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Optimization model for handoff-aware channel assignment problem for multi-radio wireless mesh networks

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ABSTRACT

Optimal channel assignment (CA) in multi-radio wireless mesh networks is an NP-hard problem for which solutions usually leave several links interfering. Most of these solutions usually consider the overall throughput as the main optimization objective. However, other objectives have to be considered in order to provide better quality wireless connections to non stationary users. In this paper, we propose a multi-objective optimization model that, besides maximizing throughput, improves fairness and handoff experience of mesh clients. In this model, we use the Jain's index to maximize users' fairness and we allow same-channel assignments to links involved in the same high handoff traffic, thus reducing handoff-triggered re-routing characterized by its high latency. Then, we propose a centralized variable neighborhood search and a Tabu search heuristics to efficiently solve our model as an offline CA process. Moreover, in order to adapt to traffic dynamics caused especially by user handoffs, we propose an online CA scheme that carefully re-assigns channels to interfaces with the purpose of continuously minimizing the re-routing overhead/latency during user handoffs. We further improve this online scheme using load balancing. Simulation results show the good performance of our proposed approach in terms of delay, loss rate, overall throughput and fairness. Particularly, performance results of our online handoff-aware CA show the effectiveness of handoffs not involving path re-routing in decreasing the delay, especially when considering load balancing.

1. Introduction

Wireless mesh networks (WMNs) consisting of single radio mesh routers (MRs) operating on a single channel suffer from a dramatic decrease in network capacity as the number of wireless hops increases. Equipping MRs with multiple radios on non-overlapping or partially-overlapping IEEE 802.11 channels can significantly increase the WMN capacity if a special care is taken in the assignment of channels to the radio interfaces. However, a channel assignment (CA) in multi-radio WMN (MR-WMN) that achieves good performance presents considerable challenges. In fact, the problem of optimal CA in maximizing performance by minimizing interferences has been proven to be NP-hard since it can be mapped into a graph-coloring problem in arbitrary mesh topology [1]. Therefore, several heuristic algorithms providing more or less good CA solutions for MR-WMN were proposed and evaluated in the literature [1–4].

In this paper, we propose a novel multi-objective CA optimization model in opposition to existing models/schemes that usually tackle the optimization problem of a single or two objectives tightly related to interferences [2–4]. In particular, our proposed model, besides maximizing throughput and fairness, minimizes handoff overhead and minimizes traffic load variance to achieve load balancing. Fairness can be seen as the capability of the network to

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always provide each client its fair share of the maximal achieved overall throughput in the WMN. Thus, when the WMN is saturated, the maximal throughput is equally divided between demanding clients. The minimization of handoff overhead is implemented by determining solutions that build MR-WMN logical topologies with less rerouting overhead; in fact, it allows most of the re-routed traffic (because of handoff) to change only first-hop MRs along the pre-handoff paths. This will significantly minimize service disruption without the resources and overhead generated by existing approaches [5].

Our contributions, in this paper, can be summarized as follows: (1) we propose a novel multi-objective optimization model that assigns channels to interfaces in MR-WMNs; the proposed model includes four objective functions and therefore provides a better flexibility compared to existent CA schemes; moreover, it is the first model to consider handoff traffic in CA and (2) the CA problem being NP-hard, we propose two meta-heuristics, called MHALB and MTABU, to search for a near-optimal CA solution of the proposed model. MHALB is based on variable neighborhood search (VNS) [6] which is used for solving combinatorial optimization problems in which a systematic change of neighborhood within a local search is carried. MTABU is based on Tabu search which keeps history of the search process and prohibits comebacks to previous solutions [7]. We also propose a greedy search Heuristic (Algorithm 1) to search for an initial feasible CA solution for load balancing and throughput maximization problem, called HALBTH; thus, starting with this good initial solution rather than a randomly generated one, MHALB and MTABU provide a better final solution; and (3) we propose a distributed handoff-aware channel re-assignment, called HA, that improves handoff performance by limiting most of the flow path re-routings to first-hop MRs. It dynamically re-assigns channels whenever the handoff rate, which is measured at local MRs, exceeds a predefined threshold that significantly degrades the performance. We also extend HA to take into account load balancing in a scheme called HALB with the purpose of efficient utilization of network resources.

While in the first and second contributions we provide centralized static CA heuristics (MHALB/MTABU) that compute near optimal solutions by considering several objectives, in the third contribution we provide a distributed dynamic CA algorithm that continuously improves/adapts the near optimal solution produced by the static heuristics to the dynamic variation of traffic load and handoff rates (see Fig. 1). The process of computing a CA solution by HALBTH, MHALB and MTABU combined with the continuous adaptation by HA and HALB is called HALBTH+ (i.e., HALBTH +HALB), MHALB+ and MTABU+ respectively.

The remainder of the paper is organized as follows. Section 2 provides a brief overview of related research. Section 3 defines the WMN CA problem and presents a mathematical formulation of the problem solution. Section 4 proposes a resolution of the proposed model using a greedy search algorithm, variable neighborhood search algorithm and Tabu search algorithm. Section 5 proposes on-line CA scheme. Section 6 evaluates the proposed solution via simulations. Finally, Section 7 concludes the paper.

2. Related work

There exists a vast literature on CA schemes in wireless networks; a thorough study can be found in [8]. These schemes can be broadly classified in three categories: (1) fixed CA (FCA): it assigns channels once; indeed, channels assignment does not change over time [1,2,9]; (2) dynamic CA (DCA): it continuously updates the assignment of channels to improve performance [3,4,8,10–12]; and (3) hybrid CA (HCA): it applies a fixed CA scheme for some interfaces and a dynamic CA scheme for others [13–15].

In FCA, a set of channels are permanently allocated to interfaces with respect to the interface switching time; they can be reused in other MRs, sufficiently distant, such that co-channel interference is tolerable. The advantage of FCA is its simplicity; its drawback is that it does not adapt its channel reuse to accommodate the varying offered load. Such schemes can be further subdivided into (a) common channel assignment (CCA) [1]: the radio interfaces of each node are all assigned the same set of channels; and (b) varying channel assignment (VCA) [2,9]: the interfaces of different nodes may be assigned different sets of channels, such as in CLICA (connected low interference channel assignment) [9] and in MesTiC (mesh-based traffic and interference aware CA) [2].

In DCA any interface can be assigned any channel, and interfaces can frequently switch from one channel to another. Therefore, when nodes need to communicate with each other, a coordination mechanism [1,2,8–10] has to ensure they are on a common channel. The benefit of DCA is the ability to switch an interface to any channel, thereby offering the potential to use many channels with few interfaces. However, the key challenges involve channel switching delays (typically on the order of milliseconds in commodity 802.11 wireless cards), and the need for coordination mechanisms for channel switching between nodes. Distributed-HYAcinth (D-HYA) which is a distributed version of Centralized-HYAcinth (C-HYA) [3,12] builds a spanning tree network topology and reacts to traffic load changes to improve both load balancing and aggregate throughput. However, it poses a potential problem to multipath routing in mesh networks and does not consider the network connectivity.

In HCA the concepts of fixed and dynamic strategies are combined by applying FCA to some interfaces and DCA to others [13]. HCA can be further classified based on whether the fixed interfaces use a CCA or VCA approach. HCA schemes are attractive because, as with FCA, they allow for simple coordination algorithms, while still retaining the flexibility of DCA. Link layer protocol (LLP) [13] categorizes available interfaces into fixed and switchable interfaces, i.e., can be switched over short time scales among non-fixed channels based on the amount of data traffic. LLP assigns different channels to fixed interfaces of different nodes; then, all channels can be used; the switchable NICs are used for connectivity only. However, it does not

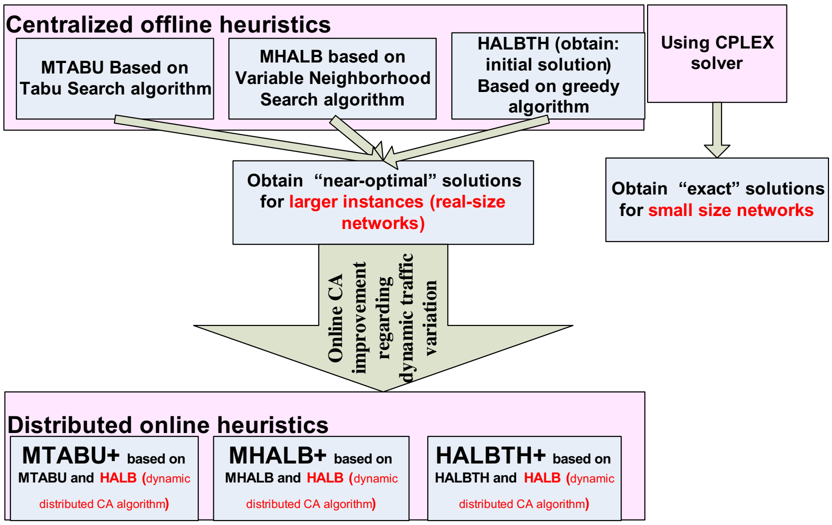

Fig. 1. Hiearachy of different proposed heruistics.

take into account the traffic load in assigning the fixed channels. Interference-aware channel assignment (IACA) [15] is based on the multi-radio conflict graph (MCG) and assigns one radio in each node to operate on a default common channel. IACA provides alternate fallback routes, and avoids flow disruption by traffic redirection over a default channel. Nevertheless, it does not consider the traffic load in assigning channels.

In several contributions, the CA problem is combined with other performance problems in MR-WMN and is modeled as *an optimization problem*. In [3] authors formulate the joint CA, interface assignment, and MAC fairness problem as a cross-layer non-linear mixed-integer network utility maximization problem. The authors choose to maximize a utility function that reflects the proportional fairness among the MAC flow rates. However, they neglect optimizing the overall throughput since they show its absolute value without showing how far it is from the optimal one and if a tradeoff between throughput and fairness can be achieved. Besides, they do not consider the non uniformity of the traffic on logical links within a clique (i.e., a clique is a graph that has all its vertices adjacent to each other), which is generally affected by traffic demands and routing protocol. Subramanian et al. [4] consider the problem of CA with the objective of minimizing the overall network interference. They formulate the problem using semi-definite and linear programs. They extend their model to non-uniform traffic through weighting the interferences by traffic loads. Then, using a distributed Tabu search CA and a centralized greedy CA, they obtain tight lower bound solutions to this NP-hard problem. However, the authors in [4] do not consider the MAC fairness in their problem. Furthermore, due to the centralized nature of the Tabu search CA approach, it is adequate only for 'managed' WMNs. Indeed, their approach is run as an offline CA that does not adapt to dynamic traffic variation.

Several CA schemes in the literature [9,11,12] take into consideration the load in establishing logical links in MR-WMNs. In our CA scheme, we take into account both (1) the non uniformity of handoff traffic between different MRs; and (2) the non uniformity of traffic load over the MR-WMN. In fact, due to the mobility of a fraction of mesh clients (MCs), the load on each MR is usually dynamic. Therefore, a standard load-aware CA scheme taking into account only the heterogeneity of the offered load has to be reconsidered/reevaluated in the case of dynamic load incurred by handoff traffic. The first issue related to MC handoff is that a handoff on a different channel causes channel scanning and re-association (latency) that may disrupt real-time services; this is usually resolved in the literature using proactive scanning [16]. The second issue, which is tackled by our scheme, is that handoff may also involve re-routings on other MRs (e.g., second-hop MRs) in addition to first-hop MRs; this may result in much more latency and therefore much more service disruption. To the best of our knowledge, the second issue has not been considered, in the literature, using a dynamic CA scheme. Indeed, most existing approaches [17,18] make use of proactive multipath routing schemes that establish/reserve alternate paths a priori to handoffs; this may be very inefficient in terms of resource utilization and overhead. Thus, we propose a handoff-aware dynamic CA scheme that re-assigns channels to MR interfaces with the objective to reroute most of the handoff traffic by changing only first-hop MRs along the pre-handoff flows paths. This will significantly minimize service disruption without the resources and overhead generated by existing approaches. Furthermore, in order to increase the overall throughput of the WMN [19], we take into account load balancing when choosing among different handoff-aware assignment solutions.

