Université de Montréal

Conception des Réseaux Maillés Sans Fil à Multiples-Radios Multiples-Canaux

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Cette thèse intitulée :

Conception des Réseaux Maillés Sans Fil à Multiples-Radios Multiples-Canaux

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Résumé

Généralement, les problèmes de conception de réseaux consistent à sélectionner les arcs et les sommets d'un graphe *G* de sorte que la fonction *coût* est optimisée et l'ensemble de contraintes impliquant les liens et les sommets dans *G* sont respectées. Une modification dans le critère d'optimisation et/ou dans l'ensemble de contraintes mène à une nouvelle représentation d'un problème différent. Dans cette thèse, nous nous intéressons au problème de conception d'infrastructure de réseaux maillés sans fil (WMN- Wireless Mesh Network en Anglais) où nous montrons que la conception de tels réseaux se transforme d'un problème d'optimisation standard (la fonction *coût* est optimisée) à un problème d'optimisation à plusieurs objectifs, pour tenir en compte de nombreux aspects, souvent contradictoires, mais néanmoins incontournables dans la réalité. Cette thèse, composée de trois volets, propose de nouveaux modèles et algorithmes pour la conception de WMNs où rien n'est connu à l' avance.

Le premier volet est consacré à l'optimisation simultanée de deux objectifs équitablement importants : le coût et la performance du réseau en termes de débit. Trois modèles bi-objectifs qui se différent principalement par l'approche utilisée pour maximiser la performance du réseau sont proposés, résolus et comparés.

Le deuxième volet traite le problème de placement de passerelles vu son impact sur la performance et l'extensibilité du réseau. La notion de contraintes de sauts (hop constraints) est introduite dans la conception du réseau pour limiter le délai de transmission. Un nouvel algorithme basé sur une approche de groupage est proposé afin de trouver les positions stratégiques des passerelles qui favorisent l'extensibilité du réseau et augmentent sa performance sans augmenter considérablement le coût total de son installation.

Le dernier volet adresse le problème de fiabilité du réseau dans la présence de pannes simples. Prévoir l'installation des composants redondants lors de la phase de conception peut garantir des communications fiables, mais au détriment du coût et de la performance du réseau. Un nouvel algorithme, basé sur l'approche théorique de décomposition en oreilles afin d'installer le minimum nombre de routeurs additionnels pour tolérer les pannes simples, est développé.

Afin de résoudre les modèles proposés pour des réseaux de taille réelle, un algorithme évolutionnaire (méta-heuristique), inspiré de la nature, est développé. Finalement, les méthodes et modèles proposés on été évalués par des simulations empiriques et d'événements discrets.

Mots clés : WMN, optimisation à plusieurs objectifs, amélioration de la performance, extensibilité du réseau, groupage, robustesse, décomposition en oreilles, méta-heuristique.

Abstract

Generally, network design problems consist of selecting links and vertices of a graph *G* so that a cost function is optimized and all constraints involving links and the vertices in *G* are met. A change in the criterion of optimization and/or the set of constraints leads to a new representation of a different problem. In this thesis, we consider the problem of designing infrastructure Wireless Mesh Networks (WMNs) where we show that the design of such networks becomes an optimization problem with multiple objectives instead of a standard optimization problem (a cost function is optimized) to take into account many aspects, often contradictory, but nevertheless essential in the reality.

This thesis, composed of three parts, introduces new models and algorithms for designing WMNs from scratch.

The first part is devoted to the simultaneous optimization of two equally important objectives: cost and network performance in terms of throughput. Three bi-objective models which differ mainly by the approach used to maximize network performance are proposed, solved and compared.

The second part deals with the problem of gateways placement, given its impact on network performance and scalability. The concept of hop constraints is introduced into the network design to reduce the transmission delay. A novel algorithm based on a clustering approach is also proposed to find the strategic positions of gateways that support network scalability and increase its performance without significantly increasing the cost of installation.

The final section addresses the problem of reliability in the presence of single failures. Allowing the installation of redundant components in the design phase can ensure reliable communications, but at the expense of cost and network performance. A new algorithm is developed based on the theoretical approach of "ear decomposition" to install the minimum number of additional routers to tolerate single failures.

In order to solve the proposed models for real-size networks, an evolutionary algorithm (meta-heuristics), inspired from nature, is developed. Finally, the proposed models and methods have been evaluated through empirical and discrete events based simulations.

Keywords: WMN, multi-objective optimization, improving performance, network scalability, clustering, robustness, Ear decomposition, meta-heuristics.

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ABFS	Augmented Breadth First Search
AP	Access Point
BCN	Bi-Connected Network
BCR	Balanced Channel Reuse
CGPA	Clustering based Gateway Placement Algorithm
CL	Candidate Location
CPF	Common Pareto Front
EI	Expected Improvement
MC	Mesh Client
MG	Mesh Gateway
MOOP	Multi-Objective Optimization Problem
MOPSO	Multi-Objective Particle Swarm Optimization
MR	Mesh Router
MR-MC	Multi Radio-Multi Channel
NPSA	Network Planning Solution Algorithm
PF	Pareto Front
PPR	Pareto Potential Region
TS	Traffic Spot
WMN	Wireless Mesh Network

À la mémoire de mon père,

À ma très chère mère,

À toute ma famille.

Chapitre 1

Introduction

1.1 Contexte de Recherche

Les problèmes de conception de réseaux constituent une classe importante de problèmes d'optimisation représentant, sous diverses formes, une large variété de domaines, dont les réseaux de communications. Vu le succès remarquable des technologies sans fil et la croissance des services Internet, la conception de réseaux sans fil abordables et efficaces devient de nos jours une nécessité absolue. À cette fin, les réseaux maillés sans fil (*Wireless Mesh Networks* – *WMN*) sont des réseaux qui ont le potentiel d'offrir un accès Internet à haut débit à prix raisonnable, tant pour les propriétaires des réseaux que pour leurs clients.

Grâce à la technologie sans fil et plus précisément aux WMNs, beaucoup d'organisations mondiales, notamment dans le secteur de l'hôtellerie, ont été capables de réduire les dépenses énormes liées au câblage Ethernet tout en améliorant le temps et les points d'accès des utilisateurs au réseau Internet. Il est à noter que le potentiel de remplacement du câblage est impressionnant. À titre d'exemple, pour une construction de taille moyenne de 4 645 m^2 comprenant 150 utilisateurs, il faut approximativement 8 046 m de câblage pour connecter chaque utilisateur, contre seulement 800 m de câblage si l'on installe de simples équipements traditionnels de réseaux locaux sans fil (*WLAN*). Aussi, selon la compagnie internationale « Connect802 Wireless Data Solutions », dans un WMN, le coût des opérations quotidiennes effectuées dans les réseaux, telles que les déplacements, les modifications ou les additions de nouveaux composants, est 98 % moins élevé que dans un réseau câblé.

Les WMNs sont composés essentiellement de deux types de nœuds : les routeurs sans fil maillés et les clients maillés. On distingue trois catégories de routeurs sans fil qui forment ensemble une infrastructure relativement statique dans le WMN. Les routeurs vers lesquels se connectent les usagers du service sont des points d'accès du réseau qui envoient le trafic à d'autres routeurs qui servent de relais. Les relais, à leur tour, acheminent le trafic vers d'autres relais via une connexion point-à-point jusqu'à ce qu'un routeur doté d'une connexion au réseau Internet soit trouvé. Un tel routeur sans fil est appelé une passerelle. La figure 1.1 illustre les différents types de nœuds composant le WMN.

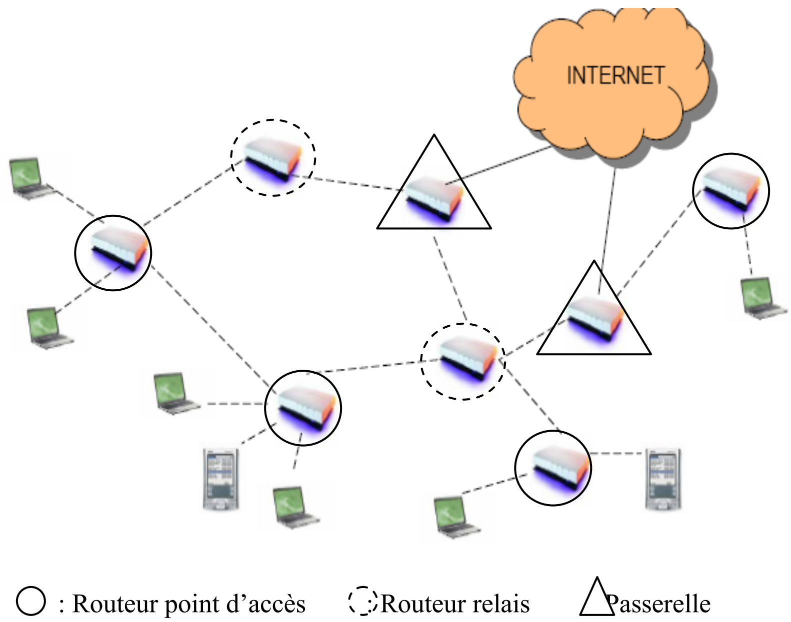

Figure 1.1 : Architecture d'un réseau maillé sans fil, WMN.

La distinction entre les clients et les routeurs facilite l'utilisation de multiples radios. Un routeur sans fil maillé peut être équipé de plusieurs interfaces radio, qui permettent ainsi des communications simultanées, mais fonctionnent sur des canaux différents. Cependant, vu le nombre très limité de canaux différents/orthogonaux, la performance du réseau est sérieusement affectée par les interférences sans fil qui causent des pertes et des délais importants.

1.2 Motivation et objectifs

Il existe de nombreuses situations où les réseaux maillés sans fil sont susceptibles de fournir une solution plus polyvalente et abordable qu'une infrastructure câblée. Ce type de réseau permet aussi de se connecter à un réseau câblé ou vers d'autres réseaux sans fil.

