and the necessary bandwidth in the context of bandwidth.

Hence, the necessary quality of service is completely met when xi,s = 1.0.

To manage how much the QoS satisfaction ratio is affected by the QoS offered by the assigned wireless network, we include a sigmoid function in Eq. (20). The steepness of the sigmoid curve around xi,s 1 increases as the gain gi,s increases, as seen in Figure 3. As an example, when the available bandwidth is lower than the needed bandwidth, the QoS satisfaction ratio xi,s stays low using this function. In other words, the quality-of-service satisfaction ratio drops significantly once a wireless network with less bandwidth than needed is sometimes assigned to an application. The result is a drop in activity and the application's start of using the noise term to randomly choose a wireless network. Consequently, resource allocation becomes unstable when gi is big. Conversely, a minor gi,s softens the gradient. Consequently, the QoS satisfaction ratio xi,s remains high, even when application i is assigned to a wireless network with inadequate QoS and its QoS requirements are not fully met. The activity level also reaches sufficiently high, so resource allocation becomes steady and no further improvement is anticipated.

Algorithm

We show how our proposal determines network for application i in Algorithms 1 and 2, where the function *Normal DistributionRandom*$(0, \sigma)$ derives the white Gaussian noise with mean zero and standard deviation σ and Δt is the calculation interval.

3. Numerical experiments

In this section, we show and discuss results of numerical experiments using a vehicular application scenario as an example.

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Algorithm 1 Calculate $s(\alpha)$ and $d(\alpha)$

Require: $g > 0$, $\beta > 0$, $\gamma > 0$
Ensure: calculate $s(\alpha)$ and $d(\alpha)$
  for all i **do**
    for all s **do**
      derive QoS satisfaction ratio $x_{i,s}$ of QoS s
      $q_{i,s} \leftarrow \frac{1}{1+\exp(-g_{i,s}\log(x_{i,s}))} (x_{i,s} > 0), \quad 0 (x_{i,s} = 0)$
    end for
    $\bar{q}_i \leftarrow \sum_{s=1}^{K_i} w_{i,s} q_{i,s}$
    $\sigma_i^2 \leftarrow \sum_{s=1}^{K_i} w_{i,s}(\bar{q}_i - q_{i,s})^2$
    $Q_i \leftarrow \bar{q}_i - \sigma_i^2$
  end for
  $\bar{Q} \leftarrow \sum_{i=1}^{N} W_i Q_i$
  $\sigma_Q \leftarrow \sqrt{\sum_{i=1}^{N} W_i(\bar{Q} - Q_i)^2}$
  $S \leftarrow \frac{1}{\bar{Q} + b\sigma_Q}$
  $p_l(S) \leftarrow \max(\min(p_l^-, S + \zeta_l), S - \zeta_l)$
  $h_l(p_l(S)) \leftarrow \frac{1}{1+\exp(-g p_l(S))}$
  $\alpha_0^* \leftarrow \frac{1}{P}\sum_{t=1}^{P} h_l(p_l(S))$
  $\alpha \leftarrow \sum_{t=0}^{T} \alpha_t^*$ (α_t^* is the instant activity of t intervals ago)
  $s(\alpha) \leftarrow \alpha(\beta \times \alpha^\gamma) + \frac{1}{\sqrt{2}}$
  $d(\alpha) \leftarrow \alpha$

Algorithm 2 Select network for application i

Ensure: select j with the largest $m_{i,j}$
  for all j **do**
    $\eta_{i,j} \leftarrow NormalDistributionRandom(0, \sigma)$
    $m'_{i,j} \leftarrow m_{i,j} + \Delta t \times \left(\frac{s(\alpha)}{1+(\max_{1\le k\le M} m_{i,k})^2 - m_{i,j}^2} - d(\alpha) m_{i,j} + \eta_{i,j}\right)$
  end for
  $m_{i,j} \leftarrow m'_{i,j}$
  select j with $\max(m_{i,j})$

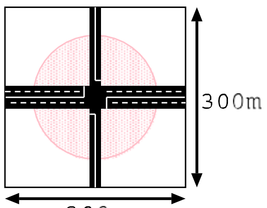

Fig. 4. Road model used in numerical experiments.

3.1. Definitions and settings

Our focus here is on the road model shown in Figure 4 for the purpose of considering resource allocation in a vehicle application scenario. The area is a torus with dimensions of 300 m × 300 m. The geographic centre of the area is at the intersection of two roads. There are four lanes on the horizontal road and two on the vertical one. At the junction, traffic lights influence the flow of vehicles.