There has been a vast literature on mobility management in wireless networks; a thorough survey can be found in [29]. In this paper, we classify existing work into three categories: IP layer solutions, MAC layer solutions, and physical layer solutions.

IP layer solutions mainly solve the problems of IP addressing and IP routing during the handoff process. To support unique IP addresses in mobile computing environment, the Mobile IP protocol [30] was standardized to allow the transparent routing of IP datagrams. However, mobile IP is not suitable for user movement between different Access Points (APs) in the same domain; indeed, packet tunneling causes a long latency from the Home AP to the Foreign AP. To reduce such latency, a diversity of mobility management solutions has been proposed, including HMIP [31], IDMP [32], MIP-RR [33], and mesh mobility management (M3) [34]. To facilitate the handoff process from the routing aspect, Ren et al. [35] proposed a scheme called MEsh networks with MObility management (MEMO); MEMO integrates routing and mobility management into a single solution and solves the mobile node roaming handoff problem using an on-demand distributed scheme. MEMO updates routing tables to reestablish the connection after handoffs, thus extra overhead is generated. Therefore, to achieve lower overhead and then faster handoff, Zhenxia and Boukerche [36] proposed a hybrid routing protocol which involves both link layer and network layer routing. With this routing algorithm, rerouting and location updates are avoided during the handoff process; this is achieved thanks to ARP messages which provide new routing information (the mesh client access router's MAC address).

In the MAC layer, Velavos and Karlsson [37] proposed a solution to reduce handoff time for real-time applications. The handoff was split into three phases, typically performed in sequence, detection, search and execution. They reported that the time of the detection phase could be reduced by quick reaction to packet losses and by smaller beacon intervals. Moreover, they demonstrated that the search phase could be shortened by using active scanning. Physical layer solutions mainly solve the problem of channel scanning delay. As shown in the literature, extensive studies have been conducted on this topic [38–43]. The effort of reducing channel scan delay basically includes two approaches, i.e., reduce the number of channels to scan [38,39] and reduce the time spent on scanning each channel [40]. Some researchers have also attempted to completely eliminate handoff delay by using sensor overlay [41], multiple radios [42], and proactive scan; the latter initiates the channel scanning process much earlier than handoff initiation but without affecting the ongoing traffic. In fact, it divides the channel scanning phase into small periods interleaved by the ongoing traffic [43].

3. Formulation

3.1. Problem description

We consider the problem of CA in MR-WMN by exploiting the tradeoffs among throughput, fairness, traffic load balancing and handoff overhead. Indeed, maximizing fairness will significantly reduce the overall throughput (as observed in 802.11 networks [20]); in opposition, if load balancing is maximized, the overall throughput is indirectly increased [21]. Assigning a same channel to interfaces of neighboring MRs minimizes handoff overhead (compared to handoff on different channels); however, this may cause high interference levels and thus degrade network performance in terms of throughput. Therefore, optimizing one of these criteria will affect/undermine other criteria; thus, a multi-objective approach is definitively recommended for this kind of problems. In this section, we propose a multi-objective optimization model that offers the possibility to optimize a combination of several criteria. Further the NP-hard property of the proposed CA model (property of CA problems in general), the evaluation cost of multi-objective functions is very high compared to single objective functions; therefore, appropriate heuristics must be carefully designed to resolve the problem.

The objective of our proposed CA scheme is four fold: (1) perform a static initial near optimal CA over the whole network while considering throughput, fairness, load balancing and handoff; (2) perform a dynamic CA only if necessary to minimize packets losses and delay degradation caused by handoffs; while considering (a) handoff overhead reduction and (b) traffic load balancing to improve the performance of the MR-WMN for a dynamic handoff traffic; (3) increase the capacity of MR-WMNs by accepting more users through throughput maximization; and (4) ensure users fairness in utilizing the shared capacity, i.e. each user has its fair share of throughput.

3.2. Network model

We consider a MR-WMN as illustrated in Fig. 2. MRs forward traffic from/to MCs that are associated to them. MRs also forward traffic between each-other while forming a meshed multi-hop wireless backbone network. This network forwards the user traffic, i.e. MC's traffic, to/from the gateways, which are connected to the Internet.

We formally model the wireless meshed backbone of MRs as an undirected graph, called connectivity graph, $G = (V, E)$ where V represents the set of mesh nodes and E the set of edges between these nodes. Among these nodes, $P \subset V$ represents the set of the gateways that connect to the Internet. $\forall (u, v) \in V$, an edge $e = (u, v) \in E$ if the distance between u and v, denoted $d(u, v)$, is smaller than the minimum range, denoted $\min(r_u, r_v)$, of u and v (i.e., $d(u, v) \leqslant \min(r_u, r_v)$) where r_u and r_v represent the radio transmission ranges of nodes u and v respectively. The connectivity graph after channel assignment is denoted $G_A = (V, E, A_G)$ where $A_G = \{A_G(u), \forall u \in V\}$ and $A_G(u)$ is the set of channels assigned to u. We denote NC the number of channels per radio, and R the number of radios per node; typically, we have $R < NC$.

3.3. Cliques

A good CA avoids, as much as possible, situations where adjacent links use the same channel; this allows achieving efficient channel utilization and minimizing interferences. However, in most cases, heuristics [1] leave some adjacent links using the same channel. Channel conflicts will happen if these adjacent links transmit the data at the same time. To solve this problem, we apply the concept of clique from graph theory to

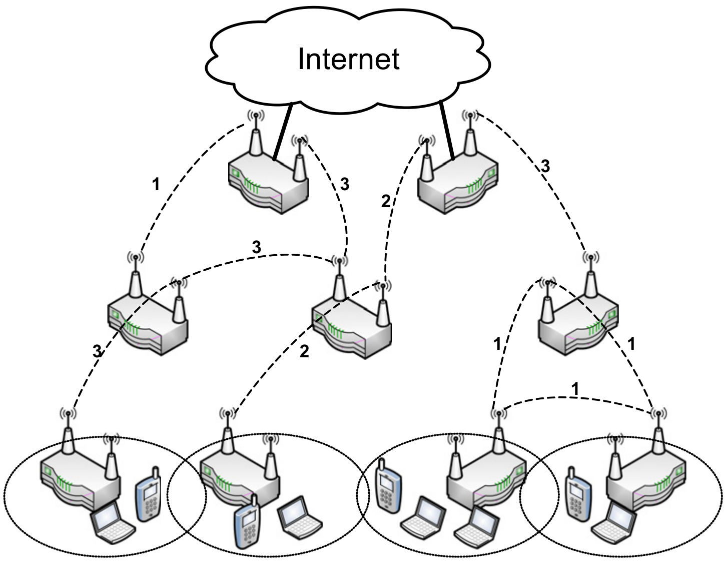

Fig. 2. A 2-radios MR-WMN with three orthogonal 802.11 frequencies assignment.

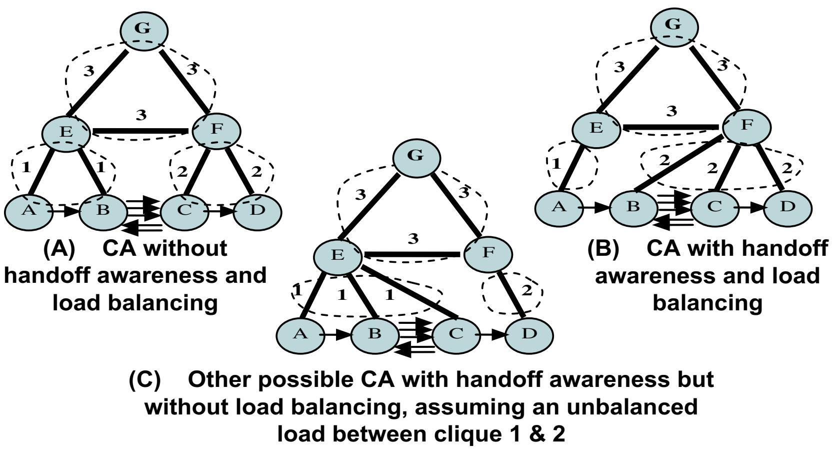

Fig. 3. An example of MR-WMN CA schemes.

MR-WMNs [22]. The motivation behind cliques is to identify the conflicting links (see Fig. 3).

Definition. "*Clique*": Let $G = (V, E)$ be an undirected graph, where V is the set of vertices and $E \subset V \times V$ is the set of edges. A subset $S \subset V$ of vertices is called a clique if for every pair of vertices in S there is an edge in E, i.e., the sub graph introduced by S is complete.

Definition. "*Maximal clique*": A maximal clique S is a clique of which the proper extensions are not cliques i.e. for any S' if $S \subset S'$ and $S \neq S'$ then S' is not a clique.

Therefore, two logical links (i,j) and (p,q) that belong to the same clique must not be active simultaneously. In this paper, a clique is defined as a set of links sharing the same channel and having a pair wise distance smaller than or equal to the minimum radio transmission range of the pair links. A maximal clique is a clique that belongs to no other clique. We use maximal cliques to determine the nodes which compete to access the same channel. In this paper, clique and maximal clique are used interchangeably. Obviously, a handoff user is better off using the same clique during the handoff process; in this case, no path re-routing involving MRs beyond the first hop is performed. This is desired because path re-routing involving other hops beyond the first hop MR generates considerable overhead. This can be critical to real-time flows, such as voice over IP.

Fig. 3A shows a sample MR-WMN that consists of three cliques where a number of MCs are performing handoffs (due to mobility) between B and C. We use the algorithm reported in [22] to compute cliques for the 7-nodes MR-WMN. A CA scheme without handoff awareness and without load balancing, called W.O.HALB, has no impact on the clique's formations regarding handoff and load dynamics (Fig. 3A). In Fig. 3B, we illustrate clique formation that provides best load balancing between clique 1 and clique 2; the load of a clique is the aggregate traffic load generated by MRs composing the clique. Fig. 3B illustrates the clique formation (using HALB) that places the highest inter-MR handoff traffic inside one of the cliques. Fig. 3C shows another clique's formation under HA, i.e. HALB without load balancing.

3.4. Problem formulation

We formulate the CA problem as a multi-objective optimization model. Table 1 shows the notations used to describe the model.

We suppose initially that the MRs operate using the same number of radios u, each with K channels ($K > u$). K can be 12 non-overlapped channels when using IEEE 802.11 a and 3 non-overlapped channels when using IEEE 802.11 b.