Effectivement, les WMNs ont été déployés dans des environnements divers, tels que les réseaux à domicile, les entreprises et les universités. Néanmoins, les utilisateurs de ces réseaux continuent à connaître des problèmes de connectivité et de performance. Parmi ces problèmes, citons : les connexions intermittentes, une performance dégradée qui est largement attribuable aux interférences dues à la réutilisation des mêmes canaux et, souvent, un manque de couverture. En général, ces problèmes sont causés par une mauvaise planification des réseaux sans fil. Autrement dit, la conception de réseaux maillés sans fil efficaces reste un problème d'optimisation difficile qui n'a reçu à ce jour que peu d'attention dans la littérature.

Considérons un graphe G=(V, E), où V est l'ensemble des sommets et E est l'ensemble de liens dans G. En général, le problème de conception de réseaux consiste à choisir des sommets et des liens de sorte que la fonction *coût* soit optimisée et les contraintes impliquant les sommets et les liens soient respectées. Ainsi, en choisissant d'une façon adéquate les critères d'optimisation ainsi que l'ensemble de contraintes, on peut représenter des problèmes pratiques différents.

Le problème de conception de WMN prend deux formes. La première forme est liée à l'optimisation de protocoles ou d'architectures, étant donné une topologie existante a priori. Par contre, la deuxième forme du problème concerne la planification du déploiement du réseau; dans ce cas, les emplacements et les caractéristiques des nœuds composant le réseau ne sont pas préalablement définis.

Dans cette thèse, nous nous concentrons sur le problème de conception d'infrastructures de réseaux maillés sans fil où le terme conception désignera la planification de leurs déploiements. Dans ce type de conception, les paramètres qui influencent la performance du réseau doivent être pris en compte. Autrement dit, cette phase de conception (la planification) permet de déterminer le nombre optimal de routeurs requis pour couvrir la zone d’intérêt, le nombre optimal de passerelles pour une connexion Internet garantie, une assignation réalisable de canaux pour un minimum d’interférence et un nombre optimal d’interfaces radio par routeur tout en respectant les contraintes financières de l’opérateur du réseau.

Un autre aspect qui s’ajoute à la complexité de ce genre de problème de conception est le conflit que présente la nature de la majorité des paramètres cités ci-dessus, ce qui rend le problème de conception de WMN difficile à résoudre. À titre d’exemple, l’opérateur a tendance à augmenter le nombre de routeurs pour résoudre le problème de couverture, ou encore à ajouter quelques passerelles pour assurer un meilleur débit. Or, cela ne fait qu’accroître la complexité du problème d’assignation de canaux. Par conséquent, un niveau important d’interférence en résulte, ce qui entraîne une détérioration de la performance finale du réseau. Ainsi, le problème de conception de WMN se transforme en un problème d’optimisation multicritère pour tenir compte de nombreux aspects, souvent contradictoires, mais néanmoins incontournables dans la réalité.

Cette thèse aborde le problème de conception de WMN sous trois volets : le premier volet traite de l’optimisation du déploiement des WMNs à multiples radios et multiples canaux par une approche d’optimisation simultanée de plusieurs objectifs. Il existe un grand nombre de solutions proposées pour la planification des réseaux cellulaires et les réseaux sans fil à un seul saut (*WLAN*); cependant, étant donné les caractéristiques uniques que présentent les WMNs, ces solutions ne peuvent être appliquées pour une planification adéquate des WMNs. Une grande partie des études liées à la conception des WMNs se concentre sur l’amélioration de la performance du réseau en prenant pour hypothèse que la topologie est fixée a priori. Il existe une autre catégorie de travaux dans le contexte de conception de réseaux maillés sans fil où toute la topologie n’est pas connue à l’avance; seule une partie d’elle est fixée. Autrement dit, dans un cas, les positions et les caractéristiques des routeurs points d’accès ou routeurs relais sont définies et il reste à déterminer les positions et les caractéristiques des passerelles pour satisfaire certaines contraintes de QdS; dans l’autre cas, il s’agit tout simplement de fixer les positions des passerelles et de trouver les positions potentielles des autres nœuds du réseau. Nous verrons dans la section 2.4 qu’il y a très peu de travaux qui s’intéressent à la conception de

WMN où rien n'est connu à l'avance. Cependant, ces travaux suivent le même pattern de modélisation pour optimiser le problème de conception de WMN. Ils considèrent la fonction coût comme l'unique objectif à optimiser. Pourtant, la performance du réseau est tout aussi importante, que ce soit pour l'opérateur du réseau ou pour ses utilisateurs.

Pour toutes ces raisons, nous considérons le problème de conception de WMN sous un angle différent des travaux précédents, qui est basé sur une optimisation à plusieurs objectifs. Ce type d'optimisation produit plusieurs solutions dites non dominées : aucune solution n'est meilleure que l'autre par rapport à tous les objectifs. Puisqu'il est souvent impossible de trouver une solution qui optimise simultanément tous les objectifs, le résultat attendu sera donc un ensemble de solutions représentant un compromis raisonnable entre les objectifs plutôt qu'une seule solution optimale. Ce genre d'optimalité est mieux connu dans la littérature sous le nom d'*optimalité Pareto (Pareto optimality)*. Ainsi, le décideur, (*decision maker*) ayant en main un large éventail de bonnes solutions, choisira la meilleure, celle qui répond le mieux à ses exigences qualitatives et/ou financières.

Le deuxième volet de cette thèse examine des solutions stratégiques permettant aux WMNs de passer à l'échelle dans les deux cas suivants : (1) croissance de la demande de trafic agrégée et (2) extension géographique du réseau. Il a été démontré dans des travaux de recherche précédents [AB06] que le passage à l'échelle des réseaux maillés sans fil n'est garanti que lorsque chaque nœud du réseau envoie son trafic aux passerelles avoisinantes seulement sur un rayon fixe et indépendamment de la taille du réseau. De ce fait, nous nous intéressons, dans cette partie d'étude, à trouver des emplacements stratégiques pour placer les passerelles, de façon à limiter le nombre de sauts entre chaque nœud transmetteur et la plus proche passerelle; cela est fait éventuellement avant le déploiement du réseau.

Étant donné que l'emplacement des passerelles joue un rôle déterminant dans la performance du réseau (bande passante/débit, congestion, délai), beaucoup de chercheurs se sont employés à étudier le placement optimal des passerelles dans les WMNs. Toutefois, peu d'entre eux ont exploité cet emplacement pour analyser l'extensibilité du réseau. Ils proposent néanmoins des techniques de groupage basées sur des structures arborescentes. Bien que ces techniques soient avantageuses par rapport à d'autres, elles entraînent une dégradation dans la robustesse du réseau et incitent à déployer plus de passerelles. Dans cette partie d'étude, nous nous intéressons à trouver les positions stratégiques des passerelles qui favorisent l'extensibilité du réseau et augmentent la performance du réseau sans, bien évidemment, augmenter considérablement le coût total d'installation du réseau.

Afin de garantir une communication fiable, une des possibilités envisagées est de placer des nœuds supplémentaires afin de tolérer les pannes de routeurs. L'ajout de composants redondants dans un réseau augmente la fiabilité du réseau, mais il accroît aussi substantiellement le coût total de déploiement du réseau, d'autant plus que la performance du réseau peut se dégrader dans une telle situation. À notre connaissance, il n'existe qu'une seule solution dans la littérature [BH08c] permettant de déterminer toutes les positions et les caractéristiques des composants du WMN de façon à garantir la continuité du service de ce réseau en présence d'une panne à la fois. Néanmoins, l'approche utilisée dissocie l'étape de la conception du réseau de sa robustesse. Cela ne garantit pas la convergence de la solution proposée et il se peut donc qu'on échoue à trouver une topologie-solution qui est également robuste, malgré le fait que cette solution puisse exister.

Le type de panne le plus fréquent dans les réseaux sans fil, tel qu'il est démontré dans [TD07], est la panne d'un seul nœud à la fois. Le dernier volet de cette thèse traite le problème de conception de WMN qui sont à la fois fiables, face aux pannes de routeurs, et performants à un coût acceptable.

1.3 Contributions et organisation de la thèse

Les points de recherche évoqués ci-dessus ont abouti à plusieurs résultats que nous avons soumis/publiés sous forme d'articles dans des revues et conférences internationales avec arbitrage. La thèse est constituée de quatre articles sélectionnés parmi les treize que nous avons produits (neuf articles acceptés, dont deux articles de revue, et quatre articles de revue soumis) que nous avons jugés les plus significatifs et les plus complets. Les articles sélectionnés sont numérotés en gras à la fin de cette section. Chaque chapitre est ainsi représenté par un article. Les articles étant présentés dans leur intégralité (*self-contained papers*), on notera une certaine redondance dans quelques sections (définition de modèle du réseau, recherche de la solution initiale). Cette redondance n'a pas été corrigée dans le but de conserver la conformité aux versions originales.

Dans le chapitre 2, après avoir introduit les réseaux maillés sans fil (WMNs) et leurs caractéristiques, nous passons en revue les solutions existantes dans la littérature. Une analyse critique de ces solutions nous a permis d'identifier leurs limitations et ainsi de former une plateforme de nouvelles propositions à améliorer dans les chapitres à suivre.

Le chapitre 3 propose une nouvelle approche de conception de WMN basée sur une optimisation à plusieurs objectifs. Vu que la plupart des solutions offertes dans la littérature pour l'optimisation du déploiement des WMNs se concentrent sur le coût d'installation du réseau comme unique objectif à optimiser, nous proposons une optimisation simultanée de deux objectifs d'importance égale qui sont le coût d'installation et la performance du réseau (le débit). Bien que la formulation de la fonction objectif coût de déploiement soit directe, la maximisation de la fonction performance (débit) peut être interprétée sous différentes perspectives. Nous proposons trois modèles bi-objectifs qui diffèrent principalement par l'approche utilisée pour maximiser la performance du réseau. Les modèles ainsi proposés sont soumis à des contraintes de connectivité, de capacité de liens et de couverture. Afin de résoudre les modèles pour des réseaux de taille réelle, nous avons développé un algorithme évolutionnaire dérivé de l'algorithme d'optimisation multi-objectif par essaim de particules (*Multi-objective Particle Swarm Optimization - MOPSO*) et des algorithmes génétiques (*Genetic Algorithms – GAs*). Après une étude comparative entre les trois modèles et à la lumière des résultats obtenus, l'opérateur du réseau peut donc décider quelle perspective adopter pour aboutir à des topologies de meilleure performance sous des restrictions budgétaires.

