End-to-end Virtual Resource Management across Heterogeneous Networks and Services

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Contributing Author(s): Zheng Hu(ed.) & Ping Zhang & Hui Tian & Ahmad Umair Mian & Wang Zhibo (BUPT), Ke Xu (THU), Kun Yang (UEssex), Juan-Luis Gorricho & Joan Serrat (UPC), Ebrahim Ghazisaeedi & Ning Wang (UniS), Yan Zhang (SRL).

Consortium:

Partner name	Partner short name	Country
University of Essex	UEssex	UK
Universitat Politècnica de Catalunya	UPC	Spain
Simula Research Laboratory	SRL	Norway
University of Surrey	UniS	UK
Tsinghua University	THU	China
Beijing University of Post and Telecommunications	BUPT	China

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Executive Summary

The aim of this document is to provide an intermediate report about the research activities that have taken place in WP3 of the EVANS project. This WP is concerned about the vertical management of the virtualized network resources, which is more a concern of physical network providers or network infrastructure providers. This is about resource management of individual network domains or about intra-domain resource management issues. Therefore, two types of networks are considered in this deliverable: wired core networks and wireless access networks. In each type of networks both static and dynamic resource allocation and management, which represents the two tasks identified in this WP respectively, have been researched into.

The virtualized resource management issues related to wired and wireless access networks have been discussed in this document. In this regard, the resource scheduling and allocation problem in virtualized wired access networks has been formulated and possible solutions have been presented. Another important problem related to sleeping link optimizations in wired virtualized environment is discussed. The objective is to minimize the power consumption in the physical network, while still satisfying bandwidth demands from individual virtual networks (VNs) on the top. The solution for this problem is presented as the energy efficient splitting of physical links during peak and off peak hours.

The resource scheduling problem in virtualized wireless networks is differentiated from the virtualized wired networks and an algorithm for joint network virtualization and resource allocation of IEEE 802.16 wireless networks is formulated, which not only provides network virtualization (isolation) but also achieves network resource efficiency. Finally the virtualizing radio resources for LTE networks are discussed and random access model for virtualized radio resources is presented. Our work is focused on allocating wireless resources among multiple virtual mobile operators (VMOs). A bankruptcy game based dynamic wireless resource allocation approach among multiple VMOs is proposed and investigated. The satisfaction of payoffs (i.e., resources) each VMO is paid is evaluated with expectation index (EI). Particularly, the Long Term Evolution (LTE) is chosen as the case study to evaluate the proposed approach.

1. Introduction

There are two types of important stakeholders in the Internet business market: infrastructure providers (InP) that own and manage the physical network infrastructure, and service providers (SP) that provide end-to-end services to end users without necessarily owning any physical infrastructure. Instead, SPs may "rent" network resources from the underlying InPs according to their specific business and service plans. In virtualised networks, an SP typically creates its own virtual networks by "concatenating" the rented (virtual) resources from multiple InPs in order to offer Internet-wide services. On the other hand, an InP needs to concern how to optimally slice its resources, for instance bandwidth, CPU time, memory etc, to various requesting SPs, such that the overall infrastructure resources can be efficiently allocated for maximising its own profits. Therefore, two orthogonal dimensions of management tasks in a virtualised network environment can be envisioned, as depicted in Figure 1.

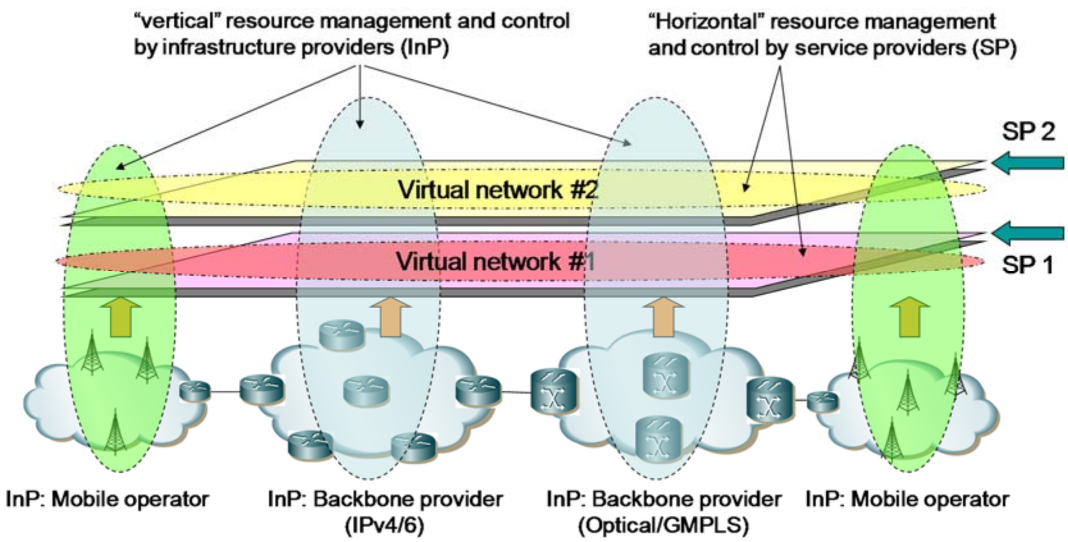


Figure 1. Two Dimensions of Management of Virtualised Networks

Firstly, an InP needs to manage its own physical resources, which involves tasks such as how to describe the physical resources, how to slice them, how to handle incoming resource requests from heterogeneous SPs and allocate virtual resources in a cost-efficient way, etc. This project names this type of management as *vertical* resource management for easy reference. Another dimension of network management is how an SP manages and controls its virtual network resources which are rented from multiple heterogeneous InPs in order to offer its specific services across the corresponding geographical area. This type of management is called *horizontal* resource management, in this project. This deliverable D3.1, which falls into WP3, deals with vertical resource management within individual InPs. Its counterpart in WP4, namely, D4.1, deals with horizontal resource management.

This document records the project's progress regarding investigations into management issues that need to be carried out on the InP side in order to provide network infrastructure support to various services, for instance computation-intensive services such as grid/cloud computing applications and bandwidth-hungry services such as content delivery, as identified in Deliverable D2.1. This WP addresses intra-domain issues with each domain owned by one InP. A domain, or an InP, can take be a wired network provider or a wireless mobile network provider. The former is necessary for the core networks that constitute the Internet backbone, whereas the latter is for various broadband wireless network technologies for mobile access in addition to the conventional fixed access. In order to provide an end-to-end service solution to end users, wireless mobile access network technologies have to be considered as an increasing number of users use mobile devices to get access to the Internet. The EVANS project aims to create a network virtualisation environment over a fully heterogeneous network infrastructure and to provide an integrated network management system across different types of network platforms.

Therefore, the document is organized according to network types: wired networks and wireless networks, as presented in Section 2 and Section 3 of this document respectively. Within each type of network, both static (e.g., at the subscription level of virtual resource requesting) and dynamic (after the invocation of resource leasing)aspects of the management system are described as are represented by Task 3.1 and Task 3.2 respectively in the DoW (Description of Work).

2. Virtualized Resource Management in Wired Networks

2.1. Research Issues in Wired Network Virtualization

In the network virtualization environment, both virtual nodes and links in the VN should be assigned to a specific set of physical nodes and physical paths in the substrate network, with certain constraints on virtual and physical components, which is known as the VN embedding problem. Here virtual network embedding problem across multiple physical network domains (i.e., InPs) has been considered, which will address interactions among multiple domains and facilitate provisioning of the end-to-end virtual networks.

In our research, we consider three parties in the business model, including virtual network user, virtual network provider (VNP) and infrastructure provider (InP). For each virtual network, the VNP is interested in how to get VN's requirements satisfied while minimizing the embedding expenditure. To this end, VNP is desirable to get more detailed resource information (e.g., available node/link capacity) in each substrate network domain. For instance, since the price of intra-domain links is usually much cheaper than that of inter-domain ones, therefore, VNP prefers to embed as many virtual nodes as possible within the same domain that can be interconnected by intra-domain links.

However, InPs are traditionally reluctant to have their private network topologies exposed, especially to their competitors. Each InP is willing to take virtual network requests and then make independent embedding decisions with as little information shared as possible.

To address this tussle among VNP and InPs, we define a reasonable information sharing scheme, from which each party involved can benefit while maintaining the core commercial secrets of InPs. Then an end-to-end virtual network can be embedded by the following three steps:

1) VN Request Creation: in order to deliver end-to-end services, a VN user needs to design a virtual topology that will cover areas where their potential customers are located or connect their geographically distributed private networks together. Therefore, an end-to-end virtual path usually starts from and terminates at the access network. A virtual network request is generated by indicating the topology attributes, including node requirements (i.e., expected location and capacity) and link requirements (i.e., capacity).

2) VN Request Decomposition: upon receiving a VN request from VN user, VNP first conducts node pre-mapping that aims at finding a set of candidate substrate nodes for each virtual node. Then VNP should identify a path for each virtual link, which will minimize the provisioning cost of the whole VN request. Finally, a VN request can be decomposed into several sub-VN requests, each of which corresponds to a specific substrate domain.

3) VN Embedding: after receiving the sub-VN requests from VNP, each InP involved in will independently get its portion embedded according to its own strategies, such as minimizing the embedding cost, performing load balancing across its substrate, and so on.Since the general embedding problem is computationally intractable, we will resort to heuristic solutions to derive a practical virtual network embedding algorithm.

2.2. Resource Allocation and Scheduling

The resource allocation problem in virtual networks is concerned with an efficient embedding of virtual nodes and links to substrate nodes and links. In the figure below, we represent two virtual networks sharing resources of a substrate network. In this scenario, we consider two resource types: CPU Capacity for the nodes and Link Bandwidth for the links. The figure is a representation of the network at a given time, when VN 1 has a ring topology and VN 2 has a star topology. In the figure, the resources are represented in terms of units. 100 CPU Units could represent 3.5GHz, while 100 Link bandwidth units could represent 1.0Gbps. We require that each substrate node or link has a unique identifier.

The virtual networks determine their own topologies based on their demands as well as availability of substrate resources. We can note that for example while VN 1 actually has a topology with three nodes, it actually also uses three other “hidden nodes”, which should also have capacity to forward its traffic. In the above case, we use a case where the number of CPU units for forwarding is equal to the number of Link units being forwarded (this is based on assuming packets of size 1400Bytes and a requirement of 40,000 cycles to process each packet).

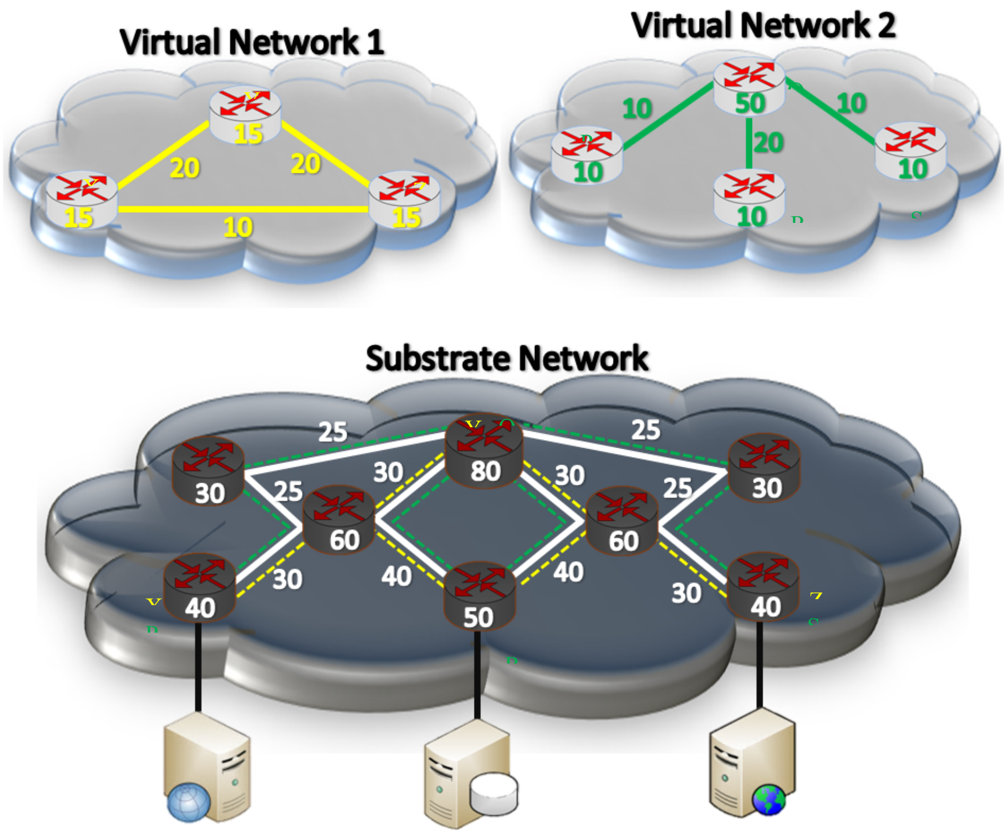


Figure 2 Resource allocation in wired virtualized networks

The virtual networks continuously receive traffic from users. The user requests specify BW requirements and destination. Based on this information and the substrate network status, the following situations may arise:

- Using the same network topology, the VN sends a request for resources to the SN,
- If this request cannot be supported by the substrate network considering current topology, the VN may change topology to use other available links and/or nodes,
- If the change in topology cannot be supported by available substrate resources, the VN through admission control decide to reject the user request. (When we start looking at cooperation and negotiation, this will be a point to consider negotiating with other VNs that are occupying resources that are of interest so they can free up these resources).

We also can also consider possibilities for path splitting, in which case a given traffic flow can be routed over more than one parallel substrate link.

We can therefore represent a virtual network as a graph $G_V = (N_V, L_V)$, where N_v is the set of virtual nodes and L_v is the set of virtual links. The k^{th} virtual node $n_V^K \in N_V$, has an associated CPU demand $D(n_V^K)$, while the virtual link that connects nodes *a* and *b*, $l_V^{(a,b)} \in L_V$ has an associated link bandwidth demand $D(l_V^{(a,b)})$. In the same way, a substrate network can be represented as a graph $G_S = (N_S, L_S)$, where N_s is the set of substrate nodes and L_s is the set of substrate links. The k^{th} substrate node $n_S^K \in N_S$, has an associated CPU capacity $C(n_S^K)$ which represents the available (free) node capacity, while the substrate link that connects nodes *a* and *b*, $l_S^{(a,b)} \in L_S$ has an associated (available) link bandwidth $C(l_S^{(a,b)})$. Therefore, the virtual network mapping problem is in effect a mapping of the graph G_V to G_S. Ideally, we can split the mapping problem into two stages: first mapping the nodes, and then mapping the links (or may be in the opposite order? In any case, the mapping of anyone of them could be highly dependent on the other).

2.2.1. Problem statement

Network Virtualization – which enables the building of multiple virtual networks over a shared physical network – has received a lot of attention from both academia and industry. One of the challenges to Virtualization is efficient resource allocation. Due to the problem complexity, solutions are usually static and based on multiple simplifying assumptions such as availability of unbounded resources in the substrate network and others. In this paper, we propose to apply techniques from Artificial Intelligence to the resource allocation problem. Our objective is to derive a solution that is dynamic and online (including topology optimization); to allow for cooperation and negotiation between substrate and virtual networks; and to achieve an Autonomic Management solution, implying that the networks are self-configuring, self-optimizing, self-healing and user context aware.