The objective of our model is to minimize the inter-cliques handoff, i.e. handoffs occurring between different neighboring cliques which generally operate on different channels, while minimizing the traffic load variation between them. Furthermore, our proposed model maximizes the overall throughput on the network and ensures fair share of throughput among MCs. Accordingly, our CA model is formulated as follows:

Objective functions

$$Min\left[\max_{q_i^k\in Q_K, q_j^{k'}\in N(q_i^k), q_i^k\neq q_j^{k'},}\left|\eta_{q_i^k}-\eta_{q_j^{k'}}\right|\right] \quad (1)$$

$$Min\left[\sum_{\substack{i\in q_m^k, j\in q_l^{k'}\\ q_m^k\neq q_l^{k'}}} h_{ij}x_i^{q_m^k}x_j^{q_l^{k'}}\right] \quad (2)$$

$$\max\left(\sum_{i\in N/\{V_m\}}\frac{f_{ig}^k}{C_{ig}}\right), \quad \forall k\in NC, \ \forall g\in G \quad (3)$$

$$\max(\mu) \quad (4)$$

Subject to constraints

$$\sum_{j\in V_m} f_{ij}^k \leqslant \lambda_i, \quad \forall i\in TS, \ \forall k\in NC \quad (5)$$

$$\sum_{j\in TS} f_{ji}^k + \sum_{k'\neq k}\delta_{ik'} + \sum_{v\in N} f_{vi}^{k'} = \sum_{v\in N} f_{iv}^{k'}, \quad \forall i\in V_m, \ \forall k,k'\in NC \quad (6)$$

$$\sum_{j\in N-1} f_{ji}^k = \sum_{j\in N-1} f_{ij}^k, \quad \forall i\in N\setminus\{V_m\}, \ \forall k\in NC \quad (7)$$

$$\sum_{j\in N-1} f_{jg}^k \geqslant \sum_{i\in TS}\lambda_i, \quad \forall k\in NC, \ \forall g\in G \quad (8)$$

$$\sum_{k\in NC} y_i^k = 1, \quad \forall i\in N-1 \quad (9)$$

$$\sum_{k\in NC} l_i^k = 1, \quad \forall i\in N-1 \quad (10)$$

$$\sum_{q_j^k\in Q_k} x_i^{q_j^k} = 1, \quad \forall i\in N-1 \quad (11)$$

$$y_i^k \geqslant x_i^{q_j^k}, \quad \forall q_j^k\in Q_k, \ \forall i\in V_m \quad (12)$$

$$l_i^k + y_i^k \leqslant 1, \quad \forall k\in NC, \ \forall i\in V_m \quad (13)$$

$$x_i^{q_l^k} + x_j^{q_l^k} + b_{ij}^{q_l^k} \leqslant 2^* z_{ij}^{q_l^k} + 1, \quad \forall q_l^k\in Q_k, \ \forall i,j\in V_m \quad (14)$$

$$x_i^{q_l^k} + x_j^{q_l^k} + b_{ij}^{q_l^k} \geqslant 3^* z_{ij}^{q_l^k}, \quad \forall q_l^k\in Q_k, \ \forall i,j\in V_m \quad (15)$$

$$\sum_{k\in NC}\sum_{i,j\in N} z_{ij}^{q_l^k} = 1 \quad \forall q_l^k\in Q_k, \quad (16)$$

$$z_{ij}^{q_l^k} \leqslant M\times f_{ij}^k, \quad \forall i,j\in N, \ \forall M\in R^+ \quad (17)$$

$$M\times z_{ij}^{q_l^k} \geqslant f_{ij}^k, \quad \forall i,j\in N, \ \forall M\in R^+ \quad (18)$$

$$\sum_{j\in N-1} b_{ij}^{q_l^k} \geqslant \sum_{k\in NC} x_i^{q_j^k}, \quad \forall i\in V_m, \ \forall q_l^k\in Q_k \quad (19)$$

$$\sum_{j\in N-1} b_{ij}^{q_l^k} \leqslant \sum_{j\in N-1}\sum_{k\in NC} x_j^{q_j^k}, \quad \forall i\in V_m, \ \forall q_l^k\in Q_k \quad (20)$$

$$\sum_{k\in NC} z_{ij}^{q_l^k} \leqslant b_{ij}^{q_l^k}, \quad \forall i,j\in N, \ \forall q_l^k\in Q_k \quad (21)$$

$$\eta_{q_j^k} = \sum_{i\in V_m} t_i x_i^{q_j^k} + \sum_{j\in TS}\sum_{i\in V_m} f_{ij}^k, \quad \forall k\in NC \quad (22)$$

$$\sum_{k\in NC}\delta_{ik} = t_i, \quad \forall i\in V_m \quad (23)$$

$$\sum_{k\in NC}\varphi^{q_l^k} = 1, \quad \forall q_l^k\in Q_k \quad (24)$$

$$x_i^{q_l^k} \leqslant \varphi^{q_l^k}, \quad \forall q_l^k\in Q_k, \ \forall k\in NC, \ \forall i\in N \quad (25)$$

$$\sum_{j\in N\setminus\{V_m\}}\sum_{q_l^k} b_{ij}^{q_l^k} = 1, \quad \forall i\in V_m \quad (26)$$

In our model, the objective function (1) minimizes the traffic load variance between all neighboring cliques to balance the load. The objective function (2) minimizes the handoff frequency between two MRs belonging to different cliques. We assume that the handoff traffic between MRs is known a priori when MHALB/MTABU/HALBTH are performed; we set the handoff traffic values (h_{ij}) according to extensive simulations performed using ns-2. In Section 5, we consider the case where the handoff traffic is not known a priori and changes dynamically. The objective function (3) maximizes the total throughput by

Table 1
Notations parameters and variables.

N	The set of MRs in the network
R	The set of radio interfaces on each MR
NC	NC = {1..K}, the set of K channels, |NC| = K
TS	$TS = \{TS^1, \ldots, TS^s\},\ s < \ \|N\|$, the set of traffic spots (positions of traffic concentrations in the service area)
G	The set of gateways
λ_i	The traffic generated by TS^i to the Internet
V_m	$V_m = \{MR^1, \ldots, MR^m\}$, $m < \|N\|$, the set of MRs with access point functionality
ψ^h	The handoff threshold which is measured by MR to trigger the CA
Q_k	$Q_k = \{q_1^1..q_n^K\}$, the set of cliques with K channels
h_{ij}	The handoff traffic from MR^i to MR^j, MR^i, $MR^j \in V_m$, $i \neq j$
δ_{ik}	The traffic load on channel k of $MR^i \in V_m$
t_i	The traffic load of $MR^i \in V_m$
b_{ij}	A binary connectivity parameter that assumes 1 if two MRs, $MR^i, MR^j \in N$, $i \neq j$ are connected via a wireless link; 0 otherwise
z_{ij}	A binary activation parameter that assumes 1 if a traffic flow exists between MR^i, $MR^j \in N$, $i \neq j$; 0 otherwise
r_i	The transmission range of MR^i where $(d(i,j) \leqslant \min(r_i, r_j) \Rightarrow b_{ij} = 1)$
$x_i^{q_j^k}$	A binary variable = 1 if $MR^i \in q_j^k$; 0 otherwise
$\varphi^{q_l^k}$	A binary variable = 1 if channel k is assigned to clique q_l^k
$N(q_i^k)$	The set of the neighboring cliques $q_j^l \in Q_k$ in the transmission range of q_i^k
y_i^k	A binary variable that assumes 1 whenever $MR^i \in V_m$ has interface radio with $MR^j \in N$ which is assigned to channel k; 0 otherwise
l_i^k	A binary variable that assumes 1 whenever $MR^i \in V_m$ has interface radio with TS^i which is assigned to channel k; 0 otherwise
f_{ij}^k	The traffic flow routed from MR^i to MR^j on channel k , $k \in$ NC,$MR^i, MR^j \in N,\ i \neq j$
η_i	The traffic load of clique $q_i^k, k \in NC$
C_{ij}	The capacity of link (i,j)

maximizing the sum of all flow-capacity ratios over all wireless links in the MR-WMN. The objective function (4) aims to fairly supply all MCs (TSs) by maximizing the closely related function (Eq. (35)) to Jain's fairness index (μ) [23] since it is difficult to linearize Jain's fairness index. We approximate μ as follows:

$$\mu = \max TH_i - \min TH_i \tag{27}$$

where

$$\max TH_i \geqslant TH_i \quad \text{and} \quad \min TH_i \leqslant TH_i \tag{28}$$

$\max TH_i$ assumes the maximum value of TH_i and $\min TH_i$ assumes the minimum value of TH_i, where TH_i is the throughput generated by TS^i and s is the number of TSs and $0 \leqslant \mu \leqslant 1$. We express TH_i as follows:

$$TH_i = \sum_{j \in N} f_{ij}^k, \quad \forall i \in s,\ \forall k \in NC \tag{29}$$

In this case, the objective function (27) consists of minimizing μ.

Ideally, all TSs have access to the same throughput; in this case, μ is equal to 1. In the worst case, μ becomes 1/s, i.e. the inverse of the number of TSs.

Constraints (5)–(8) define the flow balance equations for each MR. Constraints (9) and (10) prevent a MR from selecting the same channel more than once to assign it to its interfaces. Constraint (11) states that the MR with IEEE 802.11 access point functionality (i.e., MR interfacing with MCs) belongs to one clique; this constraint ensures that every node, except gateways, has to belong to one or more cliques containing nodes with access point functionality. Constraint (12) states that node $j \in V_m$ has an interface configured with the same channel as the new clique to which it will move. Constraint (13) states that the number of links from a node is limited by the number of its radio interfaces; it also states that the channel assigned to the interface interfacing with MCs (TSs) must be different from the channels assigned to the other interfaces of the MR. Constraints (14)–(16) prevent link interferences and allow only one link to be active in the same clique. Constraints (17) and (18) ensure that if a traffic flow exists between two nodes, then the link, between these 2 nodes, is active; M is a positive big value. Constraints (19) and (20) ensure that the new node added to clique q_l^k is connected to all nodes in this clique. Constraint (21) ensures that a link is active only if it exists. Constraint (22) computes traffic load in each clique. Constraint (23) sums the total traffic load for all the MR's channels. Constraints (24) and (25) ensure that all nodes in a clique use the same channel. Constraint (26) forces each node with access functionality to connect to at least one MR located on a higher level (e.g. MRs A, B, C and D must each be connected to E or/and F as shown in Fig. 4).

The objectives functions (1), (2), and (4) are not linear. In the following, we propose a method to linearize them. We modify the objective function (1) to

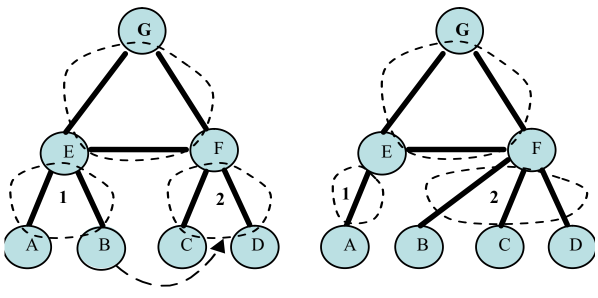

Fig. 4. Node move.

$$Min\ w \tag{30}$$

Subject to the following constraint:

$$|\eta_{q_i^k} - \eta_{q_i}^{k'}| \leqslant w \Rightarrow \begin{cases} w \geqslant \eta_{q_i}^k - \eta_{q_i}^{k'} \\ \quad \text{and } \forall q_i^k \in Q_K, q_i^{k'} \in N(q_i^k) \\ w \geqslant -\eta_{q_i}^k + \eta_{q_i}^{k'} \end{cases} \tag{31}$$

In order to linearize the objective function (2), we define a new variable $T_{ij}^{q_m^k q_l^k} = \begin{cases} 1, & if \quad X_i^{q_m^k} = 1 \quad and \quad X_j^{q_l^{k'}} = 1 \\ 0, & \text{otherwise} \end{cases}$ the objective function (2) becomes:

$$Min\left(\left[\sum_{\substack{i\in q_m^k, j\in q_l^{k'} \\ q_m^k \neq q_l^{k'}}} h_{ij} T_{ij}^{q_m^k q_l^{k'}}\right]\right) \tag{32}$$

Subject to the following constraints:

$$T_{ij}^{q_m^k q_l^k} + 1 \geqslant X_i^{q_m^k} + X_j^{q_l^{k'}}, \quad i,j \in V_m,\ q_m^k, q_l^{k'} \in Q_k \tag{33}$$

$$T_{ij}^{q_m^k q_l^{k'}} \leqslant X_i^{q_m^k}, \quad i,j \in V_m,\ q_m^k, q_l^{k'} \in Q_k \tag{34}$$

$$T_{ij}^{q_m^k q_l^{k'}} \leqslant X_j^{q_l^{k'}}, \quad i,j \in V_m,\ q_m^k, q_l^{k'} \in Q_k. \tag{35}$$

Constraints (28) ((30) (), (32)–(34), (3)) ensure that the objective functions (1), (2), and (27) are linear and could be used during the resolution of the proposed model.