Networks that operate without wires
In the area, you can choose from four different wifi networks. These include cellular (3G-HSPA), WiMAX, DSRC (ARIB STD-T75 or later protocol), and Wi-Fi (IEEE 802.11g). The whole area is covered by DSRC, WiMAX, and cellular networks, however the Wi-Fi network's access area is restricted to a radius of 100 m, as shown in Figure 4. To keep things simple, the speed of communication is unaffected by the distance between a node and a base station or access point. Thus, movement around a Wi-Fi access area and competition among applications and nodes are the major causes of dynamic changes in wireless networks.

With the use of empirical data, we can summarise the features of wireless networks in Table 1. For example, cellular networks may support data rates of up to 2 MB/s, whereas DSRC, Wi-Fi, and WiMAX can support up to 40 MB/s each. The DSRC, Wi-Fi, and WiMAX networks are assumed to have a constant delay jitter of 100 ms, 500 ms, 200 ms, and 100 ms, respectively. We assume a constant gearbox cost, even though it could vary depending on the pricing plan.

in the case of the DSRC, Wi-Fi, WiMAX, and cellular networks, correspondingly, 10−7, 10−9, 10−8, and 10−5 unit/b.

Table 1
Characteristics of wireless networks assumed in numerical experiments.

Network	Capacity [Mb/s]	Delay jitter [ms]	Transmission cost [unit/b]
DSRC	4	100	10^{-7}
Wi-Fi	20	500	10^{-9}
WiMAX	40	200	10^{-8}
Cellular	2	100	10^{-5}

Table 2
QoS requirements of applications assumed in numerical experiments.

Application	Bandwidth [kb/s]	Delay jitter [ms]	Transmission cost [unit/s]
Web (1)	300 (0.3)	10,000 (0.1)	0.1 (0.6)
VoIP (3)	64 (0.5)	150 (0.4)	1 (0.1)
Video (2)	3000 (0.6)	1000 (0.1)	0.1 (0.3)

in order to keep things simple. To keep things simple in the numerical experiments, we pretend they are constant even if some of them will change over time in reality.
The apps that are given access to the Wi-Fi network share its capacity. The available bandwidth for an application may be found by dividing the capacity of the Wi-Fi network by the number of apps utilising it. Similar to how DSRC and WiMAX networks distribute their capacity among applications, the WiMAX network limits the maximum bandwidth that a node may utilise at 15 Mb/s. Applying this logic to cellular networks, the amount of accessible bandwidth changes as the number of connections grows. With a single application using the cellular network, the application has access to 2 MB/s of bandwidth. For cellular networks with two or three applications, 1 Mb/s bandwidth is sufficient for each application. As the number of apps increases from four to six, the available bandwidth for each application drops to half a megabit per second. Lastly, each application may only utilise 0.25 Mb/s when there are seven to twelve apps utilising the cellular network. If the cellular network is already in use by twelve apps, then a newly assigned application will not be able to connect. Next, until the cellular network is ready to accept a new connection again, the program starts to ignore it when allocating resources by setting a state value mi, j to zero. Similarly, a node that is outside of the Wi-Fi network's access region will only

the DSRC, cellular networks, and WiMAX for the purpose of allocating resources.

While considering the overall properties of delay jitter and transmission cost, we use empirical numbers to differentiate them from one another. For instance, cellular networks often have the lowest delay jitter since they are specifically built for voice transmission. Nevertheless, when looking at the cost per bit of data transmission, it is the most expensive. We may refer to these hypothetical network technologies as "network A," "network B," "network C," and "network D" in this empirical context. As our numerical tests aim to show how our proposal may choose a suitable network for an application in a competitive and ever-changing environment, those parameter selections have little impact on our protocol's effectiveness.

In a numerical experiment, nodes are initially distributed at random across the roads, with the horizontal road having a density that is 2.5 times higher than the vertical road. Once planted, nodes continue to migrate along the route. A wireless network node enters and exits an access area. Assuming a node is travelling at 40 km/h on the horizontal road, it will remain in the Wi-Fi network's access region for an arbitrary length between 18 and 120 seconds, taking into account the impact of the intersection's traffic light. We also assume that a node will be outside of its access region for a fixed period of 9 seconds. Nodes travel at a pace of 20 km/h on the vertical road. Nodes spend 18 seconds outside of the access region and an unpredictable 36–150 seconds within it.