Dans le chapitre 4, nous introduisons la notion de contraintes de sauts (*hop constraints*) dans la conception du réseau. Ces contraintes sont très avantageuses pour limiter le délai de transmission. Dans cet article, nous nous soucions de déterminer les locations potentielles de passerelles sous les contraintes de connectivité, de limitation de délai et de budget d'installation du réseau. Nous proposons un algorithme de placement de passerelles qui consiste à subdiviser les nœuds du graphe modélisant le réseau en groupes (*clusters*), où chacun est desservi par une seule passerelle sans que cette dernière soit la racine d'une structure arborescente. L'algorithme développé a les caractéristiques/avantages suivants :

1- La position d'une passerelle candidate est choisie en tenant compte du rayon du groupe (*cluster*) et de la longueur du chemin entre cette position et tous les points d'accès appartenant à ce groupe.

2- Chaque nœud doit envoyer le trafic à la passerelle avoisinante (du même groupe), le passage à l'échelle du réseau est donc bien supporté.

3- Un nombre minimal de passerelles sont installées.

Dans le chapitre 5, une nouvelle technique est proposée pour concevoir des réseaux robustes qui continuent à être fonctionnels en cas de pannes. L'algorithme développé est basé sur l'approche théorique de décomposition en oreilles (*ear decomposition*). Le but de l'algorithme est d'installer le minimum nombre de routeurs additionnels qui garantissent le recouvrement du réseau suite à la panne d'un routeur à la fois et à n'importe quel moment.

Le chapitre 6 résume les contributions majeures de cette thèse et montre les futures directions de recherche.

1.4 Articles Publiés/Soumis durant cette Thèse

1. D. Benyamina, A. Hafid, M. Gendreau, "Throughput Gateways-congestion trade-off in Designing Multi-radio Wireless Networks", Accepted for publication in a *Special Issue of the Journal ACM/Springer Mobile Networks and Applications (ACM MONET)*, 2009.
2. D. Benyamina, A. Hafid, M. Gendreau, "On the Design of Bi-connected Wireless Mesh Network Infrastructure under QoS constraints", *IEEE GLOBECOM*, 2009, USA.
3. D. Benyamina, A. Hafid, M. Gendreau, "Optimal Placement of Gateways in Multi-hop Wireless Mesh Networks: A Clustering-based Approach, *IEEE LCN,* 2009*,* Switzerland.
4. D. Benyamina, A. Hafid, M. Gendreau, "Gateways Congestion-aware Design of Multi-radio Wireless Mesh Networks", *The Sixth International ICST Conference on Heterogeneous Networking for Quality, Reliability, Security and Robustness (QShine)*, 2009.
5. D. Benyamina, A. Hafid, M. Gendreau, N. Hallam, "Optimization Models for Planning Wireless Mesh Networks: A Comparative Study*", IEEE WCNC,* 2009, Budapest.
6. **D.** Benyamina, A. Hafid, M. Gendreau, "Design of Scalable and Efficient Multi-radio Wireless Mesh Networks", Submitted to the Journal of *ACM Wireless Networks*, 2009.
7. **D.** Benyamina, A. Hafid, N. Hallam. M. Gendreau, J-C Maureira, "A Particle Swarm Optimization for Wireless Mesh Networks Design", Submitted to *Elsevier journal of parallel & Distributed Computing*, 2009.
8. **D.** Benyamina, A. Hafid, M. Gendreau, J-C Maureira, "On Providing Reliability in Multi-radio Multi-channel Wireless Mesh Networks", Submitted to *Elsevier journal of Computer Networks*, 2009.
9. **D.** Benyamina, A. Hafid, M. Gendreau, "Wireless Mesh Networks Design – a Survey", Submitted to *IEEE communications surveys & tutorial*, 2009.

10. D. Benyamina, A. Hafid, N. Hallam, “On Optimizing the Planning of Multi-hop Wireless Networks Using a Multi-objective Evolutionary Approach”, *International journal of communications*, Volume 2, issue 4, pp. 213-221, 2008.
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12. D. Benyamina, A. Hafid, M. Gendreau, “Wireless Mesh Network Planning, A Multi-objective Optimization Approach”, *IEEE BROADNETS*, 2008, UK.
13. D. Benyamina, A. Hafid, M. Gendreau, N. Hallam, “Managing WMNs: Analysis and proposals”, *IEEE WIMOB,* 2007, USA.

Chapitre 2

Wireless Mesh network Design- a survey

D. Benyamina, A. Hafid, M. Gendreau

Abstract

With the advances in wireless technologies and the explosive growth of Internet, wireless networks, especially Wireless Mesh Networks (WMNs), are going through an important evolution. Designing efficient WMNs has become a major task for networks operators. Over the last few years, a plethora of studies has been carried out to improve the efficiency of wireless networks. However, only few studies are related to WMNs design and are mainly concerned with protocol design and routing metrics optimization. In this paper, we review different aspects of WMNs design and survey various methods that have been proposed either to improve the performance of an already deployed network or to improve its performance by a careful planning of its deployment.

Key Words: Wireless Mesh Network, performance improvement, Design problem, Multi-radio multi channel network.

Status: This article is submitted to *IEEE communications on surveys and tutorials*, 2009.

2.1 Introduction

With the proliferation of Internet, Wireless Mesh Networks (WMNs) have become a practical wireless solution for providing community broadband Internet access services. These networks exhibit characteristics that are novel in the wireless context, and in many ways more similar to traditional wired networks [HD06]. In Infrastructure WMNs, Access Points (APs) provide internet access to Mesh Clients (MCs) by forwarding aggregated traffic to Mesh Routers (MRs), known as relays, in a multi-hop fashion until a Mesh Gateway (MG) is reached. MGs act as bridges between the wireless infrastructure and the Internet. Figure 2.1 illustrates a typical WMN infrastructure. In such networks, it is possible to equip each infrastructure node with multiple radios, and each radio is capable of accessing multiple orthogonal channels, referred as Multi-Radio Multi-Channel (MR-MC) transmissions. Figure 2.2 depicts the case of multiple radios routers. In a MR-MC network, simultaneous communications are possible by using non-interfering channels, which have the potential of significantly increasing the network capacity [AB05], [BC05], [KN05], [ZH05].

WMNs can provide large coverage area, lower costs of backhaul connections, reduce end-user battery life, and more importantly provide NLOS (No Line Of Sight) connectivity among users without direct LOS links. Recent commercial and academic deployments of WMNs in real world are beginning to demonstrate some of these advantages. However, several challenges remain so that a WMN performance in terms of throughput and delays match the performance of a wired network. Furthermore, earlier deployments of WMNs have been linked to a number of problems mainly related to connectivity problems (such as lack of coverage, dead spots or obstructions) and performance problems (low throughput and/or high latency).

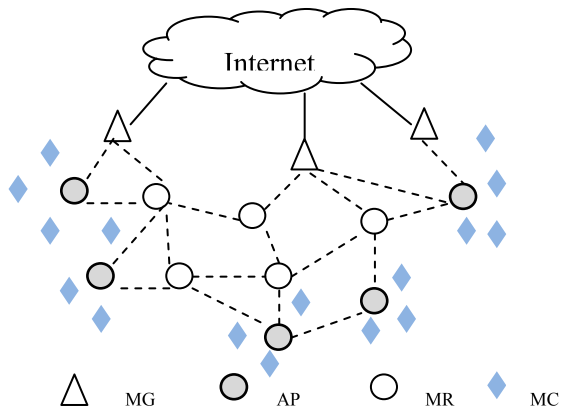


Figure 2.1: Wireless mesh network infrastructure.

Due to the scarce nature of wireless channel resources, network performance is highly impacted by wireless interference and congestion causing considerable frame losses and higher delays. Figure 2.3 depicts situations where some communicating nodes are within the interference range r_i. The most noticeable sources of performance degradation in WMNs (large co-channel, interference and inadequately configured client/AP) are mainly due to poorly planned wireless networks.

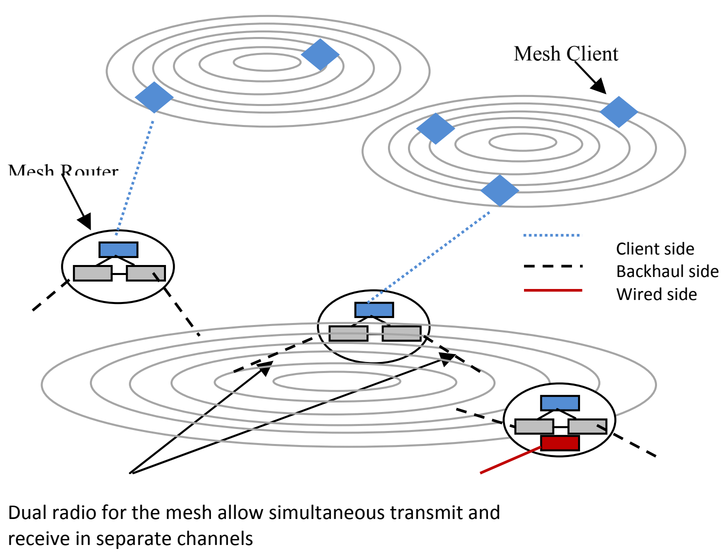


Figure 2.2: Multiples-radio Mesh Routers.

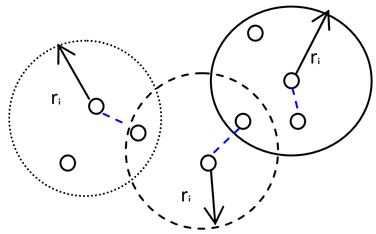


Figure 2.3: Simultaneous communications interfere with each other.

We believe that a well planned and optimized wireless network can often provide extra capacity with the same infrastructure cost; for instance, this may result in more efficient use of radio frequencies (considered as scarce resources).