4. Solving the model

In the previous section, we proposed a multi-objective model to solve the CA problem. However, for sake of simplicity (solving the problem using pure multi-objective optimization methods is for future work), we convert it to an aggregated form using a single objective function defined in Eq. (36):

$$Min\left(\alpha_1 w + \alpha_2\left[\sum_{\substack{i\in q_m^k, j\in q_l^{k'} \\ q_m^k \neq q_l^{k'}}} h_{ij} T_{ij}^{q_m^k q_l^{k'}}\right] - \alpha_3\left[\sum_{i\in N}\frac{f_{ig}^k}{C_{ig}}\right] + \alpha_4[\max TH_i - \min TH_i]\right) \tag{36}$$

where $\alpha_1 + \alpha_2 + \alpha_3 + \alpha_4 = 1$, $\alpha_1, \alpha_2, \alpha_3, \alpha_4$ are positive weight coefficients and $w = \max_{q_i^k \in Q_K,\ q_j^{k'} \in N(q_i^k),\ q_i^k \neq q_j^{k'}} |\eta_{q_i}^k - \eta_{q_j}^{k'}|$.

The determination of the "optimal" values of $\alpha_1, \alpha_2, \alpha_3$ *and* α_4 is out of scope of this paper; in future work, we will investigate the use of the analytical model proposed in [28] to determine these values.

The problem of optimal channel CA is known to be NP-hard [1]. Preliminary experiments showed that we could not obtain exact solutions for this problem when dealing with real-size networks. We therefore decided to use heuristic algorithms to obtain near-optimal solutions for larger instances. Due to the high cost of evaluating a multi-objective function, heuristics with fast descent and local minima escape strategy are preferred to accelerate the search of near-optimal CA solutions. For that purpose, we use variable neighborhood search (VNS)-based heuristic to solve our CA multi-objective problem. Our proposed algorithm, MHALB, illustrated in Algorithm 2 operates in two phases: (1) It first produces an initial/feasible solution using a simple greedy search algorithm, called HALBTH (see Algorithm 1); and then (2) it improves the initial/feasible solution using a VNS meta-heuristic.

4.1. Heuristic based on greedy algorithm

HALBTH is used to provide an initial CA solution to the proposed optimization model. First, we determine the connectivity graph of the MR-WMN, and arbitrarily assign channels to interfaces of MRs. Then, we compute cliques [22]. Finally, we run the greedy search algorithm illustrated in Algorithm 1. The algorithm, carefully re-assigns channels to interfaces with the objective of confining most of the user handoff traffic inside a clique, thus preventing re-routings involving MRs beyond first hop MRs (of pre-handoff paths) and consequently limiting handoff overhead. The greedy algorithm determines an initial solution that is certainly sub-optimal; in fact, it does not consider all objectives of the proposed model. In the next section, we present a meta-heuristic that improves the initial solution to produce a near-optimal solution. The pseudo code of HALBTH is shown in Algorithm 1.

Algorithm 1: Heuristic HALBTH algorithm

Input: connectivity graph, static CA, cliques
Output*:* new topology with new CA
Step0: initialization
Build an initial/feasible solution as follows: (1) assign channels statically; (2) determine connectivity graph; and (3) compute cliques; handoff=1;
While (*handoff* = 1) /∗ user handoff exists between $i, j \in V_m$ ∗/
Step1: building a sorted list of handoff rates
For every $i, j \in V_m$ and $i \in q_l^k,\ j \in q_m^{k'},\ k \neq k'$
Compute h_{ij}; Create a set $S = \{h_{ij} | h_{ij} \geqslant \psi^h\}$;
If $S = \varnothing$ **then** *handoff* = 0;
Else Sort elements of S in descendent order;
Step2: greedy search heuristic for near optimal solution
Take first value of S, h_{ij} associated with $i, j \in V_m$;
Generate two solutions as follows:
(1) Move i to clique $q_m^{k'}$; Switch node i to channel k';
(2) Move j to clique q_l^k; Switch node j to channel k;
Evaluate the two solutions according to the objective function (36) and choose the optimal solution.
EndWhile

4.2. A variable neighborhood search method

To improve the initial solution produced by HALBTH, we propose to use a VNS meta-heuristic, called MHALB.

Each neighborhood is explored using first-improvement local search; this means that we stop to search for better solutions in the current neighborhood when the first-improvement is found. The basic idea behind the VNS meta-heuristic is a systematic change of neighborhoods performed by the local search algorithm. Indeed, the frequent change of neighborhoods as soon as a first-improvement is found accelerates the descent to local minimums regardless of its quality in terms of improvements. This is desirable in our case since the set of the neighborhood solutions generated by each elementary move is very large and evaluating all these solutions is very expensive in terms of time (see Section 4.2.4). Generally, VNS proceeds by a descent method to a local minimum, and then explores, systematically, increasingly distant neighborhoods of this solution. The best order of applying different moves is out scope of this paper; we will investigate this issue in future work. In the proposed meta-heuristic, we consider two types of movements (1) node move; and (2) cliques exchanges.

4.2.1. Node move

A node is removed from its current clique and inserted in another clique that contains at least one mesh node interfacing with a MC. All possibilities are systematically tried until an improvement is found; an improvement corresponds to a smaller value for the objective function (36). We repeat this procedure for all MRs until a local optimum is reached. Our VNS-based heuristic jumps from the current neighborhood to a new neighborhood if and only if a better solution has been found.

A sample node move is illustrated in Fig. 4; node B moves to clique (FCD) by re-assigning it channel (2); this move produces two new cliques: (EA) and (FBCD). We repeat this procedure for all nodes in different cliques; for example a next move, in our example, may be moving node A to clique (FCD) by re-assigning it channel (2); this produces two new cliques: (EB) and (FACD).

4.2.2. Cliques exchanges

Given a pair of cliques that contains mesh nodes interfacing with MCs, two of these nodes are exchanged. All possible exchanges on every pair of cliques are considered until an improvement is found; an improvement corresponds to a smaller value for the objective function (36). We repeat this procedure for all possible cliques until a local optimum is reached.

A sample exchange is illustrated in Fig. 5; we do two movements at the same time (two nodes are re-assigned): node B switches to channel (2) and node (D) switches to channel (1).

4.2.3. MHALB

The pseudo of MHALB, using the two types of moves (see Section 4.2), is shown in Algorithm 2 (step 0–2) where: (1) N1 is the node move neighborhood; (2) N2 is the cliques exchanges neighborhood; and (3) S^j is a local optimum solution based on neighborhood j. The neighborhood moves in MHALB correspond to moves from N1 to N2 and vice-versa. MHALB stops when it improves the initial solution by β% (or a predefined timer expires or a

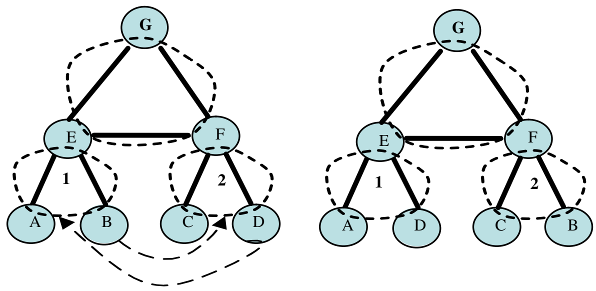

Fig. 5. Cliques exchanges.

maximum number of iterations are reached). The value of β is predefined by the network operator.

Algorithm 2: Meta-heuristic: MHALB algorithm

Step0: initialization
Create an initial solution S^0 using the greedy algorithm HALBTH (Algorithm 1);
$f^0 \leftarrow f(S^0)$;
Step1: node move
Perform a local descent based on N1;
Let S^1 be the local optimum obtained;
If S^1 is different from S^0 **then** $S^0 \leftarrow S^1$;
Step2: cliques exchanges
Perform a local descent based on N2;
Let S^2 be the local optimum obtained;
If S^2 is different from S^0 **then** $S^0 \leftarrow S^2$;
If $f(S^2) < (1-\beta) f^0$ **then** exit;
go to step 1;

4.2.4. Algorithm complexity (MHALB)

$O([h \times m \log m + (R-1) \times V_m + 2(R-1) \times V_m] \times C_F)$ is the complexity of MHALB where h is the number of handoffs in the network, m is the size of the list S, C is the number of cliques in the network, s is the number of TSs, and $C_F = O(\alpha_1 C^2 + \alpha_2 C^2 + \alpha_1 N^2 V_m^2 + \alpha_4 s N^2)$ is the complexity of the multi-objective function (Eq. (36)).

4.3. Tabu-based algorithm

Our proposed Tabu search meta-heuristic called MTABU, uses two types of moves: N1 and N2 (see Section 4.2). The pseudo-code of MTABU is shown in Algorithm 3. In MTABU, we start with an initial solution S^0 using the greedy algorithm HALBTH ($f^0 \leftarrow f(S^0)$). Starting from S^0, we create a sequence of solutions $S^0, S^1, \ldots, S^i, \ldots$, in attempt to reach a near-optimal solution according to the objective function (Eq. (36)) .

The ith iteration: In the ith iteration ($i \geqslant 0$) of this algorithm, we create the next S^{i+1} in the sequence from S^i; more specifically, we generate all N1 neighborhood solutions of S^i and we pick the solution S^{i+1} that has the lowest objective function (Eq. (36)) $f(S^{i+1})$. In order to escape local minima, the algorithm does not terminate even if $f(S^{i+1})$ is bigger than $f(S^i)$.

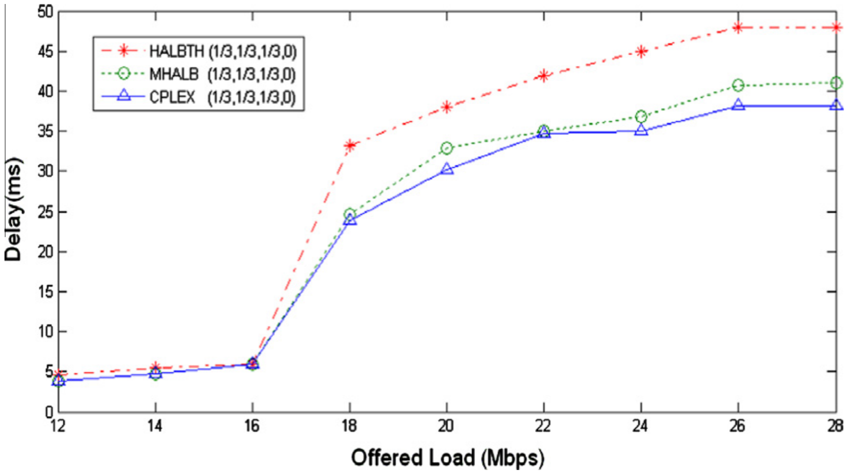

Fig. 6. Delay with HALBTH, MHALB and optimal solution.