Applications

Here, "Web" refers to the Internet and email, "VoIP" to voice over Internet protocol, and "Video" to video streaming are all programs that we assume are active. Web is used by every node. Twenty percent of nodes use all three apps, while ten percent use VoIP or video alone. The application quality of service requirements are summarised in Table 2. Tolerance for delay jitter, reasonable transmission cost, and necessary bandwidth are the three dimensions used to describe quality of service needs (QoS) in the table. See section 3.5 for information on the weight values Wi and wi,s of each application and QoS s on application, respectively, which are denoted by numbers in brackets. To illustrate, the Web demands 300 kb/s of bandwidth with a significance level of 0.3, a delay jitter of 10 s with a significance level of 0.1, and a transmission cost of 0.1 unit/s with a significance level of 0.6. All nodes and applications have the same weight value. The normalisation of the weight Wi of application i

N

i=1

Web and VoIP, on a single node with Wi=1, have weights of 1/4 and 3/4, respectively. When it comes to a

Web is given a weight of 1/6 in the event that a node has all three apps.

While the web can handle significant delays and jitter, we believe that transmission cost is its primary issue. However, in order to provide seamless and engaging communication while keeping costs down, VoIP should stick to a bandwidth of 64 kb/s and a delay jitter lower than 150 ms. The most bandwidth-intensive application is video. Video uses a play-out buffer and a pre-fetching method to somewhat tolerate delay jitter, even though it is a real-time multimedia application.

Table 2 defines the transmission cost per second, as opposed to the per bit basis used in Table 1. Multiplying the needed bandwidth by the network's transmission cost yields the per-sec cost of an allotted network (Table 1). Take cellular networks as an example. The per-sec transmission cost of Web on a cellular network is 3.0 unit/s, however on a Wi-Fi network it's 300,000 b/s109 unit/b 0.0003 unit/s. Thus, Web is better suited to a Wi-Fi network than a cellular one. The above suggests that Wi-Fi or WiMAX networks, with their abundant bandwidth and cheap transmission costs, are the most common on the web. The VoIP service is anticipated to be given a DSRC or cellular network. Due to the high bandwidth requirements, video should not be streamed via cellular networks. However, the degree of pleasure for each node is valued differently due to the fact that various candidate networks have diverse features. Consequently, the preferences of these networks vary. To represent the extent to which an application's assigned wireless network satisfies each quality of service criterion, we construct the degree of satisfaction of node, as we indicated in the preceding section. Wi-Fi, with its 20 MB/s of bandwidth, is the ideal network for video because, as shown in Table 2, bandwidth is the most important element. When considering the per-second transmission cost—a key consideration for video—Wi-Fi remains the clear winner. Following this, we have WiMAX, which offers cheap per-sec transmission costs and 15 Mb/s of node capacity; finally, we have DSRC, which offers 4 Mb/s of bandwidth at a reasonable per-sec cost. There is a limit of 99 nodes that the system can support while still maintaining a good quality of service.

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Comparison

To put this technique to the test, we take a look at another one that takes wireless network characteristics into account and has each node choose the best allocation based on the information it has locally [4,18,19]. The proposal specifies that nodes should get data on their available networks' cost, delay jitter, and remaining bandwidth at regular intervals of 1 s. The node then finds the optimal solution to the optimisation issue in order to maximise its level of satisfaction given the circumstances of the wireless network. The maximum bandwidth that an application may use is the same as its capacity, it's worth noting. Surprisingly, the amount of bandwidth a program can really consume when allotted could be more than what is actually available after the optimisation issue is solved. This gloomy assumption is based on the fact that individual nodes have no idea how many and what kinds of applications are using the wireless network, therefore they have no way of knowing how much bandwidth will be available when it is allotted. Our solution, on the other hand, would just consider the level of application satisfaction with the presently available networks when updating state variables and allocating resources.
We switch from ten to one hundred twenty-two nodes. Everyone is happy with the lack of network resources since no allocation occurs if there are more than 99 nodes. For each node count, the following figures are derived from ten numerical trials that lasted twenty thousand seconds each. Parameters for our approach are $\beta = 8$, $\gamma = 3$, $\sigma = 1$, and the gain of the sigmoid function is $g_{i,s} = 10$ for all values of i and s. T 10 is the set point for the moving average window in the calculation of activity α. The sigmoid function's hysteresis gain, denoted as g, and the number of play hysterons, P, are both 100.

in Equation (13), and in Equation (14), b is equal to 0.4.