The problem we face in this research work is the assignment of physical resources to given virtual network topologies with constraints. The problem statement and the challenges of its solution are clearly exposed in [1-3]. In summary, given a number of VN requests (the request specifies the VNs topology) that can be known in advance or appearing randomly in time, the target is to assign physical resources (nodes and links) of a given substrate network topology to satisfy the VNs requirements and at the same time fulfilling some goals or constraints. Such goals are referred either to the virtual or to the physical network and in the earliest works consisted for instance in the number of virtual nodes assigned to a physical node, number of virtual links assigned to a physical link [1], node CPU usage [2], virtual links capacity [3] and others. The problem has been treated analytically transforming the goals to be achieved in a maximization/minimization of a cost function. But this generally leads to a NP-complete problem that the only way to solve it is by heuristics.

2.2.2. Proposed solution

To achieve the objectives of our work, we propose to apply Reinforcement Learning (RL) techniques, in a context of Multi-Agent-based Systems, to the resource allocation problem. RL is a feedback based approach where an agent receives an immediate reward for its previous action, and from there on, it will try to learn a better policy for the long run, in order to maximize a given utility function. Therefore, the agent's goal – roughly speaking – is to maximize the total amount of reward it receives in the long run [4]. The rationale behind the use of that approach is because RL based approaches have been successfully used in solutions to problems that have similar requirements as the resource allocation in virtual networks [5-7]. Nevertheless, to the best of our knowledge RL has never been used before in that specific problem domain. Specifically, we represent each of the networks by a RL enabled agent. Each agent that represents a virtual network is responsible for customizing its resources to the needs of its users while at the same time minimizing the costs incurred in using the substrate resources. Each of these agents has independent objectives. Similarly, each of the substrate physical networks is represented by an agent whose main objective is to ensure that the overall resources are efficiently used. In the end, our proposal is for the different agents to not only learn from the decisions they make, but also to cooperate and negotiate with each other so as to achieve both individual level as well as system level objectives.

By conception, a RL-based approach is an autonomic solution to the allocation of virtual network resources to substrate networks exhibiting the following distinguishing features:

I) Self-Configuring: As users make requests for resources, the virtual network agents continuously evaluate their network topologies searching for possibilities of re-configuration. Whenever they find these possibilities, they can make requests for this to the substrate agents. Virtual network agents can also negotiate and cooperate amongst themselves so as to agree on the usage of substrate resources and achieve the best utility both at individual and at system levels.

II) Self-Optimizing: As the conditions of the substrate network change, substrate agents should exhibit proactive as well as reactive characteristics. For example, if a physical node and/or link are added to the network, or if their capacities are changed, the substrate agent should re-evaluate the network load to establish a potential re-allocation of resources. While in principle this would not require any action on the side of the virtual network agents, in our solution we require that these agents always look out for possibilities of optimizing their resource usage whenever there are changes in the substrate network.

III) Self-Healing: If for any reason a node and/or link become unavailable, the substrate agent – in collaboration with virtual network agents – should make decisions so as to cause the minimal possible disruptions in the customer service. This situation is different from II) in a way that while self-optimization is mainly aimed at optimizing costs, and possible improvements in customer service levels, self-healing is much more urgent as in such cases there are possibilities of violating agreements with customers.

IV) User Context Aware: Based on user context information, the virtual network agent may take decisions about the resources being used by the user. For example, a user whose location is near a Wi-Fi hot spot and this user is stationary and he is occupying a high bandwidth – say for a video on demand service – he could be offloaded to the Wi-Fi and if changes to the nodes for this specific customer are needed, these changes can be effected by substrate agent.

2.2.3. Achieved results

Efficient Resource Allocation is one of the practical challenges of network virtualization. Most of the current approaches make some assumptions that cannot be achieved in practice. While these could give solutions to specific instances of this problem, the possibility to make improvements is a major motivation of this work. Our work involves making the resource allocation task autonomic, which is a vital characteristic especially considering the complexity of current and future networks.

We have been working on a proposal to model the substrate network as a decentralised system and introduce a learning algorithm in each substrate node and substrate link, providing self-organization capabilities. We propose a multi-agent learning algorithm that carries out the substrate network resource management in a coordinated and decentralised way. The task of these agents is to use evaluative feedback to learn an optimal policy so as to dynamically allocate network resources to virtual nodes and links. The agents ensure that, while the virtual networks have the resources they need at any given time, only the required resources are reserved for this purpose. Simulations will show that our dynamic approach significantly improves the virtual network acceptance ratio and the maximum number of accepted virtual network requests at any time, while ensuring that virtual network quality of service requirements such as packet drop rate and virtual link delay are not affected. The details of the work carried out up until now is explained on section 3 of deliverable D4.2.

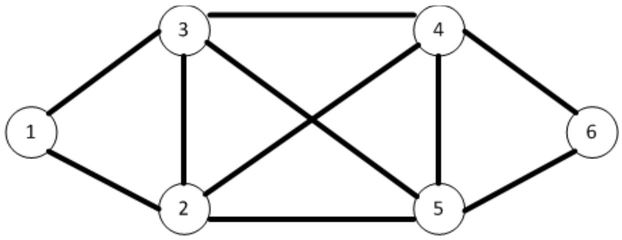
2.3. Energy Efficient Splitting

2.3.1. Overview

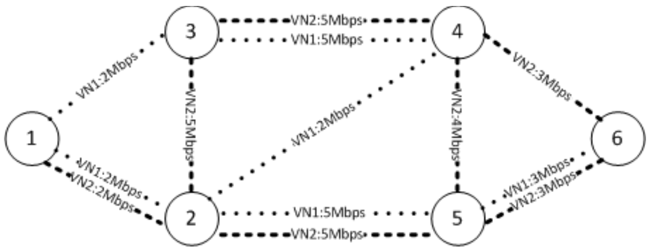
In this section, we specifically consider sleeping link optimizations in the network virtualization environment. Given the physical network topology (operated by the InP) and a set of virtual network topologies (substrate topologies), the objective is to minimize the power consumption in the physical network, while still satisfying bandwidth demands from individual virtual networks (VNs) on the top. In this regard, a heuristic offline algorithm is proposed, which tries to push maximum number of physical links into sleep mode over the off-peak period, while still guaranteeing the off-peak traffic demand of all involved VNs. The algorithm marks a physical link as a capable candidate in case the direct connected nodes are not isolated and there is a replacement path with guaranteed off-peak bandwidth demand, for all of involved VNs, in case of link inactivity. Simulation results over the GÉANT network topology with randomly generated virtual networks show our proposed algorithm is able to turn active notable number of physical links into sleep mode for energy saving over off-peak hours.

We use a simple network topology to illustrate the high-level idea of the algorithm in turning links into sleep mode over the off-peak hours in order to save energy. Figure 3.A shows a small physical network topology based on which multiple VNs can be provisioned. In Figure 3.B the mapped topology of two virtual networks, with their *peak-time* bandwidth demands over the physical network is shown. Each line model denotes one virtual network.

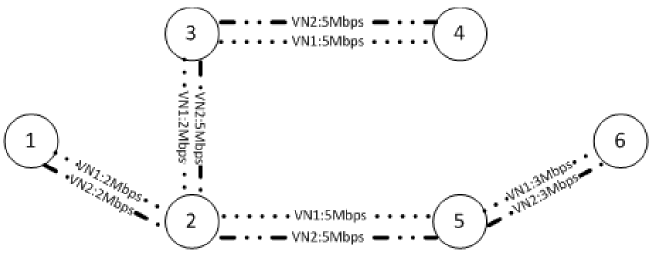
During *off-peak* time the traffic demands over the two VNs become reduced, in which case there is an opportunity to put a subset of physical links to the sleep mode. To do this, customer traffic across the virtual links in the VNs which are mapped onto the sleeping physical links need to be rerouted via alternative virtual path where there are available reserved bandwidth resources. For instance, Figure 3.C shows a resulting reduced topology to be used during off-peak time. As it is shown the physical links (1-3, 2-4, 4-5, and 4-6) are set into sleep mode while all the nodes still have full connectivity for all the previously involved virtual networks and their off-peak bandwidth demands are guaranteed through other active links. As can be observed from Figure 3.C, due to the unavailability of the sleeping link between node 2 and 4 in the reduced topology, off-peak traffic in VN1 between the two nodes needs to be rerouted via alternative paths in the reduced topology. Towards this end, Figure 3.D shows the re-routed traffic for the slept links over the defined replaced path. The replaced paths for links 4-6, 4-5, 1-3 and 2-4 are 1, 2, 3 and 4 respectively.



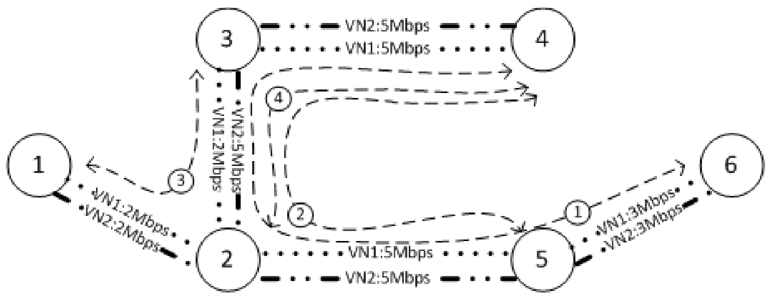
(A). Physical network topology.



(B). Peak time, mapped virtual networks topology.



(C). Reduced topology during off-peak time.



(D). Alternative paths for slept links in VNs.

Figure 3 An Example for link sleeping and traffic rerouting

2.3.2. Problem formulation

The objective is to reduce power consumption in network virtualization environment over off-peak hours, while still offering bandwidth demands. This could be happen by setting maximum number of physical links into sleep mode, over off-peak hours. The algorithm description is the following:

Given:

i) Physical substrate network topology.

ii) Overlay virtual network topologies.

iii) Physical link capacity and allocated bandwidth for each virtual network.

iv) Off-peak virtual network traffic demands.

Find: The set of links which are capable to be set into sleep mode over off-peak time.

Subject-to: Full connectivity and off-peak bandwidth constraints.

The problem can also be defined with Integer Linear Programming (ILP), precisely. The substrate network is modeled as an undirected graph $G_s = (V_s, E_s)$, where V_s is the set of substrate vertices, and E_s is the set of substrate edges.Vertices represents nodes and edges denote links in network. So, $N_s = |V_s|$ represent total number of physical nodes, and $L_s = |E_s|$ shows total number of substrate links.

The virtual network topology is asubset of the actual physical network topology. Similar to substrate network each of the overlay virtual networks is also modeled as an undirected graph $G_v = (V_v, E_v)$, where is the set of virtual nodes, and E_v is the set of virtual links. Each virtual link, between node i and j $(L_{i,j})$, in n_{th} virtual network (VN_n) is associated with a residual bandwidth allocated over substrate network. This allocated bandwidth capacity is represented here with $C_n^{i,j}$. In addition, $P_n^{i,j}$ is set of links over a path between node i and j, in n_{th} virtual network. Besides, VN_T is set of all involved virtual networks.

Over the off-peak hours, networks are less utilized while full bandwidth capacity is active over all the links. In order toderive an algorithm which sets maximum number of links into sleep mode while guaranteeing required bandwidth, we need off-peak traffic demand. Therefore, off-peak traffic demand matrices or rates, for all the involved virtual networks, are given to our algorithm as an input. Off-peak traffic demand set for n_{th} virtual network is represented by OTD_n. These sets give the off-peak demands per link. In this regard, $\gamma_n^{i,j}$ presents traffic demand between node i and j in n_{th} virtual network. Over off-peak period, available bandwidth capacity on virtual link between i and j, in n_{th} virtual network, is presented by $ac_n^{i,j}$.

In addition, P_L stands for total power consumption over substrate network links. We use $\delta_{i,j}$ to show the link status between node i and j. It is "1" in case the link is on, or it is "0" when the link is in sleep mode or off. Besides, $pl_{i,j}$ represents power consumed by the physical link between node i and j.

Considering the above definitions, it is possible to formulate the problem mathematically as follow:

Objective:

$$Minimize\left\{P_L = \sum_{i=1}^{N_s}\sum_{j=1}^{N_s}\delta_{i,j} \times pl_{i,j}\right\} \tag{1}$$

or

$$Maximize\left\{|E_s| - \sum_{i=1}^{N_s}\sum_{j=1}^{N_s}\delta_{i,j}\right\} \tag{2}$$

Subject-to:

$$\forall \gamma_n^{i,j} \in OTD_n \quad , \quad \exists P_n^{i,j} \quad \forall n \in VN_T \tag{3}$$

$$ac_n^{i,j} \geq \gamma_n^{i,j} \quad \forall L_{i,j} \in P_n^{i,j} \tag{4}$$

Eq. (1) states the main objective of algorithm which is minimizing the substrate network links power consumption over off-peak hours. This objective also can be represented by Eq. (2) which approaches the same goal by maximizing the number of possible links that are capable to be pushed into sleep mode. Eq. (3) and (4) are discussing the algorithm constraints. Eq. (3) maintains full connectivity between required nodes. It states there is at least one path for all off-peak bandwidth demands. Note that the path could be found with any desired routing protocol. Eq. (4) argues off-peak bandwidth guarantee.

2.3.3. Proposed Algorithm

This heuristic algorithm is trying to decrease power consumption over network virtualization environment while guarantees the off-peak bandwidth demands. The algorithm considers less stressed links status as inactive, and then answers the question for each link that is it necessary to set this link into active mode? This question should be answered precisely in order to guarantee full connectivity and off-peak bandwidth demands for all involved VNs.

The proposed algorithm is shown in. An initial parameter is calculated in first step in order to be used in next steps for sorting and decision making matters. Stress Rate (SR_k) isneededtobecalculatedfor all substrate network links. SR_k presents intensity of involved virtual networks over link k, and it is calculated by Eq. (5). This helps us for link sorting in third step. Besides, we use SR in step 4 in order to make decision to which links should be pushed into sleep mode at initial session.

$$SR_k = \frac{numberofVN\sin volvedinlink_k}{tota\ln umberofVNsoverISP(VN_T)} \tag{5}$$

In the second step the algorithm will calculate available bandwidth capacity for each virtual link over off-peak hours.

This is driven using off-peak traffic demand, which is given to the algorithm as an input, and with Eq. (6).

$$ac_n^{i,j} = C_n^{i,j} - \gamma_n^{i,j} \tag{6}$$

Since, we want to make network power consumption proportional to link utilization, and because the links with high number of involved VNs are more essential for connectivity and bandwidth demands, the algorithm will start setting links back to the active mode, if it is necessary, from a link which had the larger number of VNs involved and higher utilization. This happens in third step in which the algorithm sort the links in descending order, based on SR. For links with equal SR, the algorithm sorts them based on link utilization. So, the top link in the list, has the largest number of VNs involved, and is the highest utilized link over the network.

In order to maximize the number of capable links to be pushed into sleep mode, the algorithm, in step 4, pushes all the links into sleep mode, except the links which their Stress Rate is equal to 1. This makes the temporary sleep mode topology.