Specifically, Topology-aware MAC and routing protocols can significantly improve the performance of WMNs. Also, to increase capacity and flexibility of wireless systems, approaches based on radio techniques have been proposed. The noteworthy being directional and smart antenna ([Ra01] and [SR03]), MIMO systems ([XP04] and [SS04]), and multi-radio/multi-channel systems ([SV04] and [AB04]). To date, many contributions in the context of WMNs performance improvement have been proposed. Depending on what and how to optimize, we can classify these contributions into two broad classes, namely *fixed-topologies* and *unfixed-topologies* (as shown in Figure 2.4). Fixed-topologies based approaches aim at better exploiting and utilizing the network resources; they improve the channel spatial or temporal reuse and/or routing protocols/metrics together with possible admission control mechanisms. However, they assume a given topology and require that the positions and the types of all nodes be decided beforehand. On the other hand, unfixed-topologies based approaches are subdivided into two groups. The first group (partial design) encompasses all approaches that attempt to optimize the network performance by optimally selecting the positions and types of each mesh node (either MR or MG) given a different set of pre-deployed nodes. The second group is more generic and uses more complex techniques to build a network from scratch; this necessitates the consideration of many factors prior to network deployment. Some of these factors are clients' coverage, optimal placements of gateways (for better throughput and less delay/congestion), and an optimal number of channels/radio per node.

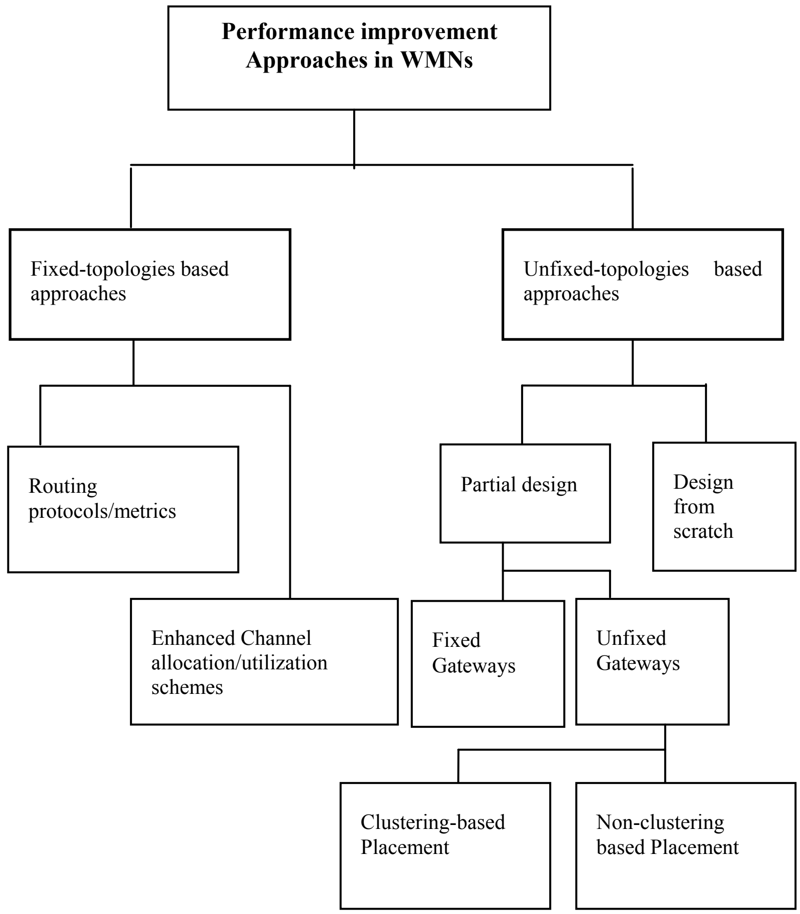


Figure 2.4: Approaches for WMN performance improvement.

The aim of this paper is to survey research studies related to performance optimization in WMNs according to the categorization shown in Figure 2.4. More specifically, we explore a representative set of approaches, for each category, and discuss the corresponding fundamental characteristics.

The rest of the paper is organized as follows. Section 2.2 is devoted to fixed-topologies based approaches, i.e., the network is *a priori* deployed. Section 2.3 presents partial deployment based approaches, i.e., either mesh routers or mesh gateways location/characteristics are not yet decided. Section 2.4 encompasses all research efforts related to optimal design of WMNs when all nodes location and network description are unknown (Design from scratch for total deployment). Section 2.5 discusses and presents potential/possible research avenues for the design of WMNs. Finally, Section 2.6 concludes the paper.

2.2 Fixed-topologies Based Approaches

In wireless networks, the network performance can be greatly improved by using multiple channels, as shown in [MR83] and [NZ04]. In such networks, a simultaneous transmission is possible as long as different/orthogonal channels are used. Moreover, the probability of packet collision can be reduced because of traffic mitigation in each channel. A number of MAC protocols have been proposed for multi-channel transmission systems ([SV04] and [GG00]) in ad-hoc networks. In this survey, we focus on multi-channel WMNs most widely adopted techniques.

In wireless networks, two neighboring nodes can communicate with each other only if they are assigned a common channel; therefore, the channel assignment may restrict possible routes between any pair of nodes in the network topology. Thus, the effectiveness of multichannel routing algorithms is closely related to the used channel assignment scheme. In the literature, many diverse studies have been proposed to address the problem of channel assignment and routing in multichannel WMNs. Raniwala et al. [RC05], propose a dynamic channel assignment and routing techniques in multi-channel WMNs. The channels are dynamically assigned through a distributed algorithm that utilizes only local traffic load information. This eliminates the need of a separate control interface and incorporates prioritized channel assignment to emulate a logical fat tree structure. It also supports fast failure recovery.

The authors use three routing metrics to determine the final tree structure (the cost metric is carried in the ADVERTISE messages). These are the *hop count*, the *gateway link capacity*, and the *Path capacity*. The *hop count* is the number of hops between a WMN node and the gateway node; however, this metric does not contribute in balancing network load. The *gateway link capacity* indicates the residual capacity of the uplink connecting the root gateway of a tree to the wired network. The *Path capacity* is more general than the other two metrics since the bottleneck of a path can be any constituent link on the path rather than always being the gateway link.

Draves et al. [DP04] propose a very interesting metric for routing in multi-radio multi-hop wireless networks. The goal of the metric is to choose a high-throughput path between a source and a destination. The metric WCETT (Weights Combination based on Expected Transmission Time) is defined as a combination of weights assigned to individual links based on the Expected Transmission Time (ETT), where ETT is a function of the loss rate and the bandwidth of the link. The authors in [DP04] conducted experiments and concluded that a path that is made up of hops on different channels is better than a path where all the hops are on the same channel (interference problem consequences). They show that unlike shortest paths, the benefits are actually limited to the cases of longer paths and heavily-loaded networks.

Alicherry et al. [AB05] propose a novel throughput optimization technique in Multi-radio WMNs. They mathematically formulate the joint channel assignment and routing problem taking into account interference constraints, the number of channels in the network and the number of radios available at each mesh router. The mathematical model is then used to develop a solution that optimizes the overall network throughput subject to fairness constraints on allocation of scarce wireless capacity among mobile clients. They used a linear program (LP) to find a flow that maximizes the throughput. The same LP is solved twice with different objective functions. The first objective function maximizes the portion λ of loads that are effectively satisfied at all nodes; the resulting optimal value λ^* is then used to minimize the second objective of link schedulability which is an intuitive measure of network total interference. The solution technique they use is nothing but an instance of the well-known aggregated objective technique. This is a classical technique to handle Multi-Objective Problems (MOPs). The major problem with the aggregate technique is its inability to find solutions in non-convex fronts as proved in [De02] and [DD97]. Basically, when the landscape of the single objective, resulting from aggregating two or more objectives, is not convex then the image of the solutions located on those concave regions might very well be overlooked (see Figure 2.5 for a minimization case of two objectives). Moreover, the setting of the relative weights for the different objectives is very subjective and often leads to favoring some and penalizing others.

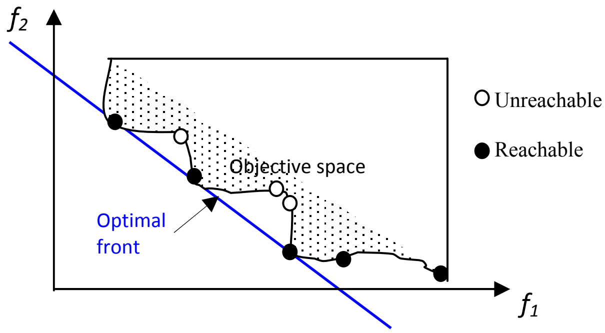


Figure 2.5: Image of the solutions located on the concave regions might be overlooked.

To improve the performance of WMNs, Interference should be taken into account; indeed, it is the foremost factor that degrades the performance of a wireless network. In [JP03], Jain et al. conducted a thorough study to show the impact of interference on multi-hop wireless network. Besides collisions, they found that frame loss is another end-result of channels interference. Frame loss may occur due to the accumulative interference resulting from nodes lying outside the silence range of the transmitter. The silence set of a transmitter *A* is the set of nodes that will detect the channel to be busy if *A* transmits [YH07].

Even though several interference models exist ([HM02], [Le86] and, [ZB07]), Xu et al.[XY08] suggest the use of a channel-bonding technique to realize a high-data-rate packet transmission by using a broadened channel; the simulation results indicate that when the traffic is low, the channel-bonding technique can achieve lower delay compared to multi-channel technique. While under high-traffic conditions, the multi-channel technique can greatly mitigate the influence of packet collisions, and thus improve the network performance.

Various are the methods proposed in order to enhance the channel utilization by improving the spatial reuse. A comprehensive survey for improving spatial reuse in multi-hop wireless networks is provided in [AZ09].

Most of the current protocol optimization techniques, applied to achieve a better WMN performance, are layer based protocols for which *layering as optimization decomposition* is applied. The key idea of "*layering as optimization decomposition*" is to decompose the optimization problem into sub-problems, each corresponding to a protocol layer and functions of primal or Lagrange dual variables [CL07]. Coordinating these sub-problems correspond to the interfaces between layers.