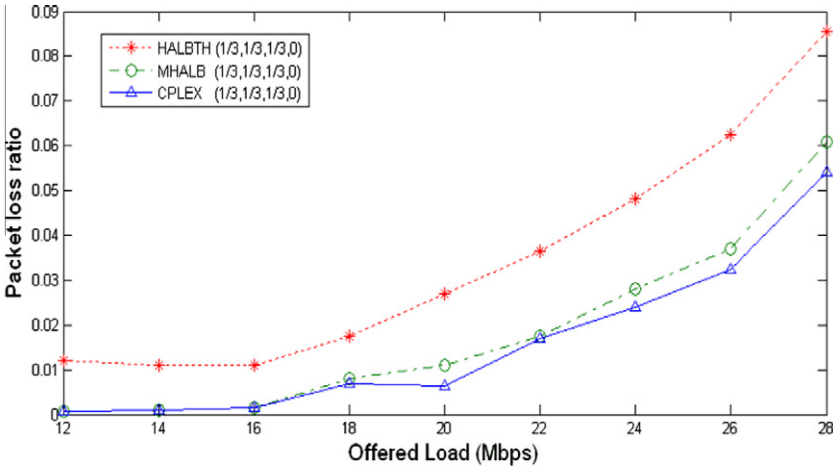

Fig. 7. Packet loss rate with HALBTH, MHALB and optimal solution.

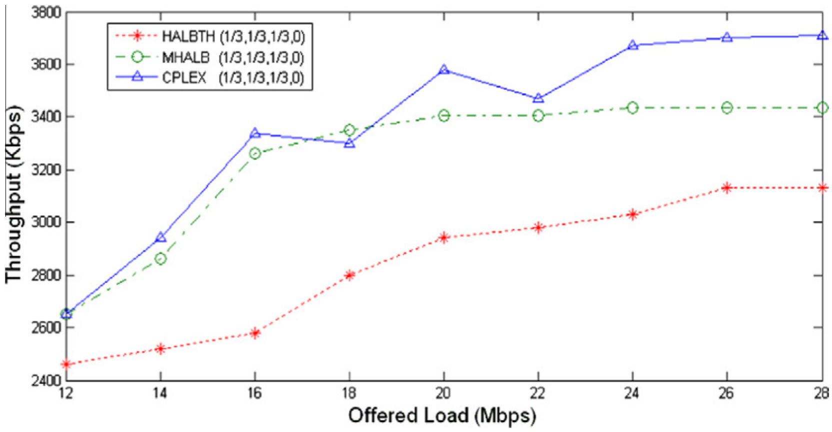

Fig. 8. Throughput with HALBTH, MHALB and optimal solution.

After a maximum number of allowed iterations, denoted by i_{max}, without improvement exploring N1, we jump to N2 neighborhood. The exploration of N2 is performed using search intensification based on N2. This search is done by a simple descent as shown in Algorithm 3 (step 2). The idea behind the concept of search intensification is that, as an intelligent human being would probably do, one should explore more thoroughly the portions of the search space that seem promising to make sure that the best solutions in these areas are indeed found.

Therefore, to make MTABU more effective, it is important to add throughout the search an intensification step (i.e., Algorithm 3 – step 2) without sampling; thus, the best solutions available in the various regions of the search space explored by MTABU will be found and recorded.

Tabu-List: To prevent cycling, i.e. exploring the same movements, we maintain a FIFO tabu-list Ω of limited size. If solution S^{i+1} is created from S^i using (movement, S^i) by assigning a new channel to the MR interface (applying N1), then we will add (movement, S^i) to Ω. When we generate solutions based on N1 movement, we ignore solutions computed using the same movement to get S^i in Ω. The size of Ω is denoted by SI. Each movement is kept in the Tabu list during SI iterations before being reconsidered again in the N1 exploration. It is also possible to assign a different number of iterations, chosen randomly, to each movement added to Ω.

Termination: We keep track of the best (i.e., with lowest objective function) solution (S^{best}) seen so far by the algorithm. The step 1 (the exploration of neighborhood N1) terminates when a maximum number of allowed iterations i_{max} was reached without any improvement in $f(S^{best})$ (the most commonly used criterion).

Algorithm 3: eta-heuristic: MTABU algorithm

Step0: initialization
Create an initial solution S^0 using the greedy algorithm HALBTH (Algorithm 1);
$f^0 \leftarrow f(S^0);\ S^{best} \leftarrow S^0;\ f^{best} \leftarrow f^0;\ \Omega = null;\ i \leftarrow 0;\ k \leftarrow 0;$
Step1: Tabu search based on N1: node move
While $i \leqslant i_{max}$ **Do**
Generate solutions of f^k based on N1;
Let S^{k+1} be the next solution with lowest objective function;
Add *movement*, S^k to Ω; If Ω is full then delete its oldest entry;
If $f(S^{k+1}) < (1-\beta) f^{best}$ **then** $f^{best} = f^{k+1}$; $i \leftarrow 0$;
Else $i \leftarrow i+1$; **Endif**;
$k \leftarrow k+1$;
End While; return f^{best};
Step2: Search intensification based on N2: cliques exchange
A simple descent; **If** $f(\tilde{S}) < (1-\beta) f^{best}$ **then** $f^{best} = f(\tilde{S})$**;**
return f^{best};

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5. Proposed on-line channel assignment scheme

In the previous section, we presented CA heuristics which are CPU intensive since they apply to the whole WMN using centralized offline algorithms. In this section, we present a distributed online CA algorithm that improves the offline CA with respect to traffic dynamics and handoff traffic variations. To deal with these traffic variations, we assume the existence of an online measurement mechanism that measures traffic/handoff variations and computes a suitable time interval, denoted by *T*, to capture periods with minimal traffic/handoff variations.

5.1. Channel assignment trigger

The proposed algorithm re-assigns channels (i.e., reconfigures radio interfaces) in real-time while traffic may be flowing through these interfaces; this may cause service disruption (data losses) during CA. To minimize disruption, our proposed scheme prioritizes intra-clique handoffs over inter-clique handoffs. Therefore, when a MR experiences an inter-clique handoff rate exceeding a fraction ψ^h of its traffic load, the online CA is triggered. The same channel, i.e. and thus the same clique, is assigned to MRs interfaces involved in the frequent handoff rate: we assign the clique's channel of one's interface to the other's interface. However, the choice of which MR will change its clique is not trivial since the network performance can be impacted by the choice of the re-assignment. Our scheme chooses the re-assignment option that minimizes the load variance among neighboring cliques in a distributed manner and the traffic load in each clique and its neighboring cliques are computed as in [24]. Note that our scheme dynamically adjusts the handoff rate threshold ψ^h, i.e. the handoff rate above which the online CA is triggered. The adjustment is triggered when a measured performance parameter, such as packet loss, exceeds a given threshold. For instance, if measured packet loss, collected from interface statistics during one or more time intervals (i.e., one or more T), exceeds a given QoS level packet loss, then the handoff rate threshold is decreased and it can be regularly adjusted (increased/decreased) at the end of each time interval [24] .

5.2. Online channel assignment algorithm

Algorithm 4 details the assignment of channels and thus the adjustment of cliques depending on the inter-clique handoff rate. We assume that the online CA is re-executed periodically each period of time *T* indicating a considerable traffic variation; during *T* no noticeable traffic variation occurs. In this algorithm, the handoff rates between two MRs is denoted by h_{ij} which is equal to the number of handoffs occurring between nodes *i* and *j* during the period of time *T*. The parameter traffic load, which is continuously measured on each MR, is used as criterion to select a unique CA solution when several ones are possible. This is done when the cliques involved in the online CA, i.e. cliques having a handoff rate between their respective MRs exceeding the threshold ψ^h, have different variances of traffic load.

Algorithm 4: Dynamic distributed CA algorithm: HALB

Input: handoff rate h_{ij}, traffic load η_i of clique q_i^k
Output: New topology with new CA
- Compute traffic load in each clique [24];
- Exchange traffic load information between neighboring cliques [24];
- Compute the variation of traffic load in clique q_l^k and the other neighboring cliques for $\forall j \in q_m^{k'}$;
- Assign the channel of the least loaded neighboring clique to the interface of the MR belonging to the most loaded neighboring clique;
- The handoff statistics h_{ij} are recorded during time period for each interface;

The pseudo-code of the MHALB+ (resp. MTABU+), which includes MHALB, HALBTH and HALB (resp. MTABU, HALBTH and HALB), is shown in Algorithm 5.

MHALB+, MTABU+ and HALBTH+ are distributed CA algorithms that continuously improve the near optimal solution produced by the static heuristics MHALB/MTABU/HALTBTH (step 0). These algorithms adapt to the dynamic variation of the traffic load and the handoff rates. In fact, they make use of handoff statistics that is collected during the period of time T, to trigger or not CA (see Section 5.1) at the end of the time period.

Algorithm 5: Distributed dynamic CA algorithm HALBTH+/MHALB+/MTABU+

Step 0:
Apply the heuristics HALBTH/MHALB/MTABU to get near optimal solution.
Step1: Online CA improvement regarding dynamic traffic variation
If $\sum_{j\in V_m} h_{ij} \gg \psi^h, \quad i \in q_l^k,\ \forall j \in q_m^{k'}, k \neq k'$ **then**
Call Algorithm 4: HALB at each Mesh Router
End if
Repeat Step 1 Every period of time T

6. Simulation results

We implemented MHALB, MTABU and HALBTH using C++ language and we executed them on a machine having a Pentium 2.1 GHz CPU, 2.0 GB of RAM and Fedora 11. To assess the quality of the solutions returned by MHALB and HALBTH, we compare them to CPLEX solutions [25]; CPLEX provides exact solution (i.e., the optimal solution) of the proposed model but only for small size networks; for realistic size networks, it does not return a solution. Using the solution produced by MHALB and the optimal solutions returned by CPLEX, we set up and configured a simulation model (see below) and conducted simulations using ns-2 [26] in order to evaluate the performance of MR-WMN in terms of delay, packet loss, throughput and fairness under the proposed CA scheme. We use a topology composed of 10/13/19 MRs respectively with our proposed schemes. The radio transmission range r takes one of the following values: 150 m, 200 m and 250 m and the transmission interference R of each wireless MR is 550 m. Also, we fix the MR-WMN packet size to 1000 kB. The voice call arrival process follows a Poisson distribution and the packet arrival process follows a deterministic distribution with a constant rate (CBR) with rate of 1 Mbps and interval of 0.01 s. The average number of simulation runs performed for each result, shown in the figures below, is 10. The throughput is defined as the average rate of successful packet delivery over a communication channel. The delay is measured as the mean MC-to-Gateway delay over all flows in the network. We used a maximum number of iterations equal to 10 for the meta-heuristic based on VNS to move to/from N1 or N2 resp. The same number of iterations is used for Tabu search to move from step1 to the search intensification step. The handoff threshold which is measured by MR to trigger the CA is equal to 55% (for our simulation setup); this value has been chosen based on extensive simulations on the network under evaluation. For a different network setup, the handoff threshold may be different (based on simulations). However, this should have no impact on the performance of the proposed techniques. This has been confirmed using different network setups we do not include in this paper.