Afterwards, the algorithm tries to check the possibility of setting a link into sleep mode by finding a replaced path, for all involved VNs in the link, which has enough bandwidth capacity for re-routed traffic. This happens in step 5, 6 and 7. At first, the algorithm tries to find a replaced path between two previously connected nodes, considering off-peak traffic demand, using the operator's desired routing protocol, for each involved VN in link. If the algorithm finds a path which supports the required off-peak demand for the link, then it returns the link as a capable for setting into sleep mode. Besides, it updates available bandwidth for all the links involved in the replaced path. In the other hand, if there is a replaced path for the VN, however one or some of the links over the path does not have enough capacity to handle the re-routed traffic, the algorithm turns the link into active mode and undoes all the capacity updates which have been done over the replaced path's links. Nevertheless, if the routing protocol does not return any replaced path between two previously connected nodes over the VN topology, the algorithm, in step 6, tries to find a replaced path over current active physical topology. In case there is a replaced path over the physical topology while one or some of the links over the path do not support the VN, which is the algorithm is working on, and then if there is enough physical capacity over the link, required bandwidth based on $C_n^{a,b}$ will be allocated and checking process of step 5 will be done again. However, if there is not any replaced path even over physical topology the link will be turned on and the bandwidth updates will be undone.

In some cases, over a physical link, one or some of the virtual links are not removable while the others are. Step 6 of the algorithm deals with this issue. It makes sure that the algorithm set a physical link into sleep mode, unless there is an un-removable virtual link over it.

Step1: Calculate Stress Rate (SR_k) using Eq. (5), for all the links over the ISP.

Step2: Calculate the off-peak available capacity ($ac_n^{i,j}$) of the links based on off-peak traffic demand, and Eq. (6).

Step3: Sort the links in descending order, based on SR. For links with equal SR, sort it based on link utilization. So, the top link in the list, has the largest number of VNs involved, and is the highest utilized link over the network.

Step4: Remove all the links from the topology, except the links with a SR equal 1.

Step5: For the top unchecked link in the list, find a replaced path by network default routing algorithm for two previously direct connected nodes (a, b) of link *k*, for all the involved VNs. Considering off-peak traffic demand, update the available capacity of the links for each VN over the path, with the following calculations and conditions:

$ac_n^{i,j} = ac_n^{i,j} - \gamma_n^{a,b} \rightarrow$

- If for all the links over the replaced path: $ac_n^{a,b} \geq 0$, then go to Step 7.
- If there is one or more links over the replaced path that $ac_n^{a,b} < 0$, then put back the link to the topology and undo the updates, then go to Step 8.
- If no replaced path is founded between node "a" and "b", go to the next step.

Step6: Try to find a replaced path, by network default routing protocol, over current active physical links, then:

- If there is a physical path however some of the links over the path does not support our desired VN, and the links have enough physical bandwidth, then allocate the required bandwidth for the VN based on $C_n^{a,b}$, and go back to Step 5 and do the checking process for this link again.
- Otherwise; put the link back to the topology and undo the updates, then go to Step 8.

Step7: Check the capability of link removal for all VNs involved in the link, then:

- If all the VNs are removable go to the next step.
- Otherwise, put back the link into the topology and undo the updates, then go to the next step.

Step8: Repeat Step 5 for the next link, unless all the links are checked; otherwise stop.

Figure 4. Proposed algorithm for link removal

2.3.4. Evaluation

In order to evaluate our heuristic algorithm, we have simulated several random network virtualization scenarios in MATLAB. Here, the objective is to assess effectiveness of the algorithm in setting the links into sleep mode, regarding off-peak bandwidth demands. The off-peak topology has to support full connectivity and off-peak bandwidth demands. Therefore, we have simulated several virtual network scenarios over GÉANT substrate topology.

We considered GÉANT as our physical substrate network topology, since it is a universal real network topology and its real link bandwidths are published. The GÉANT network has 22 nodes and 36 links. The physical capacity for each link is used as announced by GÉANT project [9]. The links are assumed with residual bandwidth. Two virtual network setups are simulated over the defined substrate network. In each setup 10 scenarios are generated randomly and the effectiveness of our algorithm has been assessed. For the first setup, each scenario contains 5 randomly generated virtual networks over GÉANT substrate network. However, in the second setup each scenario has 10 randomly generated virtual networks.

Our heuristic algorithm has been assessed over the both defined setups, for different fraction rates of off-peak bandwidth demands. The average results are shown in Figure. 2. The results show in the best condition, for the first setup, when the off-peak traffic rate is 0.01 of peak traffic rate, our proposed algorithm is able to push 36.1% of physical link into sleep mode, while still full connectivity and off-peak bandwidth demands are satisfied for all involved virtual networks. In the other hand, the algorithm still sets 0.27% of links into sleep mode, while convincing the conditions, when the off-peak traffic demand is 0.9 of peak time traffic demand. Besides, as it shown in Figure 4, by increasing the off-peak traffic demand ratio, for both setups, the number of capable links to be set into sleep mode, are decreasing. This is logical due to bandwidth constraints and virtual link availability over the network, which will be degraded by increasing the off-peak bandwidth demands. Moreover, by comparing two setup graphs in Figure 4, we see that the second setup, in which each scenario has 10 random virtual networks, is in left hand side of the first scenario, in which each scenario has 5 random virtual networks. This reveals that by increasing the number of active virtual network, the number of capable links to be set into sleep mode, will be decreased. This is happening because our algorithm to guarantee the full connectivity and off-peak bandwidth demands needs to bring a replaced path which has enough bandwidth for redirected traffic for each single virtual network. Hence, by increasing the number of virtual networks the requirements which needed to be convinced in order to push a link into sleep mode will be increased. This decreases the number of capable links to be set into sleep mode. As it is shown in Figure 4, the number of capable links in the second setup for the same amount of off-peak traffic rate is lower than the first setup.

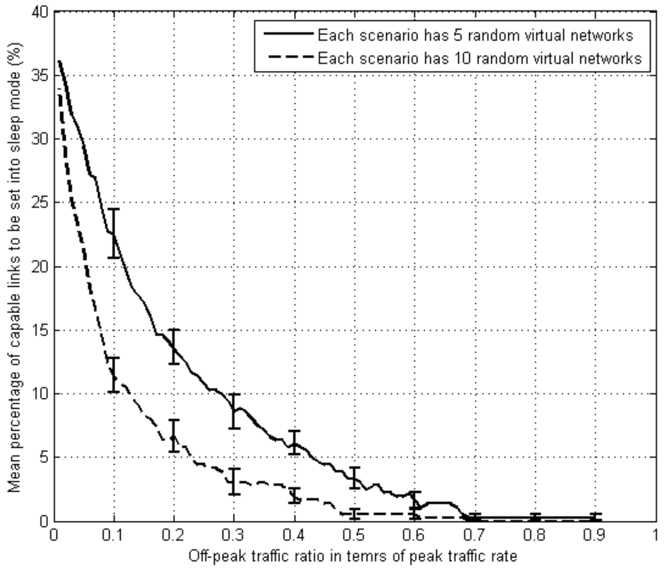


Figure 4 **Percentage of possible sleep links based on off-peak traffic demand**

In addition, in order to evaluate the error rate of our results, we calculated the Standard Error of the Mean (SME) of ten different scenarios. The error amounts are plotted in Figure 4, over the previously discussed results. The maximum error for the first setup is 1.9178% and for the second setup is 1.3386%, which are convening. By decreasing the off-peak traffic rate the algorithm has more degree of freedom since it is easier to find a replaced path which supports the redirected traffic. In the other hand, for the high off-peak traffic rates, freedom degree of algorithm is lower. Hence, we expect the algorithm experience higher standard deviation values over the lower off-peak bandwidth demands. The SME results in Figure 4, confirms our expectation.

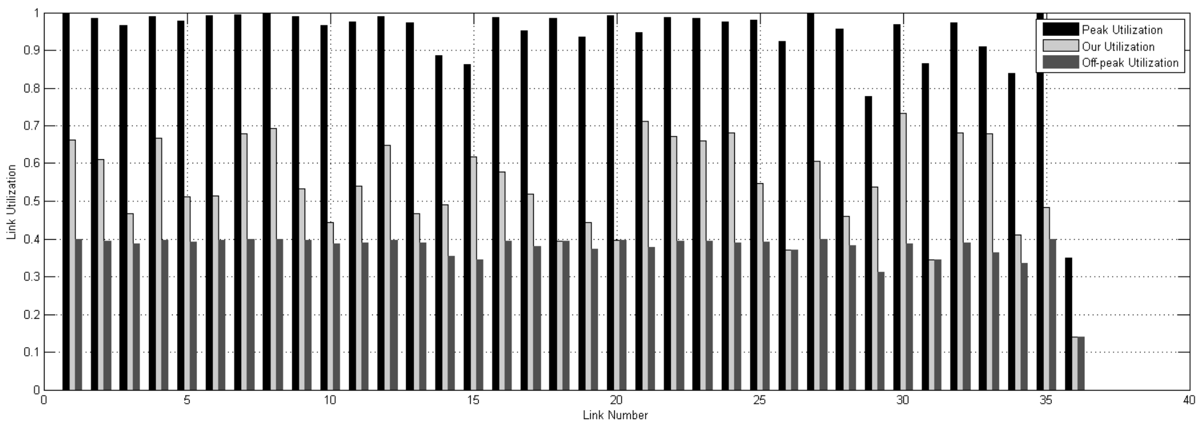


Figure 5 **Link Utilization**

Besides, we have measured the link utilization after and before using our proposed algorithm. The results of this measurement, for all the links, are shown in Figure 5. Link utilization is tested over the first setup, for 10 random scenarios, while we considered the off-peak bandwidth demand as 0.4 of the peak time bandwidth for all the links. Then, we recorded the maximum link utilization over these ten random scenarios. The link utilization of the physical links has been assessed in three different times. Firstly, it has been measured for peak hours which is considered as our maximum link utilization threshold. It has been also measured for off-peak hours when our algorithm is not considered, and off-peak hours when our algorithm is implemented. As it is drawn by using our proposed algorithm the link utilization over the link will be increased. This is due to rerouting the traffic of sleep link to the other links. However, the increased link utilization does not approach the maximum threshold which is convincing. This makes the power consumption more proportional to the link utilization over off-peak hours of virtual networks.

Therefore, the heuristic algorithm over the defined scenarios based on GÉANT substrate topology is able to save energy by setting notable number of links into sleep mode over off-peak hours. This happens while the algorithm still guarantee the full connectivity and off-peak bandwidth demands over network virtualization environment. Besides, the link utilization is more proportional to the power consumption, and not more than defined maximum threshold.

3. Virtualized Resource Management in Wireless Networks

3.1. Research Challenges in Wireless Network Virtualization

The research challenge is to extend the network virtualization from wired network to wireless cellular networks. The difference mainly between the wired and wireless domain is the broadcasting nature of the wireless links. The wireless cellular networks links suffer more interference than the wired networks. Radio resource management and scheduling could be based on different criteria such as bandwidth, data rate, channel conditions and pre-defined contracts among virtual networks. Hence in order to embed virtual links without interference, it is important to divide the communication domain into different dimensions in a slotted way as the wired network virtualization does. These dimensions can be frequency, time and space. Hence it is one scheduling problem of frequency, time, space or code allocation.

The introduction of network virtualization to mobile networks, e.g. LTE networks, is a uniqu e opportunity for mobile operators to deal with the highly increasing traffic loads and cut dow n the infrastructure investment on CAPEX and OPEX costs through sharing the physical infra structures by multiple mobile operators.Radio resource management and scheduling could be based on traditional criteria such as bandwidth, data rate, channel conditions and pre-defined contracts among virtual network. Wireless resources on air interface in the case of cellular network are abstracted into unified resource and form a resource pool. The virtual network needs to provision a fair allocation of dedicated resource slices for users in order to provide more effective solutions for random access.

In wireless network, random access protocols provide a more flexible and efficient way of managing channel for access. Thus, an efficient collision resolution algorithm leads to fast system access and high throughput. The Pseudo Bayesian Broadcast algorithm is found to be exceptionally effective in practice since it makes nearly the "best possible use" of the information available on the network in determining the broadcast probabilities to use. Hence, we will try to introduce the Pseudo Bayesian Broadcast algorithm in the random access protocols to provide a dynamic back off algorithm with fast retransmission and access priority differentiation. Moreover, under the tempting market prospect, more and more Machine-to-Machine (M2M)applications have been implemented in current 2G/3G networks. Due to various advantages, the cellular networks have been considered as one of the best choices to bear M2M service. Because of the specific characteristics of M2M communication, there must be many incompatible factors in practice, and the random access performance of H2H communication will also be affected severely. Hence, we will try to propose a new algorithm, To evolve and develop competitive capabilities to support M2M communication, the system model of random access is built firstly, and then one power ramping strategy based on Logarithm is proposed for M2M.

3.2. Resource Allocation for Wireless Network Virtualization

3.2.1. Introduction

Following the IT resource virtualization in cloud computing such as CPU, memory and storage, network virtualization becomes the natural next step aiming to provide network or infrastructure providers with the ability to manage and control their networks in a more dynamic fashion. The concern of the EVANS project is on the virtualization of wireless networks, which present more challenging issues than wired networks due to specific features of wireless channels. Actually virtualization has already taken place in mobile cellular networks. For instance, there are many mobile network operators (MNOs) such as Lebara that don't have their own physical network infrastructure such as base stations (BS), etc. They typically rent such physical network infrastructure from other MNOs that own the infrastructure. For example, Lebara rents Vodafone's networks to provide mobile services to its end users. To distinguish these two types of MNOs we call the network infrastructure owners as *physical* MNOs (PMNOs) whereas the MNOs renting resource from others are called *virtual* MNOs (VMNOs). Actually this kind of virtualization is just a form of resource renting. On the other hand, the essence of wireless network virtualization, to our understanding, is to provide elasticity of resource allocation and thus the consequent pay-as-you-use business model, just like in cloud computing. However, these features are yet to be reflected in the current network renting market.

The aim of the work here is to provide a wireless network virtualization mechanism which helps enable a more agile business model where a VMNO can request and thus pay a PMNO in a more dynamic and pay-as-you-use manner. The concerned network scenario is illustrated in **Error! Reference source not found.** where, e.g., base station (BS) *A* transmits packets from both MNO #1 and MNO #2. At the BS there is a need to differentiate and isolate traffics from these two VMNOs. Isolation gives the flexibility for a VMNO to manage and control its own virtual network in a way as if they physically owned this network. This flexibility can be to introduce a new tariff scheme or a different resource allocation algorithm, etc. From a PMNO's perspective, its network node such as a base station is partitioned into *slices* each representing a virtual mobile network (VMN), as depicted in Figure 6.

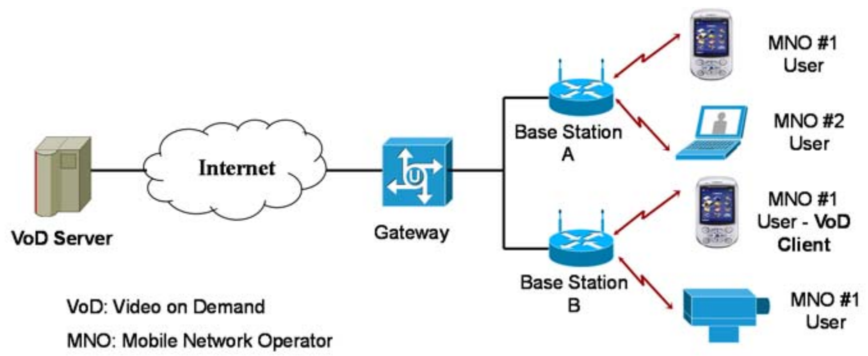


Figure 6 Wireless Networks, their End Users and their Connection to Internet

Apart from illustrating the concept of virtualizing one physical network node into multiple virtual network nodes, Figure 7 also shows the introduction of two types of networks: *local* and *foreign*. Local network refers to the original physical network, which, though, is now only part of the whole physical network infrastructure as the other part is rented out to virtual networks. Foreign networks refer to virtual mobile networks. There is only one local VMN but there can be more than one foreign VMN. No research work in the literature makes this distinction. However, in real-life practice, a PMNO needs to know this difference as it serves not only foreign traffic but also its own traffic. These two types of traffics are dealt with differently. As can be shown later in the proposed network virtualization algorithms, they follow different optimization objectives. From resource allocation's perspective, the aim for foreign networks is to use as little as possible or just enough bandwidth to satisfy resource requirement whereas the aim for local networks is to use as much bandwidth as possible after the foreign traffic has been served satisfactorily.