Yet, *cross layer design* is one of the most important tasks in protocol design for WMNs for performance optimization. However, it comes with risks due to several factors such as: the loss of protocol-layer abstraction, incompatibility with existing protocols, unforeseen impact on the future design of the network, and last but not least difficulties in maintenance and management. A good survey on cross-layer design in WMNs can be found in [AW08].

In addition to performance enhancement schemes (as seen above), there are some studies that are related to network topology control design. The main goal of the topology control is to identify a subset of possible wireless links that provide connectivity for wireless networks, with certain design criteria including power consumption [RR00], interference [BW04], broadcast [DW06], and quality-of-service (QoS) [JL04]. In particular, Lu et al. [LZ08] propose a topology control scheme such that the overall throughput can be maximized by taking into account traffic patterns in the network. The main idea of the proposed scheme is to establish multiple *wireless highways*, on both the horizontal direction and the vertical direction. Moreover, on the same direction, multiple highways can operate simultaneously, without interfering with each other. To demonstrate the merits of the proposed framework, authors also present scheduling schemes based on network coding and physical-layer network coding

Other studies, which could be classified as fixed topology design schemes, deal with the construction of networks' virtual backbones ([SK06] and [WT09]). The main objective of virtual backbone construction is to alleviate the Broadcasting Storm Problem (BSP) by reducing the communication overhead and simplifying the connectivity management. Thus, with virtual backbones, routing messages are only exchanged between the backbone nodes, instead of being broadcasted to all the nodes. The problem of finding a virtual backbone is an instance of the problem of finding a Connected Dominated Set (CDS). A simplest approach of selecting the backbone nodes is to find a minimum CDS at first then construct the spanning forest and finally create the spanning tree, which connects the entire graph.

Most of the approaches discussed in this section aim to enhance the performance of a multichannel WMN by solving one or many of the above issues, e.g. routing metric, channel assignment, routing protocol and, interference. Even though these approaches exhibit a significant diversity; they possess a considerable similarity in a sense that they address issues that are inevitably related to each other. The routing metrics serve as the basis for routing and significantly influence network performance, whereas, a different metric (e.g., hop-count, channel diversity, traffic load) leads to implement a different routing protocol. Although there is an increasing number of routing metrics, a consensus has not yet been decided. Most of actual routing protocols implementations, generally, prefer metrics with simpler designs as those in [RC05] and [DP04]. Channel assignment and routing are mutually dependent to the extent that a well designed routing algorithm for multichannel WMNs may become useless with an improper channel assignment. With respect to interferences, link scheduling guarantees free-interference communications by scheduling the links sharing the same channel within the interference range to use different time slots. Thus, the link scheduling problem is solved after the routes are defined and channels are assigned accordingly.

Though these approaches combine some or all of the above issues, which are formally converted to NP-hard formulations, they differ in the solution approach adopted to solve the problem and the QoS constraints to satisfy. A subset of these approaches model the multichannel WMN by a flow network and propose heuristics to solve their optimization models, mainly based on greedy searches. Some of them rely only on local information to quickly adapt to network dynamics (distributed approach), however, the results obtained may be far from optimality because of the partial nature of the information they rely on. While others use the entire network information (centralized approach) but assume a static traffic pattern. Notice that this kind of approaches can effectively lead to optimal or near optimal solutions since global network information is available, though, they are not applicable during network operation (do not support network changes.

Additionally, the performance improvement based schemes surveyed in this section are aimed at selecting the best routing metric to route the traffic with higher throughput or to better utilize/allocate the channels in order to minimize packets collisions and loss.

Nevertheless, all these contributions assume, in a way or another, a priori fixed topologies with the positions and types of nodes known in advance.

2.3 Partial design of WMN topologies

Another way to achieve a better network performance is to optimize the placement and characteristics of either APs or gateways before network deployment. A wise placement of gateways, may lead to less congestion, low delay and eventually better throughput if the distances AP-MG and the links capacity are taken into account. Additionally, with optimal placement of APs for a required coverage, the network setup becomes more flexible in case of addition of news APs. We classify partial design schemes into two classes, namely fixed-gateways ([SR07] and [CC07]) and unfixed-gateways ([AB06], [CQ04], [HW08], [HX07], [LB01] and [RU08]).

2.3.1 Fixed gateways

In fixed gateways approaches, the WMN design problem is viewed as the problem of looking for strategic locations to optimally place the APs and/or MRs given a set of positioned gateways and a set of connectivity, geographic coverage and financial constraints to satisfy.

Sen et al. [SR07] propose a planning solution for rural area networks to provide a set of villages with network connectivity from a given landline node (a positioned gateway). The authors study the optimization problem as minimization of the total cost affected by the multi-hop network topology and the antenna tower heights under the constraints of throughput, power, and interference. The problem is broken down into four sub-problems: topology search, optimum height assignment, antenna assignment, and power assignment sub-problems. For each sub-problem, they provide a formulation and apply a different solution technique.

In [CC07], authors consider the deployment plan for mesh routers that are equipped with directional antennas to form the mesh backbone (an urban WMN is considered). They assume that the placement of gateways is already given. The goal is to maximize the deployment profit (profit representing the amount of services a location can provide if it is deployed with a router) and maintain the cost within the budget while providing sufficient accessibility (connectivity) and guaranteeing a robust backbone. They propose a greedy-based algorithm to solve the optimization problem, however, the power/channel assignment problem is not considered.

2.3.3 Unfixed gateways

Due to the impact of MGs placement on network performance and network scalability handling, there has been a recent surge of interest in optimal placement of gateways in WMNs. Some of the key studies can be found in [AB06], [CQ04], [HW08], [HX07], [LB01], and [RU08]. Network scalability is greatly influenced by the way gateways are placed. If network nodes are divided into groups/clusters and gateways locations are set so that each cluster is served by one gateway, the problems of gateways placement and network scalability could be effectively solved both at once, as shown in [AB06] and [LW07]. We categorize gateways placement schemes into clustering-based placement and non-clustering based placement classes.

2.3.3.1 Clustering-based placement

Placing gateways based on a clustering approach has a number of benefits [LW07], including more importantly, the tight relationship between the resulting gateways placement and network throughput. When the network is partitioned into clusters, then independently of the network size, each node can send to nearby gateways within a fixed radius. Consequently, all nodes in a cluster have a bounded distance (in terms of number of hops) to reach a gateway and therefore a substantial increase in network throughput can be expected. The studies in this sub-category are, in their turn, subdivided into tree-based and non-tree based approaches, depending on whether the placed gateways are following a tree-structure or not.

Tree-based clustering

The studies in [AB06] and [CQ04] make use of different clustering techniques to optimally place gateways in WMN infrastructure. The clusters generated in these studies, are represented by trees rooted by gateways. Although, these techniques have a number of benefits (e.g., low routing overhead and efficient flow aggregation), they suffer from the well-known problem in tree-based structure, namely reliability degradation – theoretically, a tree topology uses a smaller number of links. Furthermore, as shown in [HW08], topologies restricted to tree structures, under the link capacity constraint, may require larger number of gateways and thus may increase the network deployment cost. Figure 2.6 shows how a tree-based topology tends to deploy more gateways than a mesh topology (2 MGs Vs. 1 MG). Every potential link (a dashed line) is associated to a capacity link (the value between brackets) and a traffic demand is associated to every node.

The gateway placement technique proposed in [AB06] consists of placing a minimum number of gateways, such that the three constraints of throughput, power and interference are satisfied. The technique consists of using a polynomial time algorithm to divide the WMN into clusters of bounded radius under relay load and cluster size constraints. Nonetheless, they assume that routers are already placed to construct a cluster served by a designated gateway.

Chandra et al. [CQ04] address the problem of minimizing the number of gateways while satisfying the traffic demands using a network flow model. They formulate the problem in the context of community mesh networks where the mesh routers (installed in clients houses) are fixed, leaving only the placement of gateways to be decided. The main drawback of the iterative greedy approach they apply is the unbalanced load of the gateways; indeed, new gateways are placed whenever existing ones are fully loaded.

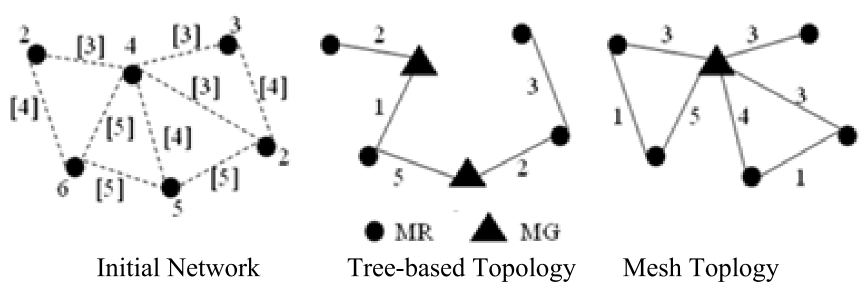


Figure 2.6: Impact of network topology in gateways deployment.

Non-tree based clustering

To the best knowledge of authors, the sole contribution that proposes a non-tree clustering scheme for the gateways placement problem is reported in [HW08]. Hsu et al. [HW08] model the gateway placement problem as a combinatorial optimization problem. They propose two algorithms namely, Self-Constituted Gateway Algorithm (SCGA) and Predefined Gateway Set Algorithm (PGSA). Both algorithms make use of a genetic search algorithm to search for feasible configurations coupled with a modified version of Dijkstra algorithm to look for paths with bounded delays. In PGSA, the number of gateways (initially set to one) is iteratively incremented by one until a feasible configuration is obtained. On the other hand, the number of gateways in SCGA is set up dynamically when needed. The design problem solved by both search algorithms does not consider bounded delay in terms of communication hops. Instead, it is seen as the ratio packet size over link capacity.

It is worth noting that the network partitioning problem (clustering) is not an NP-hard problem; it requires a simple methodology as a solution. However, when adapted to the characteristics of WMNs, the clustering solution becomes more difficult to implement because of the capacity and connectivity constraints and QoS requirements if considered. Thus, heuristics/approximation methods are needed to solve the non-tree based clustering gateways placement problem.