In our performance evaluations (case I–II–III) of the MR-WMN under different CA schemes, we choose different combinations of objectives in the aggregate function (Eq. (36)). This will help evaluate the impact of the weights given to different objectives on the real performance metrics and then prove or disprove the assumed relations between them.

6.1. Case I: Known handoff traffic

In our first simulation scenario, we evaluate the performance (delay, packet loss and throughput) of the MR-WMN using (1) HALBTH; (2) MHALB; and (3) CPLEX; using weights (1/3, 1/3, 1/3, 0), we are interested in optimizing all objectives except fairness which will be evaluated later. We do not present the simulation results for MTABU because, in this scenario, it provides similar performance as HALBTH.

Fig. 6 shows that MHALB is able to reduce the delay by an average of 17% compared to HALBTH. The optimal solution (returned by CPLEX) outperforms, in terms of delay, MHALB and HALBTH solutions by 5% (i.e., [average_delay(MHALB)- average_delay(CPLEX)]/(average_*delay*(*MHALB*)) and 20% (i.e., [average_delay(HALBTH) - *average_delay*(*CPLEX*)]/(*average_delay*(*HALBTH*)) respectively.

Fig. 7 shows that MHALB significantly reduces the loss rate compared to HALBTH; in fact, MHALB reduces the mean loss rate (over all loads) by 47% compared to HALBTH. The optimal solution outperforms, in terms of loss rate, MHALB and HALBTH solutions by 12% and 54% respectively.

Table 2
CPU time (s) with HALBTH, MHALB and CPLEX: 10-nodes network.

Load (Mbps)	HALBTH	MHALB	CPLEX
Network size: 10 nodes			
12	3	119	>10,000
14	12	133	>10,000
16	12	140	>10,000
18	12	137	>10,000
20	13	146	>10,000
22	14	149	>10,000
24	14	146	>10,000
26	15	282	>10,000
28	15	200	>10,000

Fig. 8 shows that MHALB provides better WMN throughput than HALBTH; its outperformance is even more marked starting from load 16 Mbps. This can be explained by the fact that good load balancing capability leads to efficient usage of network resources and results in higher throughput in the network. We observe, for example, that the improvement provided by MHALB over HALBTH at load 16 is about 20%. Fig. 8 shows also that the optimal solution outperforms MHALB by merely 4%.

Figs. 6–8 respectively show that the MHALB provides an average performance, in terms of delay, packet losses and throughput, very similar to the performance provided by the optimal CA, i.e. the exact solution of the proposed model given by CPLEX; we conclude that MHALB provides high quality solutions (i.e., near optimal solutions). Note that MHALB returns a solution 50 times faster than CPLEX (see Table 2). For networks with more than 10 nodes, CPLEX does not return a solution in a reasonable time (starting from 13 nodes, it is more than 3 days).

In the second and the third simulation scenarios, we consider a network with more than 10 nodes. Similarly to the first scenario, CPLEX does not return a solution in a reasonable time. Thus, we use exclusively MHALB (which returns near-optimal solutions as shown in Figs. 6–8) to resolve the proposed model. In the second simulation scenario, we vary the weights assigned to the four objectives and we evaluate the performance of the MR-WMN in terms of delay, packet loss and throughput while varying the offered load.

Fig. 9 shows that, compared to other multi-objective combinations not considering the handoff overhead, a combination that uses a non null value of α_2 (1/4 or 1/3 or 1/2) to minimize the handoff overhead decreases the MR-WMN delay by 20–25% in average under a moderate to high offered load. This can be explained by the fact that our handoff-aware scheme ($\alpha_2 > 0$) re-assigns carefully channels to MR interfaces so that most of the handoff traffic is re-routed by only changing first-hop MRs of original paths; this will definitively reduce delay compared to arbitrary re-routing that may involve second and third hop MRs.

Figs. 10 and 11 show that, considering throughput maximization ($\alpha_3 > 0$), load balancing ($\alpha_1 > 0$) and fairness ($\alpha_4 > 0$) in MHALB, we significantly decrease the packet loss (over 73% improvement in average). This can be explained by the tight relationship between all of these performance metrics. In fact, increasing the throughput, either directly or indirectly through load balancing, will automatically decrease packet losses.

In the third simulation scenario, we vary the weights assigned to the four objectives and we observe the performance of the MR-WMN in terms of fairness and throughput while varying the offered load.

Fig. 12 shows that the Jain's fairness index (μ) is almost equal to 1 for MHALB (0, 0, 0, 1); this is desired to share the WMN throughput between the MCs in a fair manner without starving some of them. In fact, MHALB (0, 0, 0, 1) improves the mean μ (over all loads) by 19% and 10% compared to MHALB (1/3, 1/3, 1/3, 0) and MHALB (1/4, 1/4, 1/4, 1/4) respectively.

Fig. 13 shows the throughput achieved by each MC in the MR-WMN when taking into account only fairness parameter and Fig. 14 when taking into consideration load balancing, handoff overhead and throughput. These graphs aim to show how it is important to establish a tradeoff between all these parameters and to take into account the intimate relationship particularly between throughput and fairness so that we could avoid that throughput values vary so widely for different loads. In Fig. 13, we observe that MCs throughput exhibits nearly the same trend when the offered load increases while in Fig. 14 the MCs

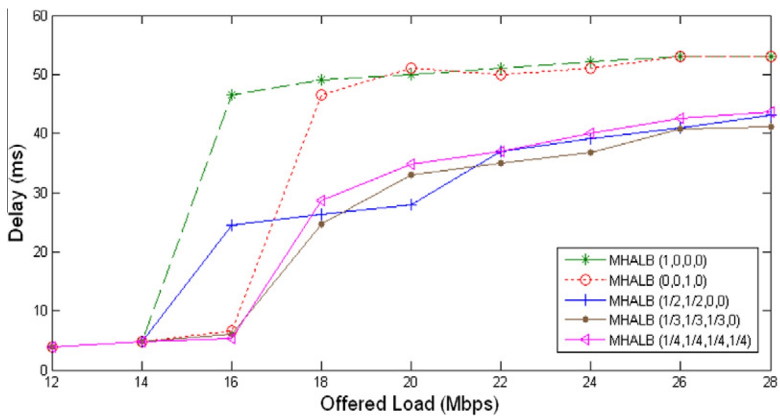

Fig. 9. Delay with MHALB.

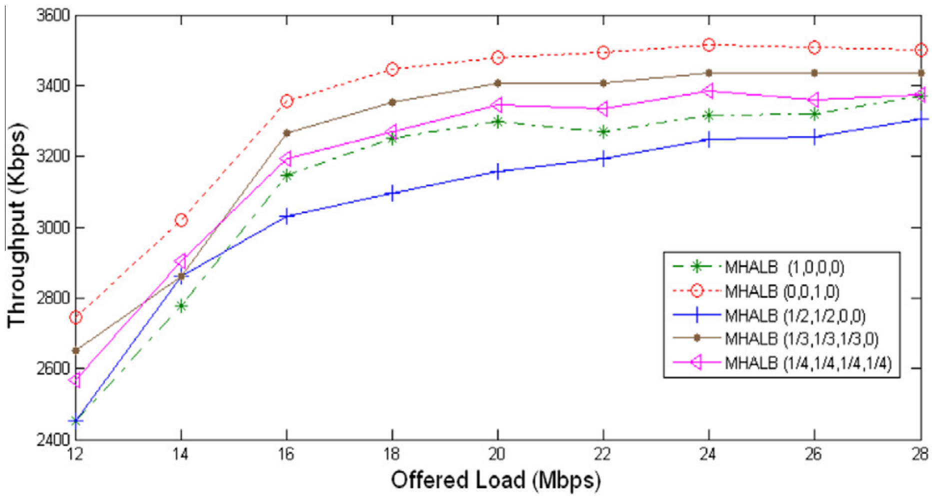

Fig. 10. Throughput with MHALB.

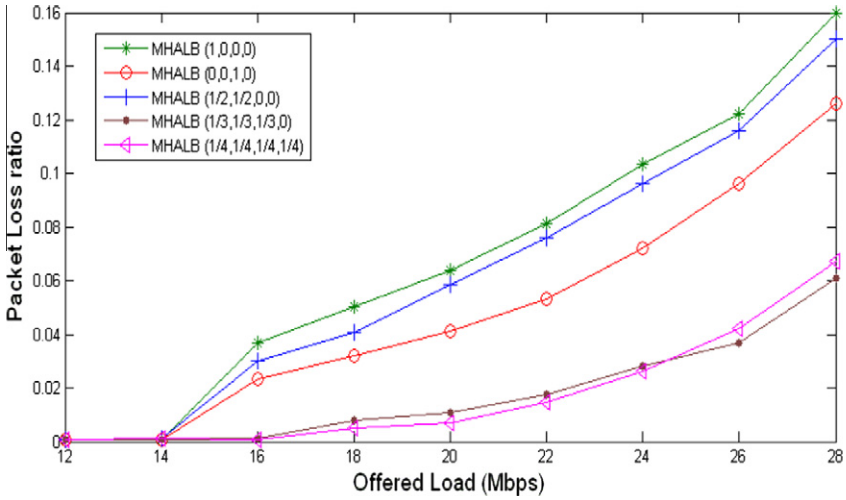

Fig. 11. Loss with MHALB.

throughput shows an irregular behavior; this proves the impact of the fairness on the underlying throughput which is also consistent with the results obtained in Fig. 12.

6.2. Case II: Dynamic CA with and without HALBTH

We compare first three schemes: (1) W.O.HALB: an existing CA in MR-WMN, such as in [8]; (2) HALB is our proposed CA scheme that dynamically re-assigns channels with one of the purposes of confining most of the handoffs in the same clique and balances the load among cliques as shown in Algorithm 4; (3) HA is the same as HALB CA scheme but without load balancing among cliques; and then we compare the two last schemes (4) HALBTH+ is the proposed CA heuristic based on handoff aware with load balancing as shown in Algorithm 5; and (5) W.O.HALBTH+ is the distributed CA dynamic scheme without good initial solution.

In Fig. 15, we evaluate the performance of the MR-WMN under our proposed CA schemes (HALB and HA) and we compare them to the existing CA scheme (W.O.HALB) that does not take into account handoff and load balancing.

Fig. 15(a) shows that HALB provides the best result in terms of delay followed by HA; the worst results are generated by W.O.HALB. This can be explained by the fact that our scheme re-assigns carefully channels to MR interfaces so that most of the handoff traffic is re-routed by only changing first-hop MRs of original paths; this will definitively reduce delay compared with arbitrary re-routing (the case of W.O.HALB). HALB outperforms HA because of the considerable delay increase in overloaded cliques (caused by HA); this, in turn, causes the increase of the average delay (shown in Fig. 15(a)). When no load balancing is considered (HA), the exponential increase of the delay in overloaded cliques results in a higher average

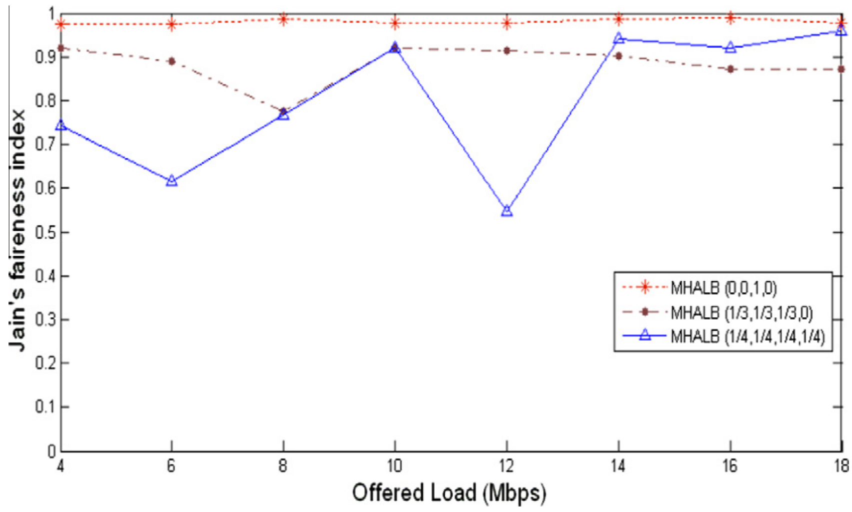

Fig. 12. Jain's fairness index.