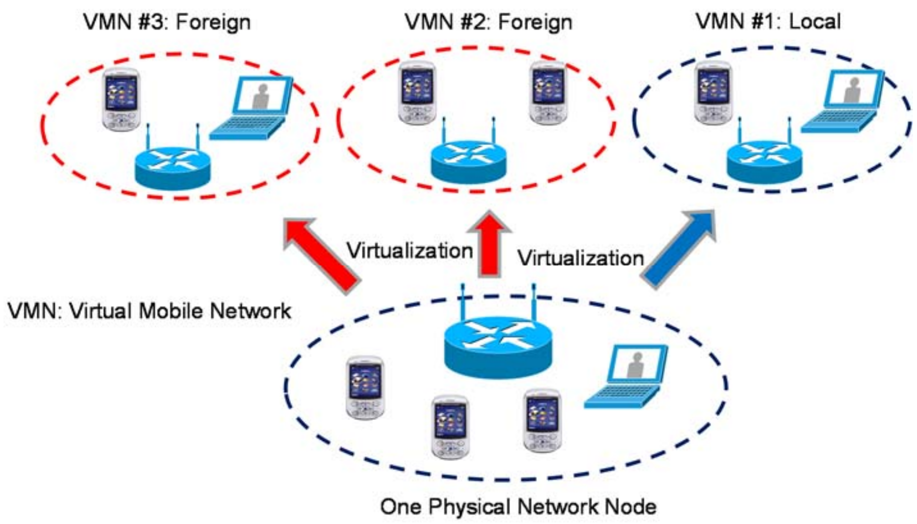


Figure 7 Wireless Network Virtualization

As far as the wireless network technology is concerned, this section uses IEEE 802.16 or so-called WiMAX. With high data rate, large network coverage, strong QoS capabilities and cheap network deployment and maintenance costs, IEEE 802.16 is viewed as a disruptive wireless technology and has many potential applications. Depending on the applications and network investment, IEEE 802.16 networks can be configured to work indifferent modes, point-to-multipoint (PMP) or mesh mode. In the PMP mode, a BS serves multiple subscriber stations (SSs) within its coverage. In the mesh mode, SSs communicate with each other without a BS. This section assumes a PMP mode and considers traffic going from SSs to BSs, namely, uplink. These BS stations can be connected to the Internet via a gateway – refer to Figure 6.

There are two goals to be achieved: virtual network isolation and resource efficiency. Namely, in addition to achieving the basic functions of virtualization (as mainly represented by isolation), resource efficiency also needs to be obtained. To this end, a joint algorithm for both network virtualization and resource allocation of IEEE 802.16 networks is proposed. The algorithm involves the following two major steps: firstly to virtualize a physical wireless network into multiple slices each representing a virtual network; secondly, to carry out physical resource allocation within each virtual network (or slice). In particular, EVANS concerns OFDM (Orthogonal Frequency Division Multiplexing) as its physical layer to achieve more efficient resource utilization. Therefore, the resource allocation is conducted in terms of sub-carriers. Though the motivation and algorithm design are based on IEEE 802.16 or WiMAX networks, the principle and algorithmic essence are also applicable to other OFDMA-based wireless networks.

3.2.2. Problem Clarification

Resource allocation is performed by the BS and is needed for both downlink and uplink. Since a BS usually knows downlink data information, downlink resource allocation is relatively straightforward. EVANS focuses on uplink resource allocation which requires an effective cooperation of a BS and its corresponding SSs, as illustrated in Figure 8. Quality of Service (QoS) is also important for VMNs but is not considered within the scope of this document.

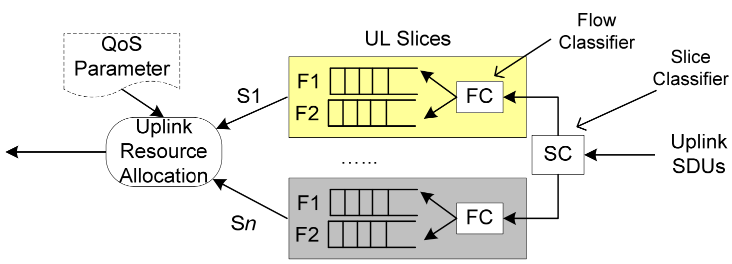


Figure 8 Uplink Packet Processing in a Virtualized IEEE 802.16 Network

Figure 8 also shows that the proposed network virtualization algorithm operates on two levels: slice and flow. Each slice represents a VMN and isolation is provided between slices. Each slice has a slice ID. There are multiple flows within a slice. A flow represents a session and each flow has a flow ID which is equivalent to WiMAX's session ID. Each uplink packet has both a flow ID showing its belonging to which VMN and a session ID identifying its session within a VMN. Virtualization is applied on network resources, namely, OFDMA sub-carriers. The problem to be solved here is how to allocate OFDMA sub-carriers to both slices and flows while aiming to maximize resource utilization.

A list of major notations used in this document is summarized in Table 1.

Table 1 Notations

Φ	Total bandwidth of system
P_T	Total transmit power of system
N_0	Noise power spectral density
N	Number of system subcarriers
M	Number of foreign slices
A	Universal set of system subcarriers
B	Subcarrier set allocated to local network flows
r_{S_i}	Rate assigned to slice S_i
$r_{f,S_i}^{\text{REQ-REAL}}$	Real rate requirement of traffic flow f in slice S_i
$r_{f,S_i}^{\text{REQ-ALG}}$	Algorithm rate requirement of traffic flow f in slice S_i
$I_{f,c}$	Assignment index indicating$f$-th flow occupy c-th subcarrier
$P_{f,c}$	Power allocated to f-th flow in c-th subcarrier
$h_{f,c}$	Channel gain of f-th flow in c-th subcarrier
$BER_{f,c}^{\text{target}}$	Target BER of f-th flow in c-th subcarrier

3.2.3. Proposed Elastic Wireless Resource Virtualization Algorithm

1) Flow rate vs. BER in subcarrier

Consider a multiuser OFDMA system with K users and N subcarriers. Our design is based on flows instead of users in order to satisfy the QoS more conveniently in the future work. Each user may produce one or more traffic flows. Then it is natural to obtain that the channel gain of f-th flow in c-th subcarrier $h_{f,c}$ is equivalent to the channel gain of the user which produce f-th flow on c-th subcarrier. For easy expression and without losing generality, this section omits the user identification in the follow description.

Assuming power being allocated averagely among subcarriers, if M-ary quadratureamplitude modulation (MQAM) is employed the the BER for an AWGN channel can be given by [8]:

$$BER_{f,c} \approx 0.2\exp\left(-\frac{1.5P_{f,c}h_{f,c}^{2}}{\left(2^{r_{f,c}}-1\right)N_0\dfrac{\Phi}{N}}\right) \tag{7}$$

Then the maximum rate of *f*-th flow in *c*-th subcarrier is:

$$r_{f,c} = floor\left(\log_2\left(1-\frac{1.5P_{f,c}h_{f,c}^{2}}{\ln(5BER_{f,c}^{\text{target}})N_0\dfrac{\Phi}{N}}\right)\right) \tag{8}$$

2) *Problem Formulation*

As mentioned earlier, there are two types of slices in the design. One type represents the original physical network operator itself, which is denoted as Slice 0. It serves traffic from this network operator's users. Another type of slices is for foreign VMNOs that are renting the network resources from this PMNO. There can be more than one such slice and they are denoted as Slice1 to *M*.

The admission of VMNOs is subject to strict admission control imposed by the PMNO. But once they are admitted to this physical mobile network, their network resource requirements shall be guaranteed. Therefore, from PMNO's perspective, it should always allocate resources to foreign slices 1 to *M* first. And then the remaining resources can be used by its own traffic. Here in this section, the resources concerned are OFDMA subcarriers. The problem of the subcarriers assignment to Slices 1 to *M* can be described by the following optimization problem:

$$\min \sum_{f\in S_i}\sum_{c\in A} I_{f,c} \tag{9}$$

s.t.

$$\text{AC1}: \quad \sum_{f\in S_i} I_{f,c} \le 1$$

$$\text{AC2}: \quad I_{f,c} = \{0,1\}$$

$$\text{AC3}: \quad r_{f,S_i}^{\text{AL}} \ge r_{f,S_i}^{\text{REQ-ALG}}$$

$$\text{AC4}: \quad r_{f,S_i}^{\text{AL}} = \sum_{f\in S_i}\sum_{c\in A} I_{f,c}r_{f,c}$$

Here AC means Type A Constraint as below is another optimization problem for resource allocation in the local slice where constraints are denoted as type B for easy reference. The objective (3) is to allocate minimum subcarrier resources to foreign flows under constraints AC1 to AC4. AC1 denotes that each subcarrier is only occupied by at most one user at any time, AC2 indicates whether the c-th subcarrier is allocated to f-th flow (value 1) or not (value 0). AC3 ensures that the rate of each flow in foreign slices meet their requirements by the inputs of the algorithm. AC4 is the total rate of subcarriers allocated to the f-th flow.

For the local slice, Slice 0, there is no explicit resource requirement and the optimization objective is to maximize the system throughput as represented by $\max \sum_f r_{f,S_0}^{\mathrm{AL}}$. So there is only BER constraint, which is expressed by $BER_{f,c}^{\mathrm{target}}$ in Eq. (8) during the resource allocation process. The optimization problem can be formulated as:

$$\max \sum_f r_{f,S_0}^{\mathrm{AL}} \tag{10}$$

s.t.

$$\begin{aligned}
&\mathrm{BC1:} && r_{f,S_0}^{\mathrm{AL}} = \sum_{\{c\in B | f\in S_0\}} I_{f,c} r_{f,c} \\
&\mathrm{BC2:} && \sum_{f\in S_i} I_{f,c} = 1 \\
&\mathrm{BC3:} && I_{f,c} = \{0,1\}
\end{aligned}$$

The optimization objective (4) denotes the system throughput of local Slice 0, BC1 and BC3 is similar to AC4 and AC2, BC2 ensures that each subcarrier is only occupied by at most one user at any time and all the subcarriers are allocated.

3) Proposed Algorithms

For the foreign slices, the optimization objective is to assign subcarriers to meet the requirements of all flows in the slices while occupy the subcarrier as little as possible. The optimization problem (9) is a typical binary integer programming problem. So it is suitable to be converted to *Office Assignment Problem (OAP)*, and use a linear programming (LP)-based branch-and-bound algorithm to solve the problem.

The form of *Office Assignment Problems* is

$$\min \quad \mathbf{q}_c{}^{\mathrm{T}} \mathbf{x} \tag{11}$$

s. t.

$$\mathbf{A_{eq}} \mathbf{x} = \mathbf{b_{eq}}$$
$$\mathbf{A_{neq}} \mathbf{x} \le \mathbf{b_{neq}}$$

$$x_i = \{0,1\}, \mathbf{x} = [x_1, \cdots x_i \cdots x_n]$$

Then, the optimization problem as expressed in Eq. 9 can be solved as follows. The operators are similar to these used in MATLAB.

ALG # 1 Virtual Resources Allocation Algorithm for Foreign Slices

1. Initialization:
2. Set $A=\{C_1,\cdots,C_N\}$, $P_{f,c}=P_T/N$, $I_{f,c}=0$, $\mathbf{A}_{\mathbf{eq}}=[]$, $\mathbf{b}_{\mathbf{eq}}=[]$
3. Create optimization coefficients:
4. for all $f\in S_i$, $c\in A$
5. $(\mathbf{x})_j=I_{f,c}$
6. $(\mathbf{q}_c)_j=1$
7. $r_{f,c}=floor\left(\log_2\left(1-\frac{1.5P_{f,c}h_{f,c}^2}{\ln(5BER_{f,c}^{\text{target}})N_0\frac{\Phi}{N}}\right)\right)$
8. end for
9. for all $f\in S_i$
10. $\mathbf{A}_{\mathbf{neq}}(i,:)$, $b_{\mathbf{neq}}(i,:)=$ the constraint of (AC1)
11. $\mathbf{A}_{\mathbf{neq}}(M+i,:)$, $b_{\mathbf{neq}}(M+i,:)=$ the constraint of (AC3)
12. end for
13. Solve OAP to get $I_{f,c}$

For the local slice, the optimization problem in Eq. 10 can also be converted to OAP, which operation is described as follow:

ALG # 2 Virtual Resources Allocation Algorithm for Local kind of Slices

---

1. Initialization:
2. Set $P_{f,c}=P_T/N$, $I_{f,c}=0$, $\mathbf{A}_{\mathbf{neq}}=[]$, $\mathbf{b}_{\mathbf{neq}}=[]$
3. Create optimization coefficients:
4. for all $f\in S_i$, $c\in B$
5. $(\mathbf{x})_j=I_{f,c}$
6. $(\mathbf{q}_c)_j=r_{f,c}$
7. $r_{f,c}=floor\left(\log_2\left(1-\frac{1.5P_{f,c}h_{f,c}^2}{\ln(5BER_{f,c}^{\text{target}})N_0\frac{\Phi}{N}}\right)\right)$
8. end for
9. for all $f\in S_i$

10. $\mathbf{A}_{\mathbf{eq}}(i,:)$, $b_{\mathbf{eq}}(i,:)$ = the constraint of (BC2)
11. end for
12. Solve OAP to get $I_{f,c}$

To efficiently utilize the channel resources, an elastic wireless resource virtualization algorithm has been designed. In this algorithm, the basic design principles for such a virtualized network need to be satisfied. Namely, the foreign flow's total data rate or throughput must be guaranteed; and then on top of this the remaining channel resources should be used as much as possible by the local traffic to provide best possible service to local traffics. For this purpose, an Elastic Resource Virtualization Algorithm called ERVA is proposed, which is a combination of Algorithm 1 and Algorithm 2, as described below.