2.3.3.2 Non-clustering based placement

Robinson et al [RU08] study the gateway placement problem as facility location and k-median problems. They propose two local search algorithms (*minhopcount*, *mincontention*) with different approaches to estimate the unknown gateways capacities. In the "*minhopcount*" algorithm, the gateway placement problem is regarded as a facility location problem; while in the "*mincontention*" solution, the gateway placement problem is interpreted as a k-median problem, however, the authors in their study, focus only on a single-radio, single-channel architecture.

Li et al. [LW07] studied the gateway placement for throughput optimization in WMNs using a grid-based deployment scheme. More specifically, given a mesh infrastructure and a number of gateways to place, the authors investigate how to place the gateways in the mesh infrastructure in order to achieve optimal throughput. They first formulate mathematically the throughput optimization problem for a fixed mesh network and propose an interference-free scheduling method to maximize the throughput. The basic idea behind the proposed solution is to sort the links based on some specific order and then process the requirement for each link in a greedy manner. Then, they use their solution as an evaluation tool to decide on the optimal gateways placement scheme. The proposed approach to place exactly *k* gateways has achieved better throughput in the grid scheme than in random and fixed schemes [LW07].

2.4 Design of WMN Topologies from Scratch

A proper WMN design is a fundamental task. If addressed carefully, it can considerably improve the network efficiency in terms of coverage, throughput, delay and cost.

There have been plenty of planning network solutions developed for Cellular Networks (CNs) and WLANs, and one would be tempted to tailor these solutions to WMNs. However, these planning solutions cannot possibly be applied to planning WMNs. Network planning in CNs is almost entirely driven by geographical coverage. More precisely, the positions/configurations of wireless transceivers, which are also gateways towards the wired backbone, depend only on local connectivity constraints between end-users and the closest network device [AC08]. In WLANs, wireless communications are one-hop length whereas in WMNs end-users' traffic is forwarded in multi-hop fashion, starting from APs, jumping from one MR to another MR via point-to-point wireless link until a gateway is reached. WMNs present unique characteristics, thus, new design solutions specially tailored for WMNs are required.

A good planning task of a WMN essentially involves a careful choice of the installation' locations, an optimal selection of the types of network nodes, and a good decision on a judicious channel/node interface assignment, while guaranteeing users coverage, wireless connectivity and traffic flows at a minimum cost. In optimization terms, this is translated into determining: an optimal number of wireless routers required to cover the area under consideration, an optimal number of gateways for efficient integration of WMNs with

Internet, an optimal initial channel assignment, and an optimal number of wireless interfaces per router, while taking into account all physical and financial constraints of the network provider. In what follows, we survey the attempts made for solving the WMNs design problem. The solutions proposed are divided into two different classes of optimization approaches: *single-objective* optimization and *multi-objective* optimization.

Amaldi et al. [AC08] construct and formulate the planning model of WMNs as an ILP problem based on user-coverage satisfaction. But, QoS requirements, such as delay and throughput are not considered. The system is solved using a heuristic optimizer based on greedy selection. Beljadid et al. [BH07] propose a unified model for WMN design formulated as an ILP problem. The objective is to minimize the total installation cost by tuning all the network parameters; they consider the delay as a constraint. Some noteworthy drawbacks are: (1) Users' coverage is not considered in the model; and (2) the problem is solved for small size instance networks because of the exponential number of constraints and variables.

WMN design problems in [AC08] and [BH07] belong to the set of problems that can be stated as an optimization problem over a cost function (*single-objective* optimization). In such problems, we are given a cost function f: $X \rightarrow Y$ where Y is totally ordered. Let F be the set of such mappings. Given f, the problem is to find the set of $x^* \in X$ which minimizes f.

However, when planning for cost-effective networks, the deployment cost is necessarily not the sole objective to optimize. In such networks, the quality can be constrained by multiple criteria such as the signal level received by the mesh clients, the performance quality in terms of throughput or delay and the installation cost. When considering the optimization of many criteria at the same time, the objective functions are to be optimized simultaneously within the same problem formulation (multi-objective optimization problem formulation). However, it is impossible to optimize all the objectives, usually conflicting with each other, at once. In such situations, one would be content with solutions that "trade-off" the conflicting objectives. There are two ways to deal with this kind of optimization problems. Either aggregate the conflicting objectives into a single, usually, weighted objective or apply a Pareto based optimization approach. We refer to the first approach as *aggregated multi-objective* approach and the second one as *pure multi-objective* approach.

The approaches applied in [KN05] and [VH06] are instances of the aggregated multi-objective approach. The main drawback of this approach is the difficulty to set the weights when the *a priori* knowledge is not trivial. In this case, the cooperation of the optimizer and the designer is a must. Moreover, as stated in Section 2.2, this technique is unable to generate proper Pareto-optimal solutions found in the presence of non-convex search spaces.

Kodialam et al. [KN05] show that the design of WMNs is by nature a multi-objective optimization problem where multiple design criteria need to be taken into account. They proposed two link channel assignment schemes based on a linear programming formulation. Their proposal allows optimizing only a single objective function at a time. The optimization technique applied is a special instance of the aggregated multi-objective approach called a lexicographic ordering technique.

Vanhatupa et al. [VH06] propose a model to estimate the performance of a WMN based on a set of parameters that describe the network and its configuration. The output of the performance model is *seven metric*s to estimate individual physical characteristic of the WMN performance. The model also provides a weighted combination of the metrics for a simultaneous use of multiple evaluation criteria in WMN optimization.

In the context of pure multi-objective optimization, Benyamina et al. [BH08a] propose a multi-objective formulation for the WMN design problem. Two conflicting objectives of deployment cost and network throughput are to be optimized simultaneously while guaranteeing full coverage to mesh clients. The throughput function is maximized by computing the utilization ratio of all links carrying flows; formally, it is specified as follows;

$$\max \sum_{j\in L}\sum_{l\in L}\sum_{q\in C}\frac{f_{jl}^{q}}{u_{jl}} \tag{2.1}$$

f^q_{jl} denotes the traffic flow routed from node j to node l using channel q. u_{jl} is the traffic capacity of the wireless link (j,l). However, with such formulation, the throughput is not calculated properly since we may have a higher value of throughput corresponding to longer paths, which in reality does not reflect the true throughput value. The above formulation is enhanced and two other bi-objective models are proposed by the same authors in [BH08b] and [BH09a] with a comprehensive comparative study presented in [BH09a]. The models in [BH08a] and [BH08b] are solved using a nature inspired meta-heuristic algorithm. A set of good “trade-off” solutions for real-sized networks is provided to network operators where each solution can be used in a different decision making scenario.

Another category of studies focuses on network topology layout to select for a total design in order to achieve better performance. Robinson et al. [RK07] studied the performance of deployment factors in WMNs where the benefits of adopting grid topologies over other topologies are shown. The authors considered three regular tessellations as their baseline grid topology: triangular, square and hexagonal tessellation (see Figure 2.7). To study which topology factors strongly influence mesh performance, they used three performance metrics: client coverage area, backhaul tier connectivity, and fair mesh capacity.

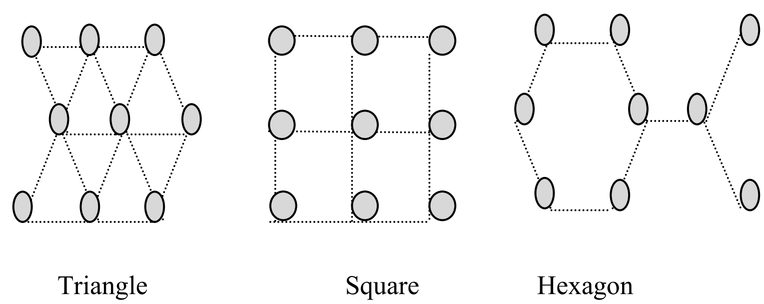


Figure 2.7: Triangle, square and hexagonal tessellations for mesh nodes placement.

The study in [RK07] did show that the hexagonal grid topology results in more uncovered spots than a square or triangular grid and therefore requires twice the node density to achieve worst-case coverage guarantees, resulting in more expensive topologies. Regarding backhaul tier connectivity, the connectivity in regular grid based topologies outperforms the random topologies for networks with high density. Finally, the average fair capacity in a random network is less than half the fair mesh capacity in a grid topology.

2.5 Discussions and Future Directions

Most of protocol optimization techniques (see Section 2.2) apply *layering as optimization decomposition technique* to improve the performance of WMNs. However, up to date, there has been no documented study analyzing the optimality of the layering technique.

The network global optimization problem can be formulated as a general network utility maximization problem [CL07]:

$$\begin{aligned} \text{maximize} \quad & \sum_s U_s(x_s, P_{e,s}) + \sum_j V_j(w_j) \\ \text{subject to} \quad & \mathbf{Rx} \le \mathbf{c}(\mathbf{w}, \mathbf{P}_\mathrm{e}) \\ & \mathrm{x} \in \mathcal{C}_1(\mathbf{P}_\mathrm{e}),\ \mathrm{x} \in \mathcal{C}_2(\mathbf{F}),\ \text{or } \mathrm{x} \in \boldsymbol{I} \\ & \mathbf{R} \in \mathcal{R},\ \mathbf{F} \in F,\ \mathbf{w} \in \mathcal{W} \end{aligned}$$

In this formulation, the user utility function U(.) and resources V_j(.) are maximized. x_s and w_j denote the rate of source s and the physical layer resources at network element j, respectively. **R** is a routing matrix, and **x** denotes the link capacity as a function of physical layer resource **w** and the desired error probability $\mathbf{P}_\mathrm{e}$ after decoding. The function **c** captures all physical layer factors, such as interference, power control, etc. The first constraint represents the behavior perceived at the routing layer. The function C_1(.) captures the coding and error-control mechanisms versus the rate, while function C_2(.) and $\boldsymbol{I}$ capture the contention-based MAC and scheduling based MAC, respectively.