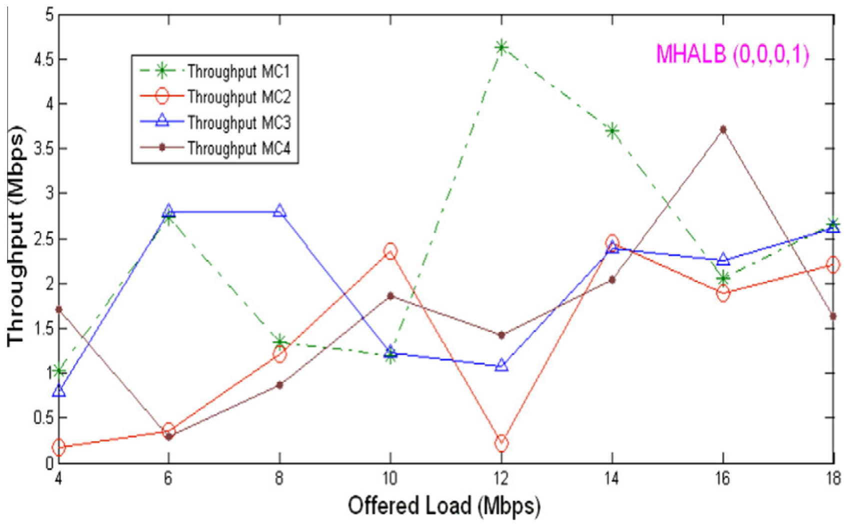

Fig. 13. Throughput achieved by MCs.

delay over all cliques compared to the average delay of load balanced cliques.

Fig. 15(b) shows that HALB outperforms considerably HA and W.O.HALB; for example, at load 16, HA (resp. W.O.HALB) generates 60% (resp. 41%) more losses than HALB. One can observe, in Fig. 15(b) that W.O.HALB produces better results than HA. This is due to higher contentions and collisions in a larger clique extended by one or more logical links (because of MRs switching cliques due to the operation of HALB) in order to confine its handoff in the same clique.

Since the throughput is tightly related to packet losses, we observe in Fig. 15(c) a slight decrease in the throughput provided by HA over W.O.HALB. Fig. 15(c) shows that HALB provides, at load 16, 10% and 6.2% more throughput than HA respond W.O.HALB respectively.

At saturation, the throughput reaches its maximal value constrained by the capacity of the MR-WMN; when operating at full capacity, new flows are rejected if admission control is implemented; otherwise, packet loss rates increase dramatically and delay reaches its maximum.

Fig. 16(a) shows the delay variation in both HALB and W.O.HALB. This figure aims to show the effectiveness of intra-clique handoffs in decreasing the delay, especially when we take into account traffic load balancing. It shows also that the delay with W.O.HALB increases significantly after the channel re-assignment process; it exceeds 0.023 s at time 6.8 s. Generally speaking, the delay with W.O.HALB after the channel re-assignment process is about three times the delay with HALB. HALB performs, whenever adequate, in-clique handoff and produces a lower delay; we conclude that intra-clique handoff has better delay performance than inter-clique handoff.

Fig. 16(b) illustrates the variation of packet loss ratio; the channel re-assignment starts at time 3.2 s and finishes at 4.5 s. Note that before this period, W.O.HALB and HALB

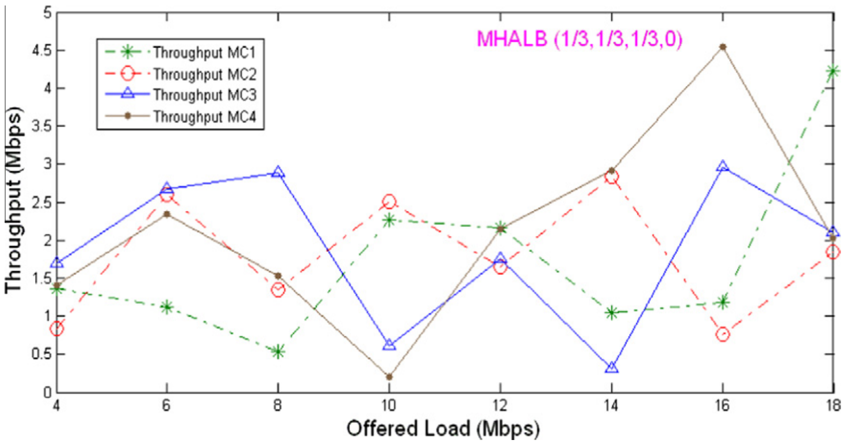

Fig. 14. Throughput achieved by MCs.

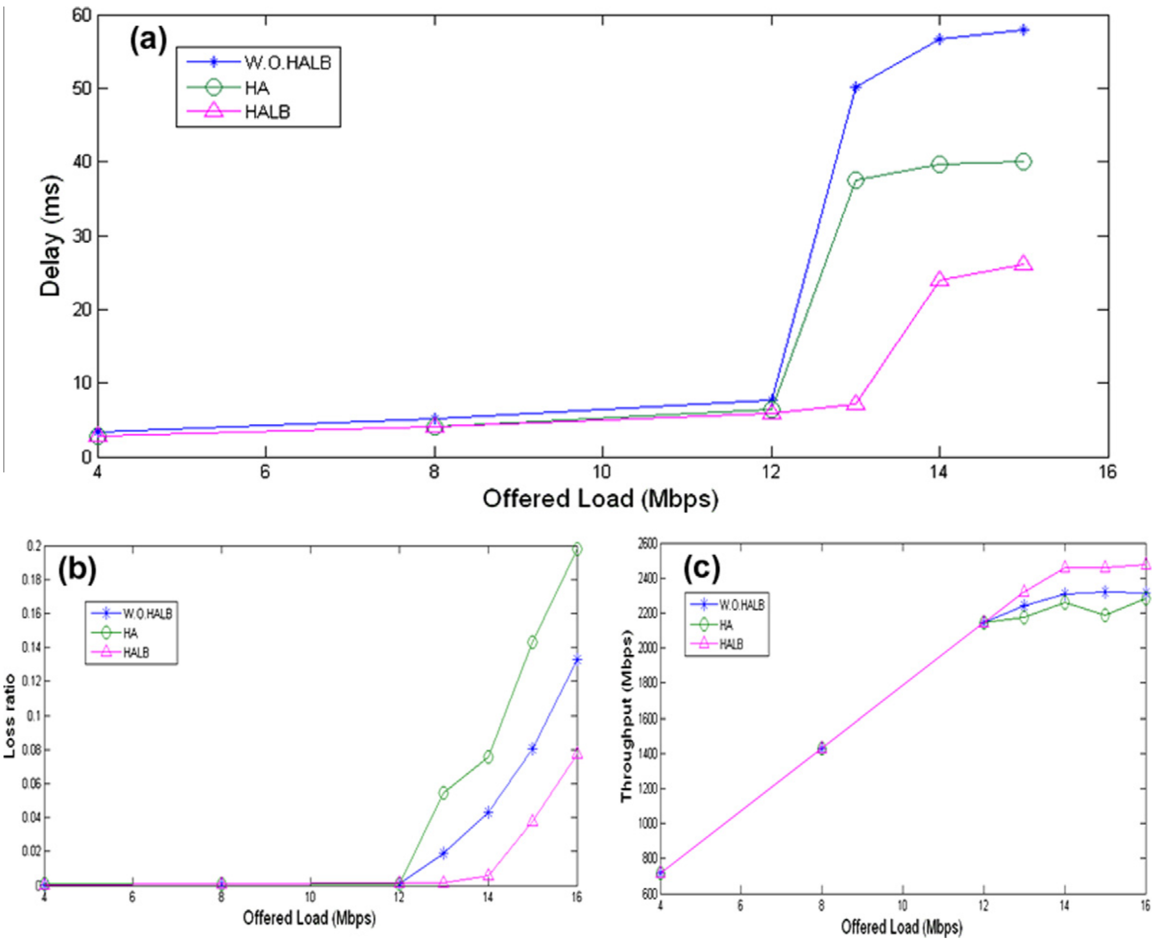

Fig. 15. Delay (a); packet loss ratio (b); and throughput (c).

provide similar loss ratios; however, during the channel re-assignment process, when using HALB, the loss rate reaches its maximum value but never exceeds the loss ratio incurred by W.O.HALB. After the channel re-assignment process, HALB outperforms handily W.O.HALB.

Fig. 16(c) shows that HALB has better throughput than W.O.HALB; its outperformance is even more marked after the channel re-assignment process. This can be explained by the fact that good load balancing capability leads to efficient usage of network resources and results in higher

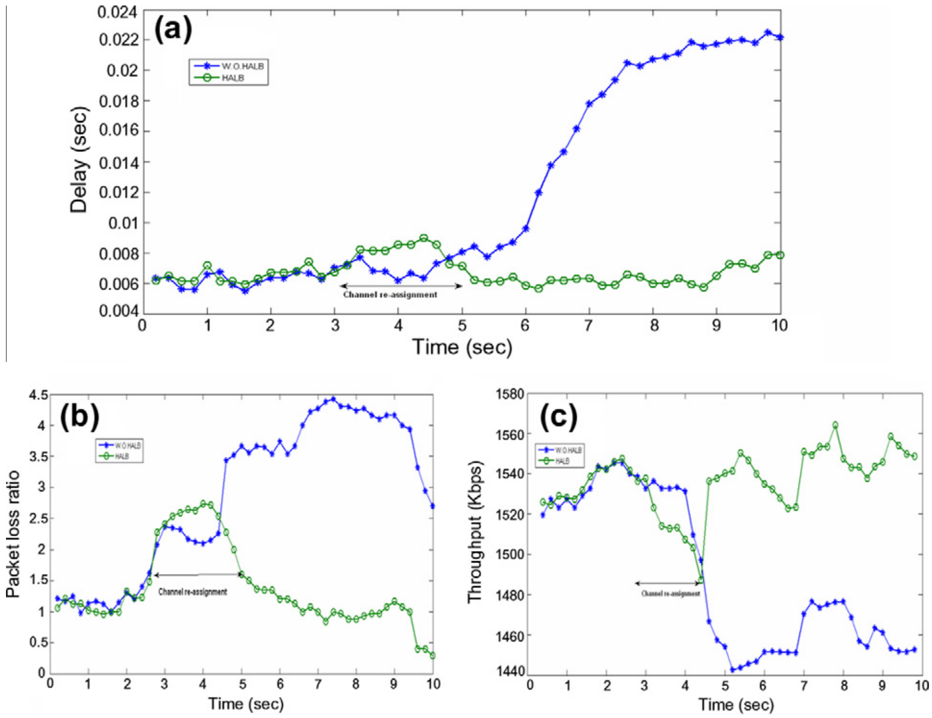

Fig. 16. Delay (a); packet loss ratio (b); throughput (c).