Elastic Resource Virtualization Algorithm (ERVA)

1. Input: M , $r_{S_i}^{\text{REQ-STATIC}}, r_{f,S_i}^{\text{REQ-REAL}}$
2. for i=1 to M // *foreign slice*
3. if $\sum_{f \in S_i} r_{f,S_i}^{\text{REQ-REAL}} \le r_{S_i}^{\text{REQ-STATIC}}$, then
4. $r_{f,S_i}^{\text{REQ-ALG}} = r_{f,S_i}^{\text{REQ-REAL}}$
5. else
6. $r_{f,S_i}^{\text{REQ-ALG}} = \dfrac{r_{f,S_i}^{\text{REQ-REAL}}}{\sum_{f \in S_i} r_{f,S_i}^{\text{REQ-REAL}}} r_{S_i}^{\text{REQ-STATIC}}$
7. end for
8. Choose $\{S_i\}, i = 1 \cdots M$ // *foreign slices*
9. Call ALG #1
10. Set $B = \left\{ C_l \middle| \sum_{\substack{f \\ l \in A}} I_{f,l} = 0 \right\}$
11. Choose $\{S_i\}, i = 0$ // *local slice*
12. Call ALG #2

From line 3 to 6, the total real traffic flow loads in foreign slices are checked to see if they have already reached the *upper bound* of the static requirement of foreign slices. If not then they are assigned invariably to input of allocation algorithm ALG #1. Otherwise, the excess portion will be clipped proportionally across all flows according to their real traffic loads, as shown in line 6. Then, the foreign slice static requirement contracts are guaranteed. And at the same time the margin between real traffic loads and static requirements of foreign slices is fully utilized. In line 8 and 9, subcarriers are allocated to the flows in foreign slices by call subroutine ALG #1. In line 10, the remainder subcarriers are aggregated to set B which is use in ALG #1 for resource allocation in local Slice 0. Line 11 and 12 denote the resource allocation process in local slice.

3.2.4. Performance Evaluation and Analysis

1) Overall Simulation Design

For comparison purpose, two other virtualization algorithms have been designed and implemented. The first one is the so-called static resource allocation, denoted as SRVA, where the available physical network resource is equally divided among M+1 networks, namely, M foreign networks and one local network. SRVA is the baseline algorithm serving to show how much improvement can be achieved by our proposed ERVA. In addition, another slightly more dynamic resource virtualization algorithm called FRVA is also proposal. FRVA allocates the same amount of resources to a foreign slice as requested in the SLA (Service Level Agreement) between the VMNO and the PMNO regardless of the real-time traffic from this particular VMNO. In contrast, our ERVA algorithm also takes into consideration the real-time traffic demand when allocating network resources to VNs (or slices), i.e., more elastic.

The simulations are designed in accordance with the system design principles, namely, VN isolation and resource efficiency in terms of overall network throughput.

2) Network Parameter Setup

In the simulation below, the IMT-2000 Vehicular Model A channel model as suggested by ITU-R M.1225 is utilized. It is a six-path Rayleigh fading model. The detailed parameters are shown in Table 2.

Table 1 Simulation Environments and Parameters

Carrier frequency		2.0 GHz	
Mobile velocity		100km/hr	
Multipath delay		Delay (ns)	Power (dB)
	Path 1	0	0
	Path 2	310	−1
	Path 3	710	−9
	Path 4	1 090	−10
	Path 5	1 730	−15
	Path 6	2 510	−20

The bandwidth is set to 2 MHz and divided into N=128 subcarriers. The cycle prefix length CP=16 for OFDM system, so the OFDM frame T_f =62.5μs, and the bandwidth of subcarrier is $\Delta f = 16$ kHz. The Vehicular Model A channel coherence bandwidth $B_c \approx 0.54$ MHz which is far larger than the bandwidth of OFDM subcarrier. Then, the frequency-selective channel is converted to frequency-flat sub-channels. Chunk-based algorithm is employed in the simulations. The subcarriers are grouped into $Z = 16$ chunks, each consisting of $n_b = 8$ subcarriers. The SNR on the subcarriers is

$$\gamma_{f,c} = \frac{P_{f,c} h_{f,c}^2}{N_0 \frac{\Phi}{N}} = \gamma_0 h_{f,c}^2 . \tag{12}$$

The following three slices are simulated: two foreign slices and one local slice. Traffic load follows the Poisson-distributed model for all flows. Each foreign slice has two flows and the local slice contains four flows. Table 3 summarizes the simulations setup for the different slices and flows. Flow 1 and Flow 2 are in foreign slice 1 and Flow 3 whereas Flow 4 are in foreign Slice 2. Since the local Slice 0 does not have maximum rate restriction, the traffic loads of Flow 5 to 8 in this slice are not limited aiming to simulating a demanding local traffic so as to stretch the physical network.

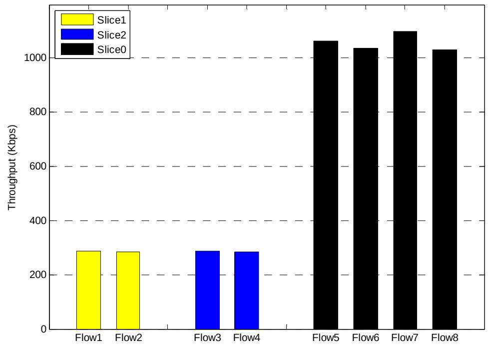
Table 3 Simulations setup for flows and slices ($\gamma_0 = 15$dB)

Simulation No.	Average flow load (λ) (Kbps)				Static Rate Requirements of foreign slices(Kbps)	
	Slice 1		Slice 2			
	Flow 1	Flow 2	Flow 3	Flow 4	Slice 1	Slice 2
Simulation 1	240	240	240	240	960	960
Simulation 2	120	120	360	360	960	960
Simulation 3	120	360	120	360	720	1200
Simulation 4	240	240	1800	360	960	960

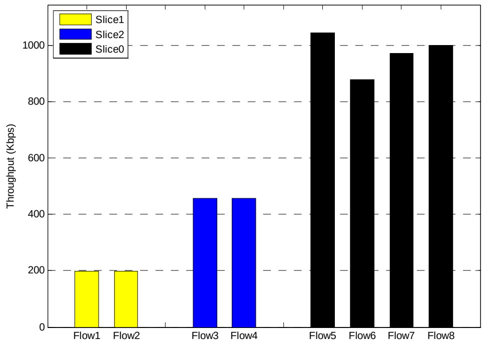
3) Isolation

These simulations aim to demonstrate ERVA's efficacy in providing slice isolation for different static rate requirements and flow traffic setup. According to Table 3, four groups of setup are evaluated for the proposed ERVA scheme and their results are shown in Figure 8 (a) to (d) respectively.

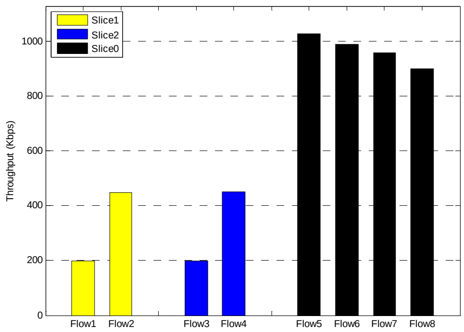
In Simulations 1, 2 and 3, the foreign average traffic flow loads are all below the static rate requirements of foreign Slice1 and 2. These are common communication scenarios where foreign networks usually don't exceed the agreed bandwidth requirement. In Simulation 1, all average flow traffic loads are same as 240 Kbps. In Simulation 2, the loads are the same across flows within a foreign slice but vary across slices. In Simulation 3, the flow loads are different within a foreign slice. From the corresponding results of Figure 9 (a), (b) and (c), it can be observed that the flows in foreign slices are allocated the requested amount of bandwidth despite the fact that the wireless channel is changing. This to certain extent shows the isolation among flows.



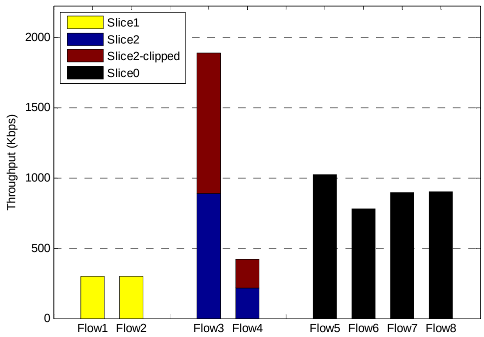
(a) Simulation 1



(b) Simulation 2



(c) Simulation 3



(d) Simulation 4

Figure 9 ERVA's Provisioning of Isolation across Slices (Virtual Networks)

In Simulation 4, the foreign traffic loads of the flows in Slice 2 are more than the corresponding static requirements. In this case only the amount agreed at the network renting stage is guaranteed whereas the exceeding amount, as represented by the top portion of the Flow 3 bar, is not served and thus dropped. This is because the isolation is designed between different slices. Flow 1 and 2 are in Slice 1 and Flow 3 and 4 are in Slice 2. So if the sum of Flow3 and 4 exceeds, both of them will be cut proportionally and this does not affect Slice1. The sum of Flow 3 and 4 meet the requirement of Slice2 after clipping.

4) Resource efficiency

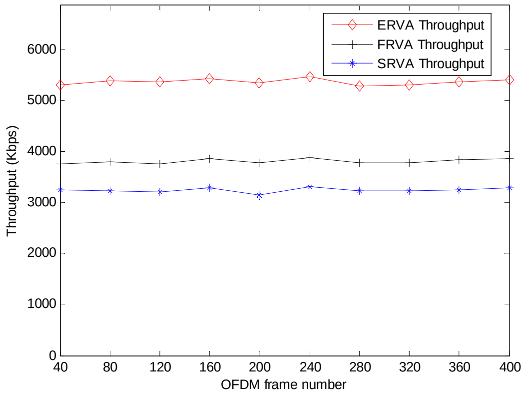
This sub-section is to evaluate the second design goal of the ERVA algorithm, namely, resource efficiency in terms of system overall throughput. Note that this throughput is measured from the PMNO's point of view, namely the throughput of the overall physical network rather than individual virtual networks. ERVA attempts to increase the throughput of the whole physical network while satisfying the bandwidth requirement from individual virtual networks.

Table 3 Simulations setup for flows and slices ($\gamma_0 = 15\text{dB}$)

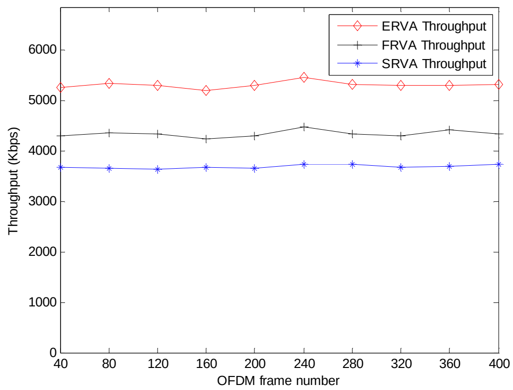
Simulation No.	Average flow load (λ) (Kbps)				Static Rate Requirements of foreign slices(Kbps)	
	Slice 1		Slice 2			
	Flow 1	Flow 2	Flow 3	Flow 4	Slice 1	Slice 2
Simulation 1	240	240	240	240	960	960
Simulation 2	120	120	360	360	960	960
Simulation 3	120	360	120	360	720	1200
Simulation 4	240	240	1800	360	960	960

The same traffic settings as in Table 3 are employed. Only results from Simulation 1 and 4 are shown in Figure 9, as in (a) and (b) respectively, because the results from Simulation 2 and 3 are similar with these from Simulation 1. The three algorithms (i.e., SRVA, FRBA and ERVA) discussed Section 5.1 are evaluated. They are invoked following an allocation cycle that is equal to the length of an OFDM frame. Network throughput is measured in each cycle. Each point on the graphs is the average of 10 runs.

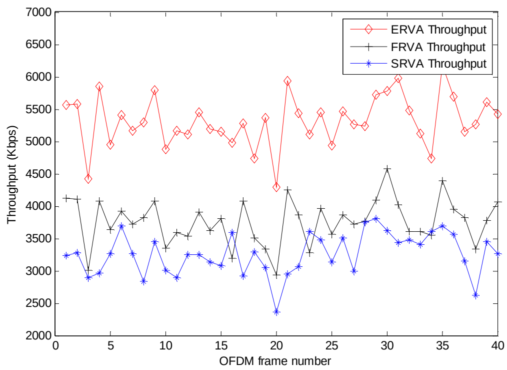
It can be observed from Figure 10 (a) and (b) that the throughput performance of ERVA is the best, which is followed by FRVA, whereas SRVA performs the worst. The main reason is that both ERVA and FRVA have employed dynamic resource allocation via optimization method whereas SRVA performs a static resource allocation and thus no selective diversity gain is obtained. The ERVA is better than the FRVA because ERVA utilizes the spare resources between static rate requirements and real traffic loads. A comparison between Figure 10 (a) and (b) shows that the throughputs of FRVA and SRVA in (b) are larger than these in (a) respectively whereas ERVA performs roughly the same. This is mainly because the traffic loads are larger in Simulation 4 (i.e., Figure 10 (b)) than that in Simulation 1 (i.e., Figure 10 (a)).



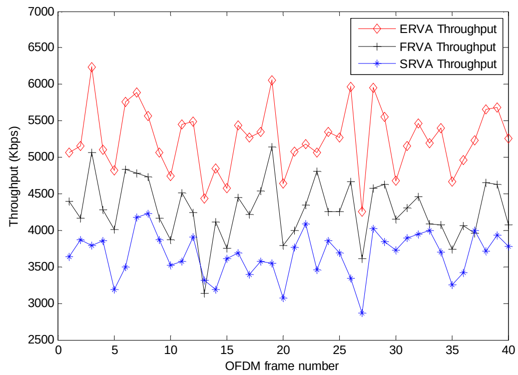
(a) Simulation 1



(b) Simulation 4



(c) Simulation 1 (zoom in)



(d) Simulation 4 (zoom in)

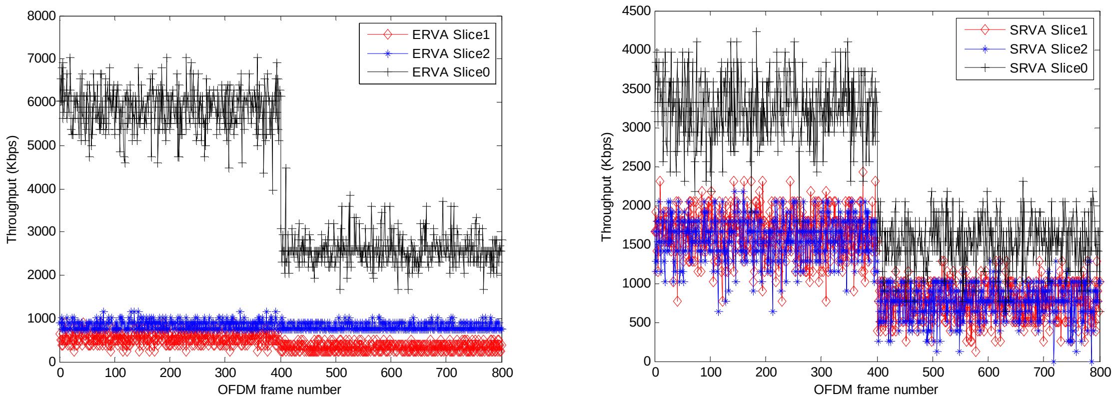
Figure 10 System Throughput of different algorithms.

Figure 10 (c) and (d) zoom into the first 40 frames of (a) and (b) respectively and show the detailed throughput performance of each algorithm. It can be observed that the trend stays the same though there are some variations between different sampling points (i.e., frame numbers).

- The Effect of Channel Quality on System Performance

In this simulation, the effects of different strategies of resource allocation among all slices are evaluated when the overall channel capacity varies due to the change of SNR (Signal to Noise Ratio). The slice requirements and flows load setup are the same as in Simulation 2, two different average SNR values, i.e., 20dB and 14dB, are used here.