More specifically, in this formulation, network performance has to be optimized at the transport layer which is subject to routing, MAC, and physical layers constraints. In that way, we can see that *layering as optimization decomposition* involves many other layers to perform optimization at a specific layer. MAC, routing and transport layer have to collaborate among themselves and work together with the physical layer to provide optimal performance for WMNs. Authors in [AW08] argue that *layering as optimization decomposition* technique does not eliminate the need for cross-layer optimization, moreover, the specific features pertained by WMNs also illustrate the need of cross-layer. Actually, cross-layer optimization schemes are supposed to be more accurate and optimal than their counterpart the conventional layered optimization schemes; however, strict guidelines need to be followed [AW09] in order to minimize the risks that come with the cross-layer design. However, a clear understanding of the relationship between WMNs capacity and the factors impacting this capacity e.g., network architectures, network topologies, traffic patterns, network node densities, number of channels used in each node interface, transmission power level, and nodes' mobility may provide guidelines for protocol development, architecture design, and deployment, and finally, operation of the network.

Another category of alternative performance improvement schemes focus on the optimization of the location of some mesh nodes so that QoS requirements are met. More, specifically, the studies in [SR07] and [CC07] attempt to plan for the deployment of WMNs by fixing the gateways positions and equipping routers with directional antennas. Although many proposals in the literature did show the benefits of using directional antennas, related research has been suspended in many research institutes (see Alaweih et al. in [AZ09]). The main reason is that directional antennas require line of sight (LOS) environments while relevant applications that can provide high LOS components can be hardly found.

Selecting strategic locations to optimally place gateways prior to network deployment in WMNs can alleviate a number of performance related problems; it can also lead to better handling of network scalability. Existing solutions that address the optimal gateway placement problem can be found in [AB06], [CQ04], [HW08], [HX07], [LB01] and [RU08]. They differ mainly in terms of the set of constraints that the placed gateways have to satisfy; thus, the resulting placements influence differently the network quality of service (QoS). Basically, the placement of mesh gateways determines the hop-length of the communication paths in the network, the amount of congestion, and the available bandwidth to and from the Internet.

A new clustering-based approach for optimal placement of gateways is proposed in [BH09b]. The aim of the approach is to attain three objectives: (1) Constructing clusters in a way such that every gateway is reachable within *h* hops; (2) Forcing each node to send traffic to its nearby gateway (scalability handling); and (3) deploying the minimum number of MGs without sacrificing the performance.

Even though there have been considerable research efforts in optimizing the gateway placement problem, we believe it would be interesting to pair these algorithms with complementary techniques addressing other criteria, such as optimal placement of APs and/or MRs, in order to improve network performance. The models proposed in [AC08] and [BH07] take into account these criteria; however, their approaches for optimal WMNs planning do consider the deployment cost as the sole concept to optimize -subject to many constraints to satisfy.

A wireless network operator (as service provider) has multiple objectives when designing WMN deployment. Providing predictable QoS to the user should also be considered as a key objective aside the deployment cost, in addition to the service area, the number of users and the resource utilization. In the other side, it seems logical to overestimate the number of mesh nodes (routers, gateways) to avoid lack of coverage and to increase throughput. However, this choice strongly impacts the complexity of the channel assignment problem and provides high interference levels, worsening final network performance.

Essentially, it can be argued that a WMN planning problem is an optimization problem where the two most important objectives are the deployment cost (to minimize) and the network performance (to maximize). Minimizing the deployment cost is mainly achieved by deploying less network devices (routers/gateways); however, this may cause longer traffic delays and bottlenecks, which undermine the network performance. Similarly, maximizing network performance can be achieved by strategically placing extra network devices, which fattens the deployment cost budget. This shows that objectives in a multi-objective optimization problem (MOP) do conflict with each other in the sense that an increase in one objective dimension undermines another objective. This clearly plays in favor of adopting heuristic multi-objective optimizers as they are the best methods to return a spectrum of trade-off solutions.

The nature of a MOP lies in the decision making process that involves various decision variables and optimizing a number of objective functions. The challenge in solving a MOP relies on the ability to search for attractive points—by simultaneously optimizing all the objectives. Hence, solutions of the problem will be the best trade-offs between these multiple objectives. In a general form of a minimization case of objectives, the multi-objective optimization problem can be formulated as Minimize $y = f(x) = [f_1(x),\ f_2(x), \ldots, f_N(x)] \in Y$

where, $x = [x_1, x_2, \ldots, x_D] \in X$. Note that WMN design problem being a constrained problem, the decision variables $x_i = [x_{i1}, x_{i2}, \ldots, x_{iD}]$ are subject to a set of constraints. Every decision variable vector x_i in the decision space X is evaluated through the objective functions. The objectives values are then represented as points in the objective value space Y. Relationships between X and Y are illustrated in Figure 2.8.

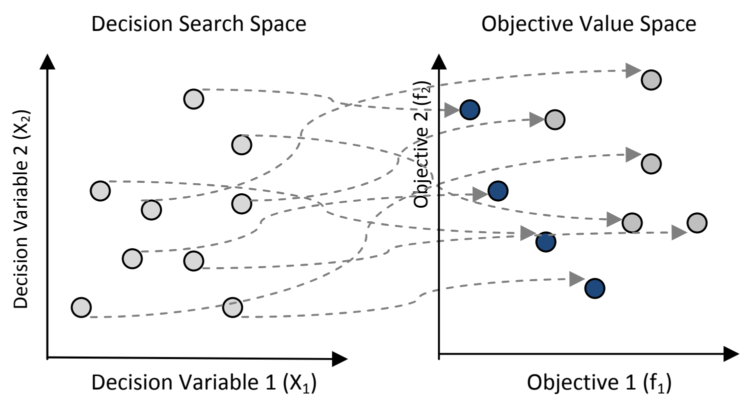
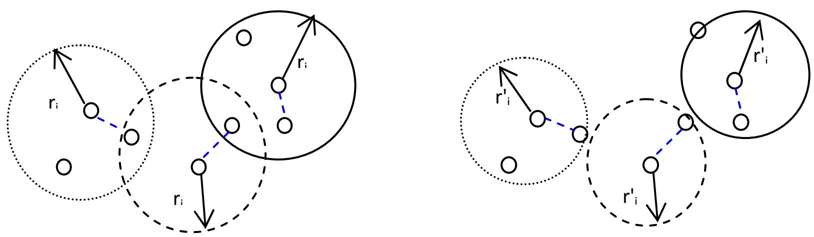


Figure 2.8: Illustration of Decision Search Space and Objective Value Space.

In a wireless multi-hop network, the network capacity, usually represented by throughput, is not the only concern for users. In fact, QoS is equally important. Usually QoS metrics include delay, delay jitter, and packet loss ratio. In order to increase the network capacity, authors in [AW09] suggest two rules to follow: (1) reducing the number of hops that a packet shall travel; and (2) reducing the interference range of transmissions. However, scheduling schemes that satisfy these rules usually improve throughput but increase delay. Thus, it seems interesting to perform resources-throughput and/or throughput-delay tradeoffs when designing efficient WMNs. This requires additional research to devise generic multi-objective optimization framework that captures and reflects the essence of the true nature of WMNs planning problems.

Rate adaptation is another important factor in improving network performance that should be considered when designing WMNs. In [BZ04], [CB04], [TC05], [QC01], and [QC02] analytical models were presented to investigate the goodput under rate adaptation for 802.11a-based WLANs. The basic idea is to select appropriate transmission rates according to the channel condition. With a good channel condition, the network efficiency (throughput) could be improved by using higher rates.



(a) (b)

Figure 2.9: Impact of rate adaptation on simultaneous communications, (a): transmissions occurring in the same time are interfering with each other. (b): successful simultaneous communications after changing transmission rate from r_i to r'_i ($r_i > r'_i$).

Conversely, in the presence of channel impairments, transmission reliability may be improved by lowering the transmission rate. Moreover, lowering this rate reduces the size of interference range, thus allowing more concurrent transmissions to coexist without corrupting each other (see Figure 2.9). Surprisingly, with the exception of the studies in [AC08] and [BH07], there has been little interest in the literature that considers rate adaptation while designing WMNs. Authors in [AC08] and [BH07] propose rate adaptation models to formulate WMN design problem; however, they did not take into account, in the proposed model formulations other essential design criteria (see Table 2.1).

Another fundamental criterion in networking study is network reliability, translated as the availability of communications paths between network pairs in the presence of nodes failure. The reliability and deployment cost are important and are largely determined by network topology. One could argue that adding redundant network components increases the reliability of a network; however, this also increases the cost substantially. To the best knowledge of the authors, the only work that integrates network reliability in the design of

WMNs is presented in [BH08c] and [BH09c]. Beljadid et al. [BH08c] define a reliability cost function that allows maximizing the reliability of the whole WMN. The approach is based on iterative policy that is performed endlessly until a reliable and satisfactory (cost-effective) solution is found.

It must be noted however, that in constraint optimization problem (e.g., WMN design problem) it is already costly and very hard to compute a good feasible solution; so when looking only for reliable solutions, the "iterative" optimization process becomes much over-burden. Moreover, the reliability of the network has to be jointly considered with network QoS requirements while designing WMNs. It is therefore essential to devise a converging algorithm that constructs reliable WMNs.

Table 2.1: List of Different WMN design characteristics

Code	***Design aspect***
Topl_F	Topology is fixed a priori (layered/cross- layer design)
MG_F	Only gateways have fixed positions (planning problem, partial deployment)
MR_F	Only mesh routers have fixed positions (planning problem, partial deployment)
Scrat.	All mesh nodes positions/characteristics are not decided (network design, deployment from scratch)
Cov	Full coverage of mesh clients criteria
QoS	QoS constraints (throughput/ delay/hop counts/congestion) satisfaction
Interf	Interference model application
RA	Rate adaptation
Rsize	Design problem solved for real-sized networks
MO	Multi-objective optimization
RC	Reliability consideration
OpRC	Optimal reliability scheme application
Clust	Design based on a clustering approach
OpClust	Clusters are free from a tree-structure
SqGrid	Square-grid layout deployment

Table 2.2: Features of references related to performance improvement in WMNs.