Results and discussion

First, in Fig. 5, we provide a streamlined summary of the comparative results based on the average node satisfaction level and its average variance. A solid line representing our approach and a dotted line representing the comparative technique reveal the average node satisfaction level. Plus marks for our suggestion and crosses for the comparable approach indicate the variation. Following is how we calculated the average level of satisfaction for each node. At the outset, we average the levels of satisfaction across all nodes at each experimental second. After that, to get an overall average of an experiment, we average the sample averages across the whole duration. At last, for every set of nodes, we can get their average level of pleasure by averaging the timestamps from all 10 trials. Following is the process for deriving the mean variance. First, for every second of an experiment, we find the standard deviation of the nodes' degrees of satisfaction. After collecting the per-second variance, the next step is to average it out throughout the whole trial. By averaging the per-experiment variation over 10 trials for every node number, we can finally derive the mean variance of degree of pleasure.
Figure shows that when the number of nodes is minimal, the comparison approach produces a mean degree of satisfaction of node greater than 0.9. When the number of nodes goes over 60, however, performance drops precipitously to about 0.28. Here is an explanation. Out of 60 nodes, 8 make use of video. The total bandwidth needed is 24 MB/s, with each video requiring 3 MB/s. When a Wi-Fi network with 20 MB/s of bandwidth is used by all video apps, the network's performance drops significantly and the apps' satisfaction level rises to new heights. This is the exact instant that the node's level of satisfaction is recorded. The next step is to transfer the unpopular apps to a different network. For instance, WiMAX is designated for video and web, and it boasts the lowest per-sec transmission cost (apart from Wi-Fi) and 15 Mb/s of bandwidth per node. With so many nodes having their resources reallocated simultaneously, WiMAX runs out of bandwidth and Wi-Fi reverts to using the media that worked best for the applications that had previously altered their allocation. This is also the point where the node's level of satisfaction is recorded. The Wi-Fi then goes down again due to a lack of bandwidth. Due to the reasons mentioned earlier, when the number of nodes surpasses 60, the average degree of satisfaction for each node is around 0.28.

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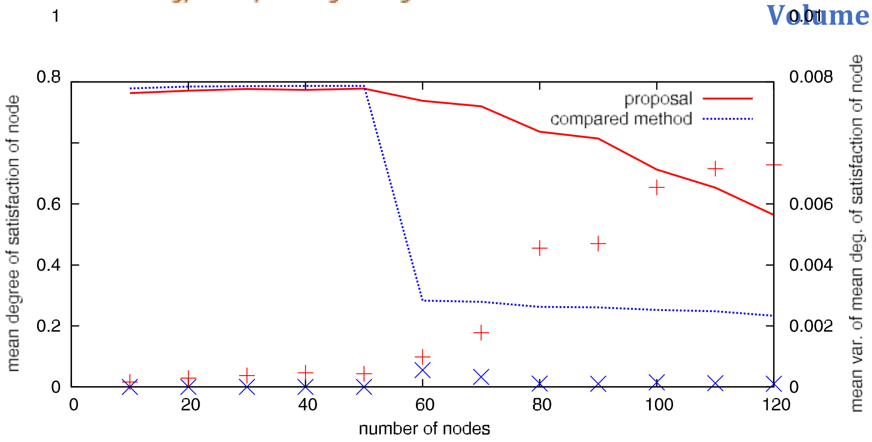

Fig. 5. Mean and variance of degree of satisfaction of node against different number of nodes.