The results are shown in Figure 10, where the SNR value is 20dB for the OFDM frame number of 0 to 400 and the SNR value is set to 14 dB for the OFDM frame number of 400 to 800. Figure 11 (a) and (b) show the throughput of ERVA and SRVA respectively. From Figure 11 (a) it can be observed that the throughputs of foreign Slice 1 and 2 are not affected by the channel capacity variation. However, there is performance degradation for local Slice 0 as SNR goes down from 20dB to 14dB. This is because channel capacity decreases as SNR gets worse. This illustrates that the proposed ERVA algorithm guarantees that the SLAs of foreign slices are satisfied and the channel deterioration mainly affects local traffic. To compensate this kind of unfairness, ERVA allows local traffic to make use of the spare resources left over by foreign slices should the traffic from foreign slices is not demanding, as illustrated in Figure 9. In contrast, SRVA does not provide guarantee for foreign slices. In particular due to the static nature of SRVA, resources are over provisioned to low-demanding foreign slices whereas high-demanding local slice suffers squeezed traffic throughput. For example, ERVA can provide about 7000Kbps when SNR equals to 20dB whereas SRVA can only provide up to 4300Kbps, as shown in Figure 11.



(a) ERVA (b) SRVA

Figure 11 Throughput across Slices under Different SNR

- Delivery Ratio

In this simulation, the delivery ratios of three algorithms under different traffic loads are evaluated. The delivery ratio is defined as: $Ratio_D = Data_D / Data_R$, where $Data_D$ is the total amount of data delivered (i.e., the summation of real flow throughputs), and $Data_R$ is the total amount of data requested for delivery (i.e., the summation of traffic flow loads). When the network congested some data may be dropped.

The static rate requirements of foreign Slice 1 and 2 are 960 Kbps, and each traffic load of Flow 1 to 4 is set from 480 Kbps to 5760 Kbps. Since the flow loads in local Slice 0 are adaptive so that the resources allocated to Slice 0 are fully used, the system delivery ratio is dominated by foreign Slice 1 and 2. From Figure 12, we can see that our proposed ERVA have the same delivery performance as FRVA. When the flow loads are light, all schemes work well. However, with the flow loads increasing, both ERVA and FRVA perform better than traditional SRVA.

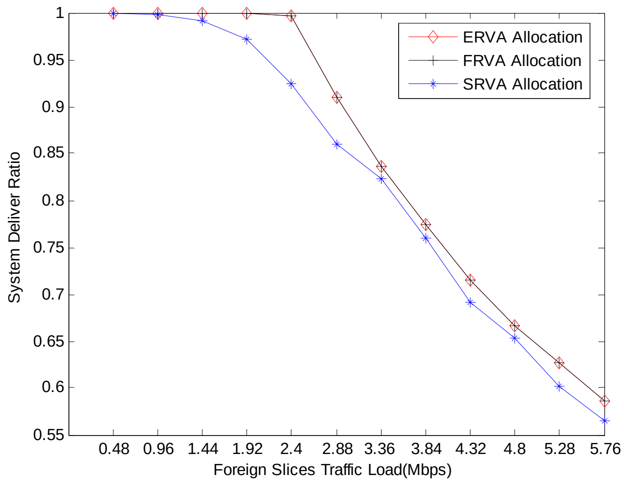


Figure 12 System Delivery ratio under different foreign flow loads

3.2.5. Summary

Based on the analysis of the existing work on wireless network virtualization, we have proposed an algorithm for joint network virtualization and resource allocation of IEEE 802.16 wireless networks. The algorithm not only provides network virtualization (isolation) but also achieves network resource efficiency. The latter is measured in terms of network throughput and packet delivery ratio. The simulation results show that the above goals have been achieved. Though the motivation and algorithm design are based on IEEE 802.16 or WiMAX networks, the principle and algorithmic essence are also applicable to other OFDMA-based wireless networks.

The next step is to introduce power allocation together with sub-carrier resource allocation during wireless network virtualization. Consideration of service differentiation (i.e., to provide QoS guarantee) is also within our future plan.

3.3. Radio Resource Management for Wireless Network Virtualization

3.3.1. Virtualizing wireless medium in LTE networks

Virtualization of the wireless resources on the air interface in the case of cellular network such as LTE and WIMAX systems means virtualizing the base station in order to schedule wireless resources among multiple Mobile Virtual Network Operators (MVNOs). Through virtualization, multiple MVNOs are able to run their own network on the same physical network infrastructure and provide custom services to their end users. In this situation, the air interface wireless resources need to be abstracted to a resource pool. Resources from this pool can be dynamically assigned to virtual networks based on some criteria (e.g., bandwidth and predefined contracts), which will improve the resource utilization. Figure 13 shows An example architecture of virtualizing radio resources, in which multiple MVNOs share the physical eNode B.

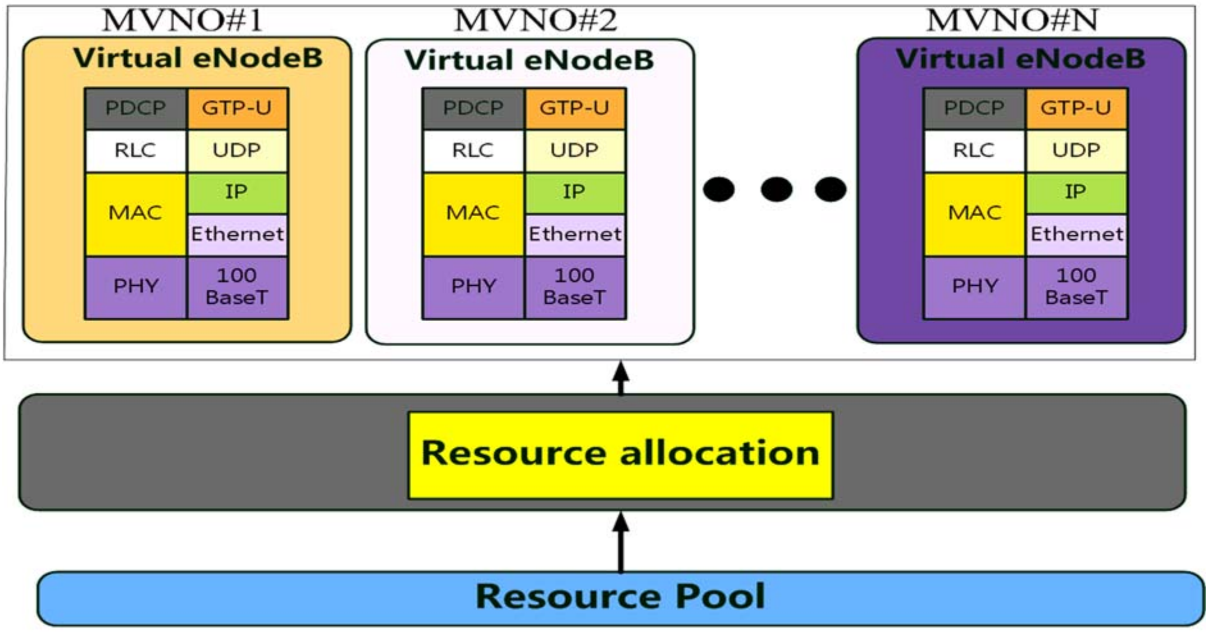


Figure 13 An example architecture of virtualizing radio resources.

LTE which was introduced by 3GPP is anticipated to be one of the promising solutions to the problems faced by today's mobile networks. Considering the characteristics of LTE, it is chosen by us as the study case of applying virtualization technology to cellular networks. In this work, we are mainly focused on LTE wireless medium (air interface wireless resources) virtualization, which is of a significant challenge. Compared with current mobile networks, where wireless resources are only assigned within one specific network, wireless resources should be allocated not only within one virtual network but also among multiple different virtual networks. Enhanced schedulers based on some criteria mentioned previously should be designed for wireless resource virtualization to allocate wireless frequency between different virtual mobile networks. In order to verify the potential performance gain through virtualization, simulations play a vital role.

3.3.2. Radio Resource Virtualized for Random Access

Random access protocols provide a more flexible and efficient way of managing channel for access. During the random access procedure, terminals must select random access channel to send access requests. If other terminals select the same channel, this situation will result in a collision and these collision terminals will back off and retransmit their access requests.

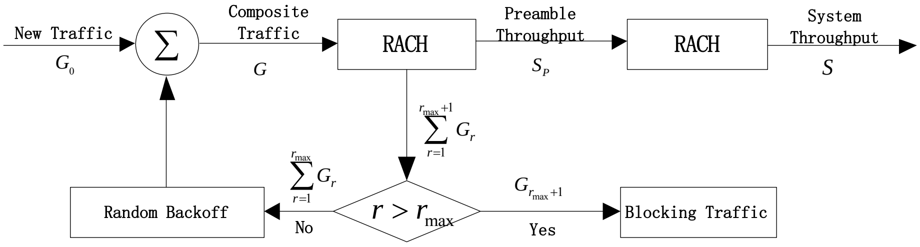


Figure 14 System model for RA

Figure 14 shows the system model of RA, which M2M traffic exists with H2H traffic. We provide a dynamic back off algorithm with fast retransmission and access priority differentiation. It can obtain high successful random access rate and low access delay, and satisfy QoS requirements. According to the access requests in uplink, the Node B estimates ATs in the next slot based on the Pseudo Bayesian algorithm. When there are collisions caused by competition in the current slot, the proposed algorithm decides whether to back off for the collided terminals in the next slot according to the load. Hence, we should firstly estimate the number of ATs. In addition, in order to provide access priority, different traffics have a different persistence value, which can be default by the systems.

With the development of Machine-to-Machine (M2M) communication, the cellular networks was one of the best choices to bear M2M service , which with the advantages of low-cost and large coverage, have nearly spread to every corner of the world. However, how to evolve and develop competitive capabilities to support M2M communication exists with H2H communication is an excellent challenge. To solve this problem, we built the system model of Random Access (RA) and proposed one power ramping strategy based on Logarithm for M2M.

The existing power ramping scheme is open-loop power control during the RA procedure. When mobile stations (MSs) fail to get through the RA procedure, they will retransmit the request with a higher power to guarantee the success rate, such as fixed ramping, linear ramping and geometric ramping. However, for the differences between M2M and H2H communication, we think that if M2M communication is treated with no difference from H2H communication, the interference generated from huge MDs is so severe that the performance of H2H communication can't be well guaranteed. Therefore, we proposed one power ramping scheme on the basis of logarithm steps for M2M to improve H2H communication performances.

3.4. Resource Allocation Approach among Virtual Mobile Operators

3.4.1. Problem statement

In the last few years, network virtualization (NV) has attracted more and more attentions from research communities such as GENI in the U.S., 4WARD in Europe, and AKARI in Asia. With network virtualization, the role of traditional internet service providers (ISPs) is decoupled into two different parts. One is referred to as infrastructure providers (InPs) which have the ownership of the physical network substrate and provide virtual networks (VNs) with virtual resources by abstraction and isolation of the physical resources, whereas the other one is called service providers (SPs) whose concentration is paid on deploying customized VNs by renting virtual resources from InPs according to a certain contract and providing customized services to its users in an isolated fashion among different VNs running on the same physical infrastructure.

In cellular network virtualization, virtual mobile operators (VMOs) don't own any physical resources such as base stations and wireless spectrum and they act more like SPs. VMOs deploy their networks by sharing resources of the InPs according to a predefined contract among them, which is a promising solution to maximizing resource utilization and reducing investment costs in cellular networks. However, to the best of our knowledge, only a little information is publicly available on the cellular network virtualization.

The authors in [10] concentrate their work on applying virtualization technology in Long Term Evolution (LTE) networks and a LTE virtualization framework is proposed by the authors. The framework is based on the enhanced NodeB (eNodeB) virtualization and an entity called "Hypervisor" is added on top of the physical resources, which is responsible for allocating these resources among different VMOs running on top. Specifically the authors focus their work on the air interface virtualization and how to schedule the air interface resources among different virtual operators (VOs, i.e., VMOs in this letter). As is shown in [10], some potential gain exists by sharing wireless spectrum resources among multiple VMOs and the needed wireless resources by each VMO are roughly determined by the "Hypervisor" based on a load estimation mechanism, which is not explicitly described. As a result, more reasonable predefined contract based wireless resource allocation approaches among VMOs need to be investigated.

In this section, the work is focused on wireless resource allocation among VMOs based on the LTE virtualization framework in [10] and the minimum radio resource allocation unit is called physical resource block (PRB) in LTE networks. After VMOs have obtained certain number of wireless resources, packet scheduling is executed within each VMO based on existing scheduling algorithms such as proportional fair (PF) [11], which is not the focus of the letter. A bankruptcy game based dynamic wireless resource allocation approach among VMOs are proposed and investigated and the satisfaction of payoffs (i.e., resources) each VMO is paid is evaluated with expectation index (EI). With the proposed approach, the wireless spectrum resources are abstracted to a resource pool which is referred to as the spectrum resource provider (SRP) and the limited resources in the pool are shared among VMOs. The proposed approach is based on a specific predefined contract between the SRP (i.e., InP) and VMOs (i.e., SPs). To sum up, the main contribution of the letter is that based on the proposed approach, the limited resources can be flexibly assigned among "big" and "small" VMOs according to the specific requirements and at the same time, the resource utilization is improved by cooperative sharing, both of which are big challenges in shared networks.

3.4.2. The Wireless Resource Allocation Approach among VMOs

The dynamic wireless resource allocation approach is based on the following predefined contract between the SRP and VMOs: the wireless resources (i.e., PRBs) owned by the SRP are dynamically allocated among VMOs in each transmit time interval (TTI). The number of PRBs allocated to each VMO depends on the traffic load and traffic rate that each VMO is experiencing. Higher traffic load and traffic rate means requiring more PRBs. The allocation should be performed in a relatively fair manner among VMOs.

The proposed wireless resource allocation approach among VMOs in this letter is based on a bankruptcy game which is a special type of N-person cooperative game. Bankruptcy game is chosen considering the following several reasons. The PRBs owned by the SRP are limited and scarce. Therefore, it is reasonable to assume that the total claimed PRBs by all VMOs are always not less than the total PRBs owned by the SRP. In addition, VMOs forming the coalitions in the bankruptcy game can get better payoffs and the Shapley value guarantees relatively fair allocation of PRBs among VMOs.

Based on the aforementioned description of the bankruptcy game, the SRP and VMOs are modeled to the bankrupt company and players in the game respectively, where a positive integer M and a finite set of $N=\{1,...,n\}$ denote the total number of PRBs owned by the SRP and VMOs in the game respectively. b_i and $c_i\left(i=1,...,n\right)$ are defined to respectively represent the minimum number of PRBs each VMO needs to operate its virtual network and the additional PRBs each VMO claims, where $\sum_{i\in N} b_i \le M$ and $\sum_{i\in N} c_i \ge M-\sum_{i\in N} b_i$. The total number of additional claimed PRBs (i.e., the total money a bankrupt company owes) is represented by an integer Y ($Y \ge M-\sum_{i\in N} b_i$). In our approach, the additional claimed PRBs by each VMO have much relationship with the instantaneous number of traffic flows and traffic rates. If a VMO is burdened with more traffic flows and the traffics require higher rate, the VMO should additionally claim more PRBs. A positive vector $R=\{r_1,...,r_k\}$ is presented to denote the traffic flow rate of each traffic type, where the positive integer k represents the number of types of traffic flows. w_j^i ($i\in N$ and $j=1,...,k$) is defined to denote the number of traffic type j in each TTI for VMO i . The additional claimed PRBs c_i ($i\in N$) is obtained through the following formulas:

$$c_i=\left(\sum_{j=1}^{j=k} w_j^i r_j \Big/ \sum_{i=1}^{i=n}\sum_{j=1}^{j=k} w_j^i r_j\right)*\left(Y-n\right)+1, \forall i\in N \tag{13}$$

$$\sum_{i\in N} c_i = Y \tag{14}$$

A coalition S is defined as a subset of N (i.e., $S \subset N$). The coalition form of the bankruptcy game is given by the pair (N,v) where v ($v: 2^n \to \mathbb{R}$) is a characteristic function of the game and there are 2^n possible coalitions with n players in a game. The characteristic function for the bankruptcy game considering here can be particularly defined for all possible coalitions as follows [6]:

$$v(S) = \max\left\{0, M - \sum_{i\in N} b_i - \sum_{j\notin S} c_j\right\} \tag{15}$$

where $v(\varnothing) = 0$ and $v(N) = M - \sum_{i\in N} b_i$.