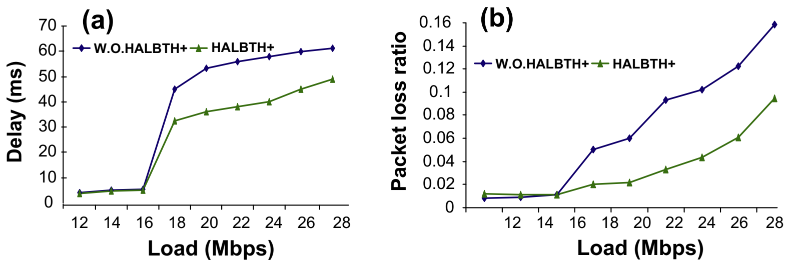

Fig. 17. Delay (a) and packet loss rate (b) with and without HALBTH+.

throughput. More specifically, when using W.O.HALB, the throughput decreases compared with HALB starting from 4.8 s; this is expected because of the increase in packet losses using W.O.HALB (see Fig. 16(b)).

During the channel re-assignment process, HALB faces slight degradation in terms of delay, loss and throughput. In fact, the latency of transmitting signaling messages that perform the re-routing and the context transfer of the session from one path to another cause a path outage, and therefore a QoS degradation, during this short transient period of channel re-assignment. This is a price worth paying to provide high throughput and low losses after this period while satisfying QoS requirements of new traffic flows.

Fig. 17 shows the performance, in terms of delay and packet loss, of the MR-WMN under a channel assignment using the proposed heuristic HALBTH+ (Algorithm 5). In Fig. 17(a), we observe that HALBTH+ is able to reduce the delay by 26% compared to W.O.HALBTH+. Fig. 17(b) shows that HALBTH+ reduces efficiently loss rate compared to W.O.HALBTH+. In fact, the mean loss rate (over all loads) of HALBTH+ decreases by 47% compared to W.O.HALBTH+. This improved performance provided by HALBTH+ (HALB combined with HALBTH) compared to the distributed CA dynamic scheme without good initial solution (HALB), shows the importance of a centralized CA heuristic in providing a good efficient assignment that serves as an initial solution to be dynamically improved by the distributed CA. However, unlike HALB, the centralized heuristic HALBTH cannot be performed dynamically in an online fashion, due to its time and message complexity.

6.3. Case III: Dynamic CA based heuristics MHALB+/MTABU+

Figs. 18–20 show the performance of the proposed dynamic CA based heuristics (MHALB+/MTABU+) in terms

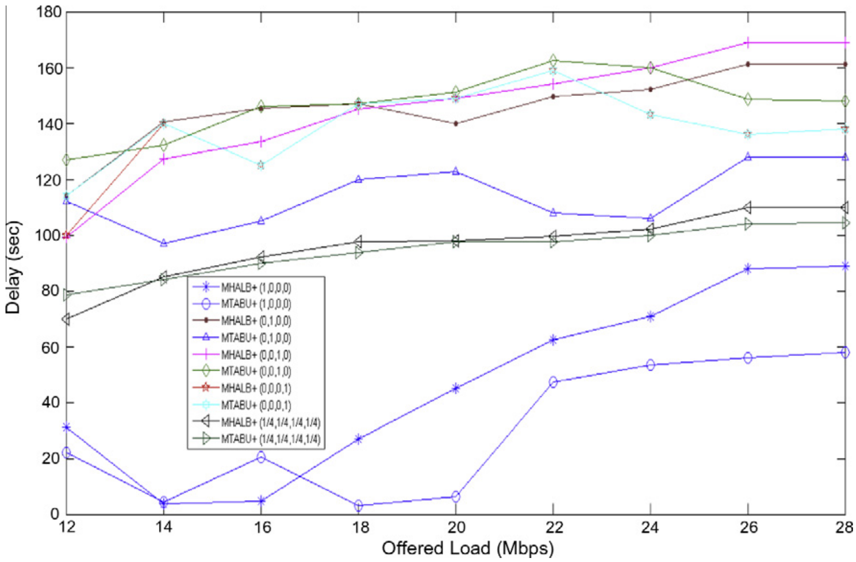

Fig. 18. Delay with MHALB+ and MTABU+ for # weights.

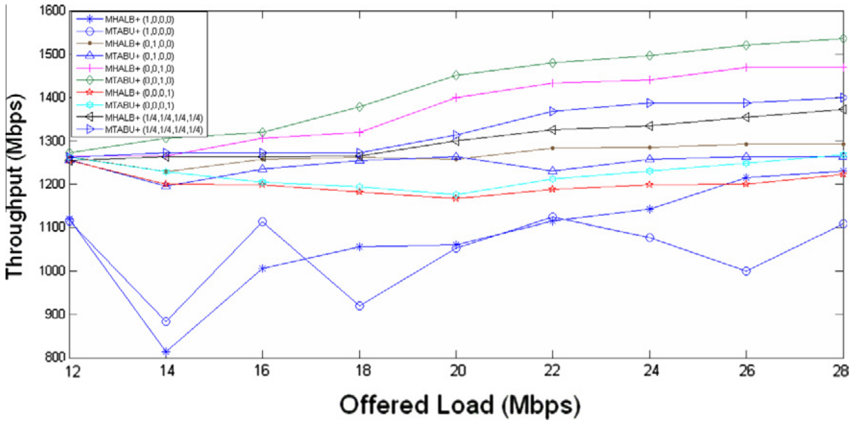

Fig. 19. Throughput with MHALB+ and MTABU+ for # weights.

of delay, throughput and packet loss. Table 3 shows the CPU time of MHALB+/MTABU+ compared to the optimal solution computed by CPLEX with network of 19 nodes.

Fig. 18 shows that the schemes, MHALB+/MTABU+, taking into account only load balancing (1,0,0,0) present the lowest delay (MHALB+: 46 ms, MTABU+: 30 ms). This can be explained by the fact that intra-clique handoff has better delay performance than inter-clique handoff. With a multi-objective giving exclusive preference to load balancing, i.e. using (1,0,0,0), our approach outperforms the other weighted approaches in terms of delay but at the expense of throughput degradation and higher losses (see Figs. 19 and 20).

However, when we consider a tradeoff between the four objective functions (1/4,1/4,1/4,1/4), the two meta-heuristics have an average delay for all loads equals to 94 ms which is good enough for multimedia traffic, such as voice which requires a maximal delay of 100 ms that does not exceed 150 ms required by ITU-T G.114 [27].

Fig. 19 shows that, considering only the throughput maximization (0,0,1,0) for the two meta-heuristics, we obtain the highest throughput (1374 Kbps for MHALB+ and 1417 for MTABU+ in average). However, combining all objectives (1/4, 1/4, 1/4, 1/4) has also a good throughput (5% for MHALB+ and 7% for MTABU+ less compared to (0,0,1,0)) which can be explained by the tight relationship between all of these performance metrics. In fact, increasing the throughput either directly or indirectly through load balancing will automatically decrease packet losses as shown in Fig. 20. The price to pay in order to provide high throughput, lower losses, and MCs fairness is an increase in terms of delay.

In summary, it is observed, through simulations, that several trade offs exist between load balancing, handoff overhead, throughput and fairness to determine a good solution that satisfies adequately all the criteria. In our simulations, we found that the combination (1/4, 1/4, 1/4, 1/4) provides the best results of our test runs; other

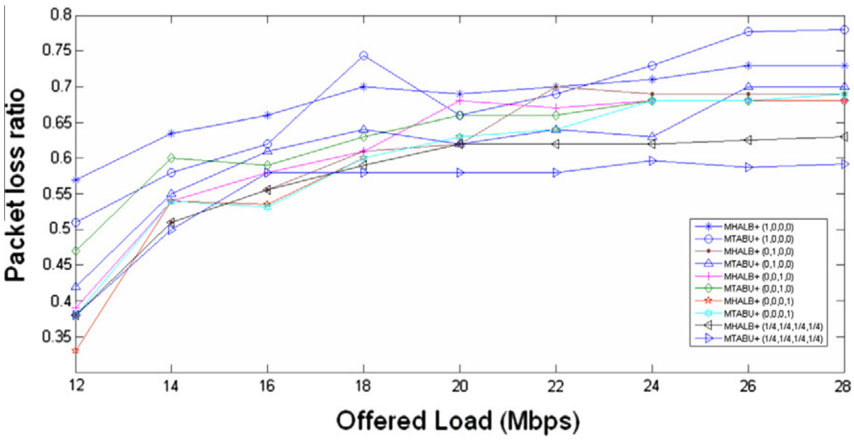

Fig. 20. loss rate with MHALB+ and MTABU+ for # weights.

Table 3
CPU time (s) with MHALB+, MATBU+ and CPLEX: 19-nodes network.

Load (Mbps)	MHALB+ (1/4, 1/4, 1/4, 1/4)	MTABU+ (1/4, 1/4, 1/4, 1/4)	CPLEX
Network size: 10 nodes			
12	639	1476	∞
14	766	1663	∞
16	829	1484	∞
18	836	1501	∞
20	902	1422	∞
22	877	1387	∞
24	957	1500	∞
26	990	1499	∞
28	990	1600	∞

combinations may provide better results since it is unfeasible to run all possible combinations. A sensitivity analysis is performed on each objective function in order to determine/study the impact and the usefulness of each objective function/criterion alone without taking into account the other criteria (e.g., (1,0,0,0)).

Tables 2 and 3 show that for a large network size CPLEX cannot return a solution in a reasonable time. Therefore, in this case meta-heuristics based on VNS or Tabu search provide a good alternative to get near-optimal solutions. As we observe from Figs. 18–20 and Table 3, although Tabu search has a higher CPU time than VNS, it provides a CA solution that gives a slightly better performance compared to VNS.

7. Conclusions and future work

In this paper, we propose a new unified/generalized model for the CA problem in MR-WMNs with handoff support. The uniqueness of our scheme lies in the fact that rather than treating just non uniform traffic load during the CA process, as has been done so far in the literature, we propose a novel CA scheme that optimizes several objectives. We developed a novel multi-objective optimization model that integrates important network characteristics, such a handoff and load balancing, by exploiting the intimate relationships among them. In this paper, we used this model to determine a CA that minimizes inter-clique handoffs and traffic load variation, besides maximizing the throughput and ensuring MCs fairness while satisfying all technical constraints.

Moreover, we propose centralized static CA heuristics (variable neighborhood search: MHALB/Tabu search: MTABU) to search for a near-optimal initial CA solution optimizing the four performance metrics regardless of traffic variation. Then, we propose online distributed dynamic CA schemes (MHALB+/MTABU+) that continuously improve the near optimal solution produced by the static heuristics to the dynamic variation of traffic load and handoff rates. Particularly, our proposed online CA schemes try to continually minimize the handoffs involving path re-routing beyond the first hop MR and to ensure a better balanced load in the network. Using simulations, we show that our proposed approaches, integrating the centralized CA heuristics with the distributed online CA schemes, achieve good performance in terms of delay, loss rate and overall throughput.

Currently, we plan to use pure multi-objective methods to solve this problem and then to produce non-dominated solutions.

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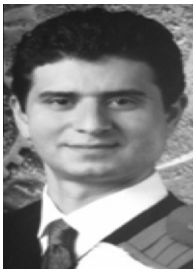

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