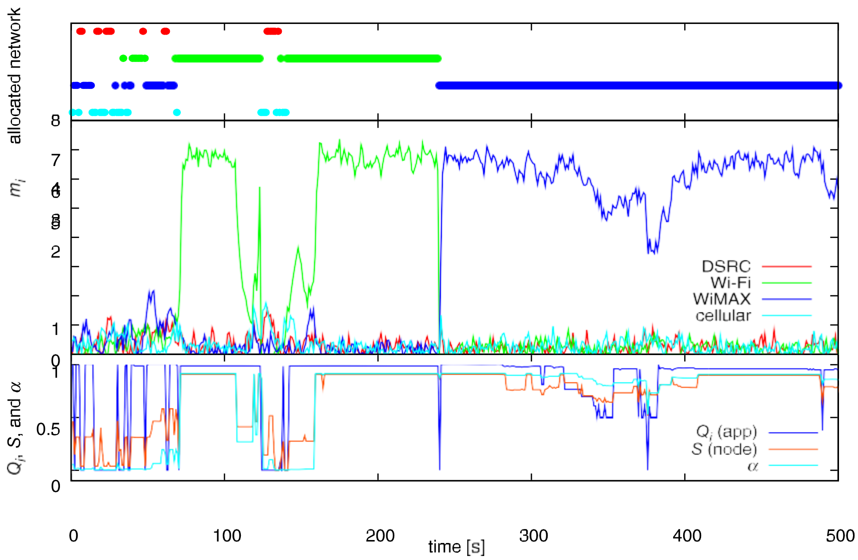

Fig. 6. Time variation of allocated network, state values, degrees of satisfaction of application and node, and activity of Video with proposal (60 nodes). (For interpretation of the colors in this figure, the reader is referred to the web version of this article.)

Conversely, even with 120 nodes in the area, our strategy can maintain a modest level of mean node satisfaction. An application is sometimes given to the second-best network because, similar to biological systems, our idea uses a probabilistic method to finding a suitable answer. The lower mean degree of satisfaction of node in the case of a limited number of nodes in Figure 5 indicates that such allocation leads in sub-optimal resource allocation. In a world where there isn't a perfect solution that satisfies every application, it still allows nodes to find a reasonable answer, even if it means sacrificing some application satisfaction.
Figure 5 shows that when the number of nodes rises, the mean variance of degree of satisfaction of each node likewise increases. This is because... Contrarily, the contrasted approach maintains a minimal mean variance. This is due to the fact that, assuming identical conditions (such as the properties of accessible networks and accommodating applications), every node finds an optimal solution that maximises its own degree of pleasure.
Figure 6 shows the results of a single numerical experiment with sixty nodes, showing the temporal fluctuations in resource allocation, state values, degrees of pleasure, and Video activity on a given node on the horizontal path. Red dots and green lines at the top graph represent DSRC, blue dots and lines in the centre represent WiMAX, and aqua represents cellular networks, respectively. A wireless network that has been assigned to the application is shown at the top by dots. Between these two ends is where the time series variance of integers mi and j representing the state! The three lines at the bottom of the graph represent the following: the activity (blue line), the degree of satisfaction S of the node (orange line), and the degree of satisfaction Qi of the application (blue line).
A wireless network that is assigned to video is constantly changing until the 70s since there isn't much activity. At various points along the random allocation process, a Wi-Fi or WiMAX network is chosen. This causes Video's pleasure level to rise to 1 (the blue line in Figure 6's bottom graph). Even though it isn't visible in the figure, the allocated networks aren't satisfying for other applications, which prevents the node satisfaction level from rising. As a result, there is insufficient activity. As a result, every now and again, all apps are designated for 70 seconds.

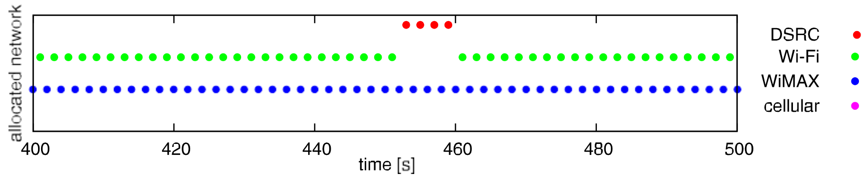

Fig. 7. Time variation of allocated network of Video with compared method from 400 s to 500 s (60 nodes).

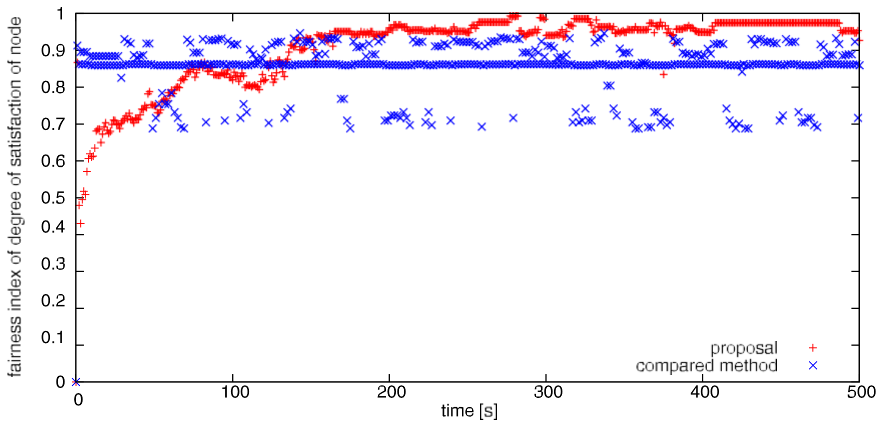

Fig. 8. Fairness index of the degree of satisfaction of node (60 nodes).