It should be noted that the VMO will not agree to get the PRBs less than the VMO could obtain without coalition. As a result, the payoff vector (i.e., the PRBs each VMO can obtain through forming coalition) $T = \{t_1,...,t_n\}$ must meet the following constraints.

$$T = \left\{\{t_1,...,t_n\} \mid \sum_{i\in N} t_i = v(N), and\, t_i \ge v(\{i\}), \forall i \in N\right\} \tag{16}$$

In addition, if the vector T is not stable, there is at least one VMO that is unsatisfied with the coalition. In order to get the stable solution vector T , additional constraints as follows should be added to (4).

$$\sum_{i\in S} t_i \ge v(S), \forall S \subset N \tag{17}$$

After the values of the characteristic function for all possible coalitions are obtained, Shapley value is adopted to compute the stable number of PRBs each VMO should be allocated. The Shapley value is the average payoff a player will get if the player enters into the coalition in a random order. In order to compute Shapley value, a function $\phi(v)$ is defined as the worth or value of a player in the game with characteristic function v . The method to compute Shapley value given by Shapley is:

$$\phi_i(v) = \sum_{S\subset N, i\in N} \frac{(|S|-1)!(n-|S|)!}{n!}\left(v(S) - v(S-\{i\})\right), \forall i \in N \tag{18}$$

where $|S|$ indicates the number of elements in the set S and $\sum_{i\in N} \phi_i(v) = M - \sum_{i\in N} b_i$ [7]. However, $\phi_i(v)$ ($i \in N$) cannot be directly seen as the number of PRBs that should be additionally allocated to VMO i , for the reason that we can't guarantee $\phi_i(v)$ is a nonnegative integer. A nonnegative integer vector $X = \{x_1,...,x_n\}$ is defined to denote the number of PRBs each VMO obtains through the proposed resource allocation approach and the vector should meet the following conditions:

$$\begin{aligned} & t_i = \phi_i(v), \forall i \in N \\ & x_i \approx b_i + t_i, \forall i \in N \\ & \sum_{i\in N} x_i = M \\ & 0 \le x_i \le c_i + b_i, \forall i \in N \end{aligned} \tag{19}$$

In order to evaluate the satisfaction of payoffs (i.e., PRBs) each VMO is paid, expectation index (EI) is defined as the following formula:

$$\lambda_i = \phi_i(v)/c_i, \forall i \in N \tag{20}$$

The fairness of the proposed approach is evaluated with Jain's fairness index [8], defined as:

$$\gamma = \left(\sum_{i=1}^{n} \lambda\right)^2 \Big/ \left(n \sum_{i=1}^{n} (\lambda)^2\right) \tag{21}$$

Obviously, if an assignment approach proportional to the VMOs' claims is adopted, the value of fairness index is 1 and the EI of each VMO is a constant, which is computed by the following formula:

$$\lambda_i^{\Pr oportional} = \left(M - \sum_{i\in N} b_i\right)/Y \tag{22}$$

The notations and the descriptions of the variables for the bankruptcy game and the proposed resource allocation approach are shown in Table I.

TABLE I
NOTATIONS AND DESCRIPTIONS OF THE VARIABLES FOR BANKRUPTCY GAME AND THE PROPOSED WIRELESS RESOURCE ALLOCATION APPROACH

Variable	*Bankruptcy Game*	*Resource Allocation*
n	Total number of players	Total number of VMOs
$M - \sum_{i \in N} b_i$	Money(estate)	Total number of additional PRBs
Y	Total money the company owes	Total additional claimed PRBs by VMOs
N	Set of players	Set of VMOs
c_i	Claimed money of player i	Additional claimed PRBs of VMO i
$\phi_i(v)$	Solution of money distributed to player i	Number of additional PRBs allocated to VMO i

3.4.3. Performance Evaluation

In order to evaluate the bankruptcy game based wireless resource allocation approach among VMOs, extensive system level simulations are conducted in the work. In addition, an assignment approach proportional to the VMOs' claims is also explored in the simulations to better evaluate the proposed bankruptcy game based approach. It should be noted that the simulation results below have much relationship with the simulation configurations in section III.

Figure 15 shows the PRBs that each VMO claims and the "Hypervisor" has allocated to each VMO based on the proposed approach. As is shown in the figure, the claimed and allocated PRBs in VMO#1 and VMO#2 are almost the same and more or less twice of those in VMO#3 due to the simulation configurations that VMO#1 and VMO#2 are burdened with the same traffic flows, which are twice of those in VMO#3. Besides, the figure indicates that the allocated PRBs to each VMO do not exceed the claimed PRBs by the VMO.

In order to quantitatively analyze the EI of each VMO in theory based on the proposed approach in the case of simulation configurations shown in section III, we assume the number of additional claimed PRBs by VMO#1 and VMO#2 is the same and twice of that by VMO#3. Based on the assumption, the EI of VMO#1 and VMO#2 is the same. Fig. 2 shows the EI variation with the additional claimed PRBs by VMO#3 ranges from 12 to 24 (i.e., the total additional claimed PRBs ranges from 60 to 120). As is shown in the Figure 16, VMO#1 and VMO#2 have higher EI value than VMO#3 when the additional claimed PRBs ranges from 12 to 18 in the case of the proposed bankruptcy game based approach, which demonstrates VMO#1 and VMO#2 can get more satisfactory allocation result. The situation is reversed when the additional claimed PRBs ranges from 18 to 24. In addition, the fairness index is close to 1 with the proposed approach. However, the EI of each VMO keeps the same based on the proportional assignment approach. To sum up, if we want to protect the "small" VMO or care more about the "big" VMO, the proposed approach is able to meet the requirements by changing the total additional number of PRBs.

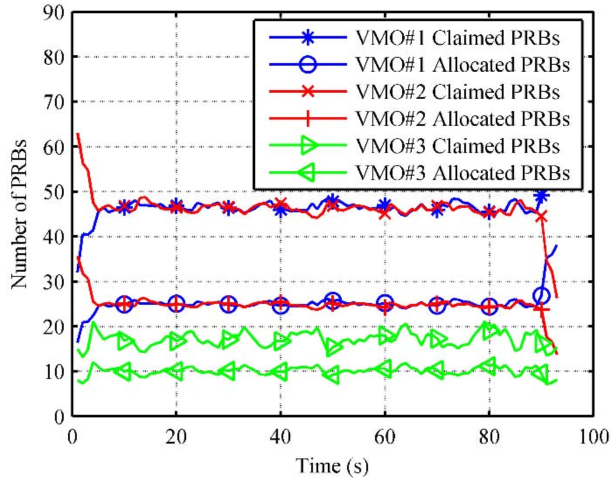


Figure 15 VMO claimed and allocated PRBs during one simulation process (the total number of claimed PRBs is 110).

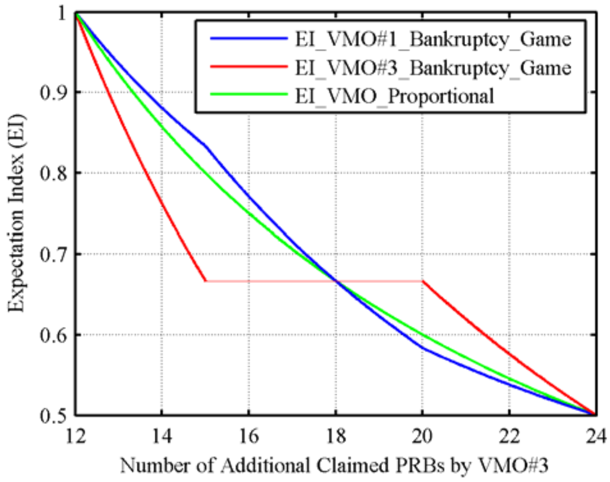


Figure 16 EI of each VMO with different assignment approaches.

Figure 17 and Figure 18 show the EI variation when the total additional claimed number of PRBs is 70 and 110 respectively based on the bankruptcy game approach during simulations, which demonstrates that the simulation results are consistent with the theoretical analysis. Figure 17 shows the situation where it is favorable to the “big” VMO, whereas “small” VMO is more satisfactory in the situation as is shown in Figure 18.

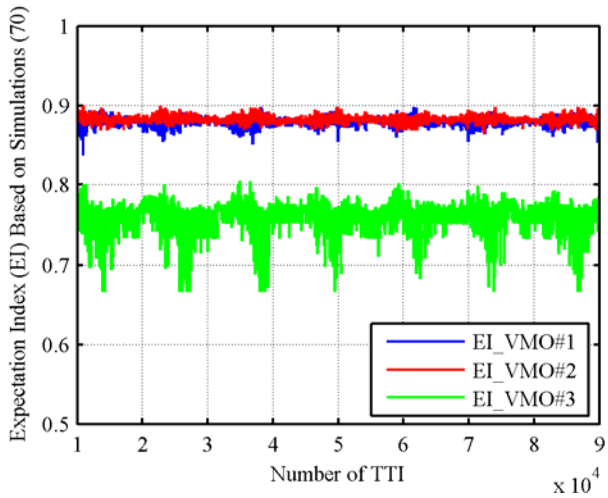


Figure 17 **EI of each VMO based on the proposed approach during simulations.**

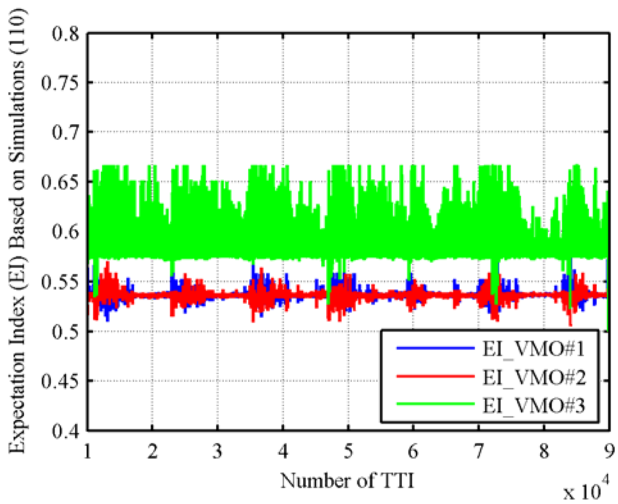


Figure 18 **EI of each VMO based on the proposed approach during simulations.**

3.5. A two-Layers Reinforcement Learning Approach for Radio Resource Management

In this work we face the challenge of designing self-tuning systems governing the working parameters of base stations on a mobile network system to optimize the quality of service and the economic benefit of the operator. In order to accomplish this double objective we propose the combined use of fuzzy logic and reinforcement learning to implement a self-tuning system using a novel approach based on a two-agent system. Different combinations of reinforcement learning techniques, on both agents, have been tested to deduce the optimal approach. The best results have been obtained applying the Q-Learning technique on both agents, clearly outperforming the alternative of using non-learning algorithms. The complete content of this section, section number 3.5 of this document, devoted to the work developed to apply Reinforcement Learning for Radio Resource Management, has been taken from the published paper [12], as one of the contributions made by the authors within the EVANS project.

The management of resources made on the radio interface for mobile access networks has traditionally followed a static approach [13, 14]. Any mobile operator, on pursuing a satisfactory quality of service, determines the amount of resources to be deployed on each base station, including the split in between those resources devoted to handovers and the remaining resources available to set up new connections [15]. Nevertheless, this working strategy seems to be too short-sighted for what will be necessary in the near future when upcoming optimization challenges will come into play. Key issues like: minimizing the energy consumption, sharing the infrastructure among different operators on deploying the 4G mobile systems, or even borrowing radio resources among them, are becoming desirable targets for the future mobile communication systems.

In this global scenario, one of the most promising approaches for an intelligent management of available resources comes from the use of machine learning techniques, learning from the system behavior to deduce suitable policies for managing those available resources [16]; policies pursuing different goals, ranging from an optimal quality of service for an individual operator to a global inter-domain efficient system. Ideally, the ultimate goal will be the implementation of self-tuning systems due to applying, for example, fuzzy neural methodologies for the radio resource management [17], similar to our present study, although our innovative contribution comes from using a two-agent approach.

3.5.1. Working scenario

In our study case we envisage a working scenario where several mobile operators are providing service in a completely overlapping fashion, as opposed to the approaches focusing on a single provider owning all the infrastructure [18]. More than that, as already pointed out for the future 4G mobile systems, we assume that all operators share the same base stations infrastructure. This way we take a step forward from other approaches dealing with more than one access technology on any base station, but still focusing on a single operator [19]. As usual, the geographical area is divided into many cells, a different base station provides service for each cell, and there is some overlapping on the coverage area provided by neighboring base stations.

Our aim is to allocate radio resources on the air interface for each base station to satisfy some given quality of service with a self-tuning system for the parameters governing the base stations' operation. To this end our strategy combines the use of fuzzy logic and reinforcement learning [16, 17], but, in our case, on each base station two different agents will work together in order to manage the corresponding resources. It has been done in this way to separate two different goals, the quality of service and the operator's economic benefit. Both agents try to maximize their corresponding goals, although only one of the agents takes actions to modify the operating parameters on the base station, as shown in figure 3.5.1. As we can see, there is in practice a closed-loop control as the QoS layer influences the Profit layer jointly with the status information from the environment, and the Profit layer takes an action, which will influence the QoS layer on the next cycle. Hence, there is a mutual interaction between both agents, although not carried out directly from the Profit layer to the QoS layer due to the way we have implemented our approach.

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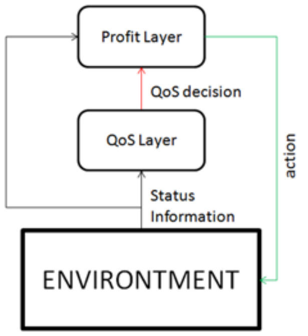

Fig. 3.5.1 Structural model

In this scenario the operational parameters to work with are the following:

- The coverage area per base station, configurable by tuning the power control mechanism.
- The distribution of channels per base station, configurable by splitting up the channels in different categories on dealing with different types of services or establishing dedicated channels for handover.
- The total amount of channels per operator at each base station, in this case a trading mechanism is considered, so different operators exchange channels on their own benefit due to the irregular demand from their respective end users.

Using fuzzy logic we can easily cope with a continuous input space defining the possible system states and actions to be taken. The alternative would be the use of reinforcement learning alone; but, in this case, the disadvantage comes from working with a discrete number of states and actions [18, 19], producing an approach with a worse performance.

Two alternatives on implementing the reinforcement learning mechanism have been tested, the actor-critic and the Q-learning techniques, as can be shown in figures 3.5.2 and 3.5.3. For both algorithms, each action takes a different fuzzy logic weight α_{R_n}, which is the output due to applying the fuzzy rule, but also an additional weight w_t to be learned [16].

For comparative reasons, a non-learning system has also been implemented using only the fuzzy logic technique. Regarding the time domain, all simulations work with the same sliding window to obtain the input for any approach. On the following section we describe in detail how both agents of our architectural model work.

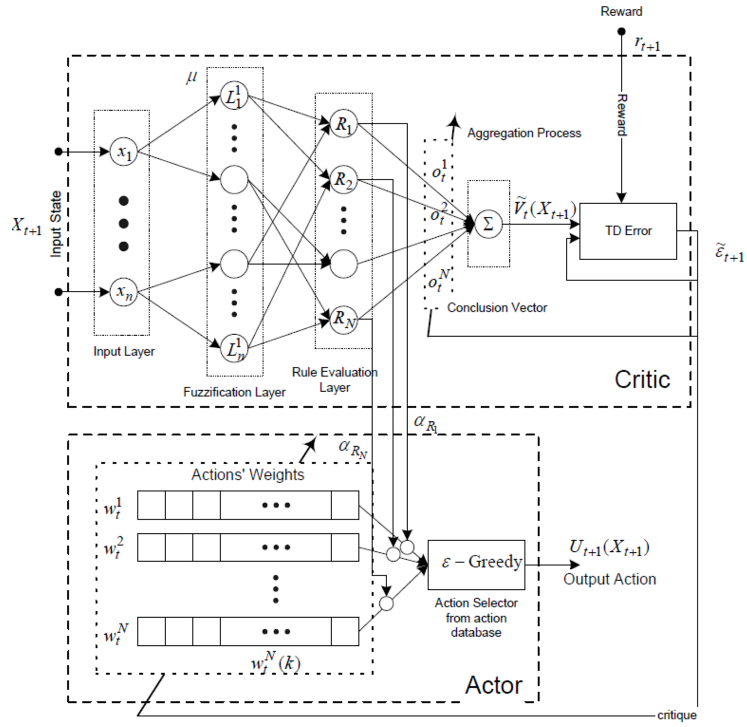

Fig. 3.5.2 Actor-critic technique

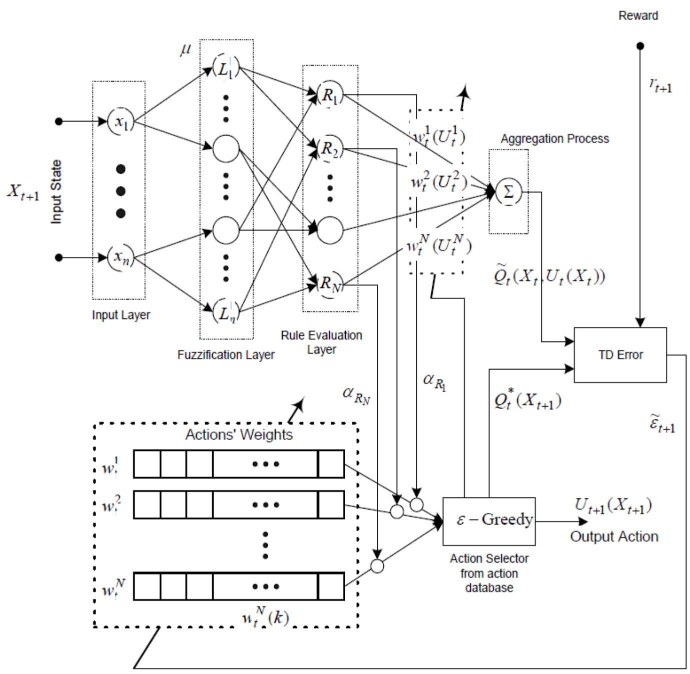

Fig. 3.5.3 Q-learning technique

3.5.2. Agents design

The purpose of the *QoS* agent is to achieve a given quality of service (QoS) regarding two basic parameters: the blocking rate (measuring the unavailability to set up a new service connection) and the dropping rate (measuring the unavailability to handover a connection between two base stations due to the user's travelling trajectory). Based on these two parameters the reward expression needed to implement the reinforcement learning mechanism is formulated as:

$$\mathrm{Re}\,ward = (T_B - B) + \beta(T_D - D)$$

Where $T_B - B$ is the difference between the actual blocking rate and a given target value, and $T_D - D$ is the difference between the actual dropping rate and a given target value. Usually the dropping rate is much more critical than the blocking rate on measuring the quality of service; consequently, a β factor is added to emphasize this parameter in front of the other. The two inputs, the blocking and dropping rates, are labeled according to six fuzzification categories, for each category we obtain a membership degree of the input through a fuzzification stage as shown in figure 3.5.4.

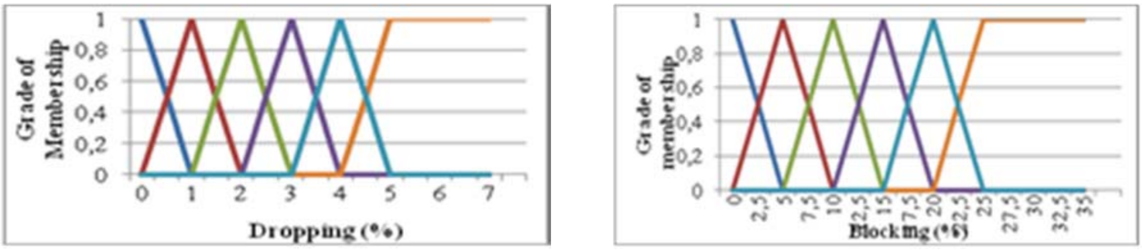

Fig. 3.5.4 Dropping and Blocking rates labeling

The fuzzification stage outputs are the inputs to a rule-matrix (2 dimensions) as shown in figure 3.5.5, the rule-matrix defines 5 rules (fuzzy rules) to produce the corresponding decision in a simple manner.

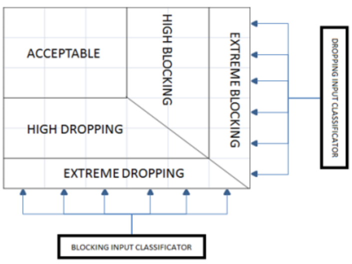

Fig. 3.5.5 Rule-Matrix

The rule-matrix output will be processed by the RL algorithm according to the reward definition, producing a decision due to the following procedure:

1. The rules weight $\alpha^{i}_{R_n}$ and action weight w^{i}_{t} are combined to produce a: s^{i}_{t} selection weight; this way a compromise is acquired between the present needs and the learned behavior up until now.
2. Each weight s^{i}_{t} is evaluated following some predefined criteria; the criteria will be the requests of the agent for each rule, these are: modification of the coverage area, modification of the distribution of channels in between handover and new service channels, and finally the request for extra channels, so for each s^{i}_{t} we will have 3 associated components.
3. The final decision is obtained by a combination of all s^{i}_{t}, deducing the definitive 3 components request for the present input. This final decision is sent to the next agent, becoming one of its inputs.

The objective of the *economical-benefit* agent is to obtain the maximum economical benefit for the operator, to accomplish this objective the reward function used by the reinforcement learning mechanism is defined as:

$$\mathrm{Re}ward = \frac{Load * \mathrm{Pr}ice * Num\_ChannelsOwned}{Call\_Duration} - Cost * Num\_ChannelsOwned$$

It is noteworthy that the QoS is not included in the reward function, this is because the QoS agent has already taken that into account, and it provides its input to the economical benefit agent. According to this, for the second agent the inputs are:

- The system Load
- The requests from the QoS Agent:
  - Modification of the coverage area
  - Modification of the distribution of channels
  - Need of extra channels

To avoid learning actions that are not feasible, some additional considerations must be applied invalidating the action, these considerations are the following: selling channels is forbiden if the minimum amount of channels that the operator must maintain is reached, reducing the coverage area is forbiden if the minimum cell radius that must be kept to assure some overlapping is reached, increasing the coverage area is forbiden if the maximum transmitted power has been reached.

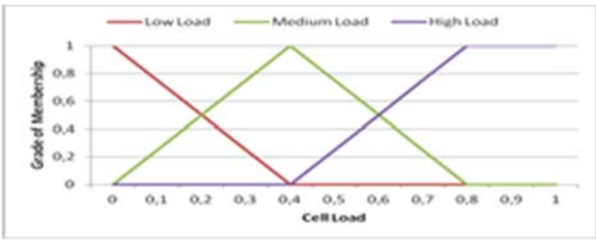

Fig. 3.5.6 Cell Load labelling

The system load is labeled according to 3 different categories, as shown in figure 3.5.6, low, medium and high. When the system detects a low load state, the weight for buying new channels is reduced and the weight for selling is increased and viceversa. This way the system tries to be led to a medium load state.

For labeling the requests of the QoS agent we need to classify the modification of the channel distribution, in figure 3.5.7 we show the classification of this input, for this study the distribution of channels is splitted in between channels reserved for handover and channels available for new services. A negative value of this parameter implies an increase on the number of channels reserved for handover, but if the demmand is high the problem cannot be solved by only increasing the channels reservation; another solution is needed, in this case a reduction of the coverage area is applied, trying to delay the time for the handover execution and also to reduce the amount of handovers managed by the base station. A positive value of the parameter allows us to free channels for new connections. As it happened before, if the demand is high the problem cannot be solved only by this approach, in this case the alternative will be to buy new channels if available. Finally, if the system performes properly in terms of QoS, it tries to increase the coverage area to benefit from more incoming calls.

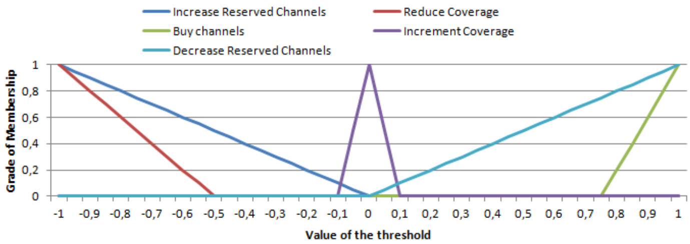

Fig. 3.5.7 Request of the QoS agent: Modification of channel distribution

The other requests of the QoS agent are evaluated directly without being classified, because there is no alternative to be applied. To avoid overacting on the system, a given time between actions is imposed, time defined by the skilled-technician, this way the system can better learn the optimal action before acting again.

3.5.3. Simulation results

To test the correctness of the algorithms by themselves without being affected by the behavior of another learning technique, each learning technique has been tested individually in the same scenario and under similar circumstances.

To simplify the notation used on the following figures any learning system will be labeled with two consecutive letters, the first one applies for the economical-benefit agent, and the second for the QoS agent, also the name of the learning algorithms are labeled by their initials, hereafter A means the agent using Actor Critic, Q means the agent using Q-Learning and N means the agent using a non-learning algorithm. Independently of the combination of learning techniques, we have run the simulations to assure that the overall system remains in a medium load state, which is one of the inputs of the economic benefit agent.

As shown in figure 3.5.8, the average degradation in term of QoS for the same clients demand is higher when the non-learning technique is used on any or both agents. The QoS for the remaining learning combinations results in a dropping and blocking rate even below their target values, 1% for dropping and 5% for blocking.

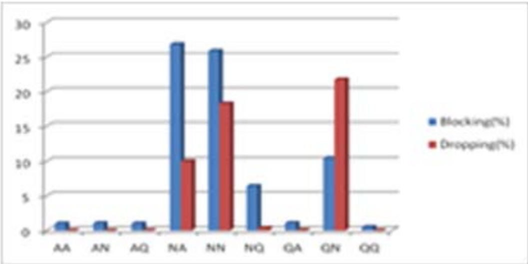

Fig. 3.5.8 Simulation: Dropping and Blocking rates results

On the other hand, the operator's profit is directly proportional to the amount of established calls, as in all simulations the price for call is kept constant; besides, the cost of maintenance is proportional to the amount of channels managed by the operator, this way more channels turns into more established calls, but the cost of maintenance is also increased. In figure 3.5.9 the cost and the income for each combination of learning techniques is shown.

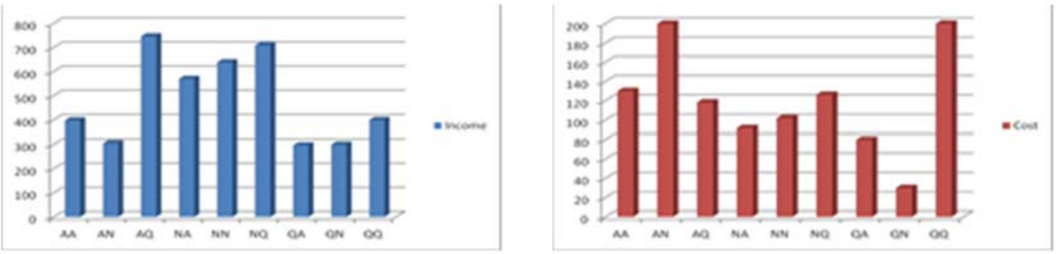

Fig. 3.5.9 Simulation: Income and Cost results

Those systems having reached an inferior QoS usually have a better economic benefit; one of the reasons is that only the economic benefit agent is able to act on the environment.

One of the drawbacks on using a non-learning algorithm is its dependency with respect to the size of the sliding window used to obtain the sequence of inputs; if the window size is too small, it overacts on sudden peaks of clients demand, producing unnecessary changes on the system parameters to cope with the incoming demand; on the other hand, if the size is too big, it works with an unrealistic view of the environment behavior.

Figure 3.5.10 shows the alteration of the coverage area and the percentile of channels reserved for handover, usually those systems with a higher income also work with smaller radius of coverage per cell.

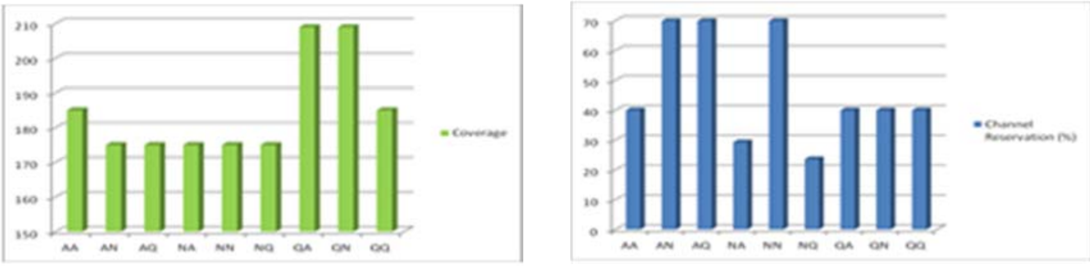

Fig. 3.5.10 Simulation: Coverage and Channel Reservation results

4. Conclusions

The issues related to vertical management of virtualized resources can be categorized for wireless and wired virtualized networks separately due to the different nature of these networks. EVANS deals with the challenges related to these environments separately to identify the problems and solution related to each of them accordingly. Our goal is to provide the basis for static and dynamic vertical management of virtualized resources. In this regard, resource allocation, resource scheduling and energy efficient link splitting for wired virtualized networks and architecture is discussed. It saves energy over off-peak hours of virtual networks, and makes the power consumption proportional to link traffic. In order to evaluate the suggested algorithm we have simulated several virtual network scenarios over GÉANTsubstrate network topology. The resource allocation for virtualized wireless networks and resource allocation approach among virtual network operators are also discussed. The proposed approach is to some extent reasonable and fair in allocating PRBs among VMOs.

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