suitable network topologies due to random wandering. With an increase to 0.90, both the activity and the allocation of resources stabilise. Due to the impact of resource allocation at other nodes, the activity drops to 0.41 at 108 s. Nevertheless, the distribution of resources remains unchanged due to the impending restoration of network conditions. The node exits the range of the Wi-Fi network after a short period of time. As a result, wireless networks are reallocated in preparation for a decrease in activity. There is little activity until 159 s, even though the node reaches the Wi-Fi access region at 133 s. This is because the node is attempting to adjust to the new Wi-Fi network configuration at this time. After 240 seconds, the node exits the Wi-Fi range once again. Consequently, Video would be able to use the node's WiMAX network. There will be no changes to the distribution of resources until 12:20 s. This is how our solution may reliably and adaptively distribute resources on a node's wireless network to its applications. Figure 7 shows that assigned networks ip-operate significantly in the comparison technique. A node will distribute Wi-Fi and WiMAX networks to Video in alternating fashion from 400 s to 452 s. There is an alternating allocation of DSRC and WiMAX networks from 452 s to 460 s, during which the node is outside of the Wi-Fi access region. Reason being, even when control timing isn't synchronised, several nodes may still switch wireless networks simultaneously due to the greedy way the comparing method decides resource allocation. Presume for a moment that the node does not have any Wi-Fi applications installed. There are a lot of empty nodes in the Wi-Fi network, leading them to believe that any application may get lots of bandwidth from it. Consequently, they choose to enable the Wi-Fi network for some apps that need a lot of bandwidth. The calculated optimum solution leads to resource allocation, which in turn causes the Wi-Fi network to become completely crowded and significantly lowers the degree of application satisfaction. Concurrently, a wireless network that those apps previously used becomes devoid of any users. Afterwards, nodes will revert to the previous network and disable the Wi-Fi network at the subsequent control time. While our idea does show a comparable behaviour during the random allocation phase, nodes are able to discover the optimal solution on a global scale and the allocation of resources converges in the end.

Lastly, we use the fairness index [20] to assess how equitable the distribution of resources is. There are n nodes in the fairness index φ.

may be calculated using the given equation.

$$\varphi = \frac{\left(\sum_{k=1}^{n} S_k\right)^2}{n \sum_{k=1}^{n} S_k^2}, \tag{21}$$

The degree of satisfaction S for node k, where $1 \leq k < n$, is represented by Sk, and n is the number of nodes. For all nodes, the level of satisfaction is the same when the fairness index is 1.0. The outcomes for the scenario with sixty nodes are shown in Figure 8. Our idea raises the fairness index from an initial low point to a maximum of 0.9 (average is 0.97) over time. Conversely, the fairness index varies substantially among the examined methods, with an average value of around 0.85. In conclusion, our idea enables nodes to equitably distribute the scarcity of network resources.

4. Conclusion

This study presents a new approach to resource allocation in which, in a constantly changing environment, each node decides for itself how much wireless network resources to allocate to the many networked applications that operate on it. Drawing inspiration from the self-organising and ever-changing nature of living systems, our solution makes use of the attractor composition model. Our method has challenging applications in automobile networks due to the fact that adaptation requires a certain length of the random walk phase. Nonetheless, the results demonstrate that our suggestion is capable of equitably sharing network resources across nodes and adaptively allocating wireless network resources to applications taking their QoS needs into account. Our technique is also shown to be better than one in which a node allocates resources by solving an optimisation issue.

As a rule, it is believed that parameter setting has little effect on biological models. The next step is to verify this claim by further simulation tests that include more realistic scenarios for modifying the quantity and properties of wireless networks, application QoS requirements, and mobility. One alternative is to apply our approach to real-world settings. Web surfing, for instance, is resilient enough to withstand sudden loss of connection. As a result, a Web application may continue to use a Wi-Fi network, which offers intermittent access to a fast-moving node. Lastly, we want to construct a model and conduct additional tests using real-world conditions.

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