References	***Design category***	***Design aspects***										
		Cov	***QoS***	***Interf***	**RA**	***Rsize***	***MO***	***RC***	***OpRC***	***Clust***	***OpClust***	***SqGrid***
[AB05], [RC05], [DP04], [JP03],	**Top_F**	**S**	+	**S**	-	**S**	-	**S**	-	**NA**	**NA**	-
[SR07]-[CC07]	**MG_F**	+	-	+	-	-	-	+	-	**NA**	**NA**	-
[AB06], [CQ04]	**MR_F**	-	+	+	-	-	-	+	-	+	-	-
[RU08], [LW07]	**MR_F**	-	+	+	-	+	-	-	-	-	-	**S**
[HW08]	**MR_F**	-	+	+	-	+	-	+	-	+	+	-
[AC08]	**Scrat.**	+	-	+	+	+	-	-	-	-	-	-
[BH07]	**Scart.**	-	+	-	+	-	-	-	-	-	-	-
[BH08a], [BH08b], [BH09a]	**Scrat.**	+	+	+	-	+	+	-	-	-	-	+
[BH09b]	**Scrat.**	+	+	+	-	+	+	-	-	+	+	+
[BH08c]	**Scrat.**	-	+	-	+	-	-	+	-	-	-	-
[BH09c]	**Scrat.**	+	+	+	-	+	+	+	+	-	-	+

Authors in [BH09c] propose a novel algorithm to construct a bi-connected WMN infrastructure based on *Ear decomposition* theoretical approach. An interesting new direction of research is to consider the construction of reliable networks at the same time when designing cost-effective WMNs.

To compare existing design solutions, we determine/identify from the previous sections, the key design aspects, shown in Table 2.1. Then we assess the most representative contributions surveyed in this paper against these aspects; the result of this assessment process is shown in Table 2.2.

In Table 2.2, if an approach satisfies/dissatisfies a design aspect (property), the corresponding table entry is marked with +/- respectively. If an aspect or a property cannot be applied, then the corresponding entry is marked by “NA” (Not Applicable). For example, The “Clust” entry for approaches that use a clustering approach to place gateways is marked by NA for all studies that have gateways position already fixed. We also mark by “S” entries where the property holds only for some of the studies to be assessed at the same time (a group of contributions).

Table 2.2 provides valuable information for new ideas to investigate/exploit when designing WMNs. Notice that most of the design aspects are not applicable in fixed and partial design topologies, because of the nature of the topology under study; however, still other applicable aspects that may ameliorate the actual performance of the network are not yet fully utilized. For instance, rate adaptation, multi-objective optimization and grid layout deployment did get little interest from current performance improvement research. Thus more studies/investigations are needed to explore the use of these aspects to improve WMNs performance. Notice also that the design of topologies from scratch provides more open slots of possible design aspects to be applied, nevertheless, none of the surveyed approaches in this category, considers all these aspects at the same time. More specifically, non-tree clustering based gateways placement, multi-objective optimization, rate adaptation, grid layout deployment and, efficient reliability consideration receive very limited attention from existing approaches. To conclude, we believe that network planning/design optimization will continue to be a challenging research topic for WMNs.

2.6 Conclusions

This study surveys the most relevant research contributions in the open literature dealing with performance improvement of WMNs. We define a taxonomy in which we classify and survey these contributions by carefully reviewing their strengths and weaknesses.

The *fixed topology* category includes all approaches where the positions and the types of all mesh nodes are decided beforehand. In the *unfixed topology* category, approaches are further categorized into two sub-classes, *partial design* (some mesh nodes are setup a priori) and *design from scratch* (positions and types of all mesh nodes are unknown). In the *partial design* category, WMNs can be deployed around a set of a priori fixed MGs (*fixed gateways* subcategory) or find the optimal MGs locations based on a set of a priori fixed APs and MRs (*unfixed gateways* subcategory), which is more scalable if a clustering approach is applied.

In the *design from scratch* category, all mesh nodes are unknown and the WMN deployment is to find the type and location of each mesh node. This is more generic than all the preceding categories. All related studies use an optimization algorithm to determine the best type selection and location of the mesh nodes taking into account network QoS constraints. Most of the surveyed work in this category optimizes the deployment cost of a single-objective problem formulation; only very few adopt a multi-objective approach to optimizing the WMNs planning problem either using an aggregated or Pareto dominance based optimization policy.

If we confide to Table 2.1 and 2.2, there are many challenges and research opportunities in optimizing WMNs planning problem. While layered protocols and cross-layer design have been successfully applied for many applications, we believe that network efficiency could be achieved at its higher level if efficient planning/design of the network resources characteristics is performed prior to any deployment. More specifically, design decisions involving trade-offs greatly impact the quality of the planned networks.

Chapitre 3

A Particle Swarm Optimization for Wireless Mesh Networks Design

D. Benyamina, A. Hafid, N. Hallam, M. Gendreau, J. C. Maureira

Abstract

Existing approaches for optimal planning of Wireless Mesh Networks (WMNs) deployment revolves around the deployment cost as the pivotal concept to optimize. In this paper, we adopt a new approach to optimize the planning of WMNs that guarantees an acceptable level of network performance prior to its deployment. It is a simultaneous optimization process of network deployment cost and network throughput objectives while taking into account all the parameters that have a significant impact on the network efficiency. We propose three multi-objective models for WMN planning problem, namely Load-Balanced model, Interference model, and Flow-Capacity model. We devise an evolutionary swarm-based algorithm that is a hybrid combination of Multi-Objective Particle Swarm Optimization (MOPSO) and Genetic Algorithms (GAs) to solve the three models. We use realistic network sizes (up to 100 mesh nodes) to perform a thorough comparative experimental study on these three instance models with different key-parameter settings. Finally, we use the network simulator OMNET++ to evaluate the three models in terms of the actual performance (network throughput). The results presented in this paper show that Load-Balanced Model totally supersedes the Flow-Capacity model and performs better than the Interference Model.

Status: This paper is submitted to Elsevier Journal of Parallel & Distributed Computing. The ideas presented in this paper are largely based on the following papers:

- Wireless Mesh Network Planning, A Multi-objective Optimization Approach, *IEEE BROADNETS*, 2008, UK [BH08a].
- A Multi-objective Optimization Model For Planning Robust and Least Interfered Wireless Mesh Networks, *IEEE GLOBECOM*, 2008, USA [BH08c].
- Optimization Models for Planning Wireless Mesh Networks: A Comparative Study, *IEEE WCNC,* 2009, Budapest [BH09a].

3.1 Introduction

Many real-world engineering optimization problems are characterized by multiple and often conflicting objectives to optimize and a huge search space to explore. The planning of a WMN is one of those complex optimization problems. A proper design of a WMN is a fundamental task and should be addressed carefully to determine the network efficiency in terms of coverage, throughput, and capacity.

WMNs [AW05] are multi-hop networks of wireless routers. Multi-hop infrastructure WMNs offer increased reliability, coverage and reduced equipment costs over their single-hop counterpart, Wireless Local Area Networks (WLANs). A WMN consists of a set of mesh nodes, offering connectivity to end user devices. The mesh nodes form a relatively-static infrastructure, composed of Access Points (APs), router/relays (MRs), and gateways (MGs) nodes for forwarding messages, and orthogonal channels using multi-radios interfaces for allowing simultaneous communications. AP nodes are the main servers to mesh clients. They also interconnect with each other through point-to-point wireless links using relay routers (MRs). Gateways are the main interface to the Internet backbone connection; they act as bridges between the wireless infrastructure and the Internet and do have extra functionalities which make them more expensive than routers. Figure 3.1 illustrates a typical WMN infrastructure.

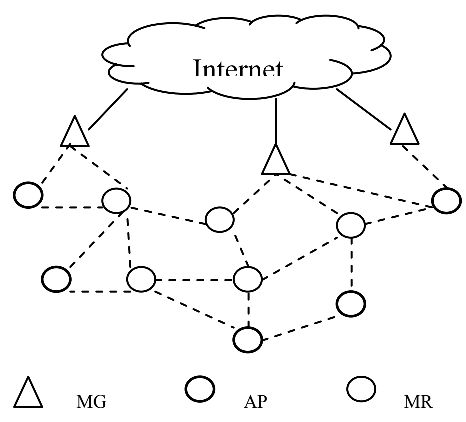


Figure 3.1: Wireless mesh network infrastructure.

Deploying such technologies requires considerable budgets even if they are relatively cheaper than other technologies such as (3G), and therefore any optimization strategy that minimizes the cost while providing a Quality of Service (QoS) is very much sought after. In fact, earlier WMNs deployments have been linked with a number of problems such as intermittent connectivity, poor performance and lack of coverage [BH07a]. Moreover, the QoS is not necessarily better supported when the number of mesh nodes increases. Indeed, it is naively tempting to correlate the increase of the number of mesh nodes to, for instance, a better coverage or higher network throughput. On the contrary, it is quite usual that a mere increase in the number of mesh nodes usually increases the complexity of the channel assignment problem thus inducing high interference levels, which results in network performance degradation. Therefore, there is a need to develop sound solutions for optimizing the planning of WMNs.

It is worth noting that there are plenty of planning network solutions developed for Cellular Networks (CNs) and WLANs, and one would be tempted to tailor these solutions to WMNs. But, these planning solutions cannot possibly be applied to planning WMNs because of the unique properties of WMNs, conveying new difficulties and challenges.

A good planning task of a WMN essentially involves a careful choice of the installation' locations, a wise selection of the types of network nodes, and a good decision on a judicious channel/node interface assignment, while guaranteeing users coverage, wireless connectivity and traffic flows at a minimum cost. In optimization terms, this is translated into determining: an optimal number of wireless routers required to cover the area under consideration, an optimal number of gateways for efficient integration of WMNs with Internet, an optimal initial channel assignment, and an optimal number of wireless interfaces per router, while taking into account all physical and financial constraints of the network provider.

The main trend of the works related to WMN planning found in the literature tends to focus on the problem of performance improvement by assuming *a priori* fixed topologies as in [AB05], [DP04], [JP03] and, [RC05]. Other studies (e.g., [SR07] and [CC07]), consider topologies where the gateways positions are fixed beforehand as well, while the studies in

[AB06], [CQ04], [HW08a], [Hw08c], [HX07], [LW07], [MS07] and, [RK08] attempt to optimize the number of gateways given a fixed layout of mesh routers. On the other hand, recent contributions in [AC08] and [BH07] propose WMN planning schemes where the location of routers and gateways are not fixed. The work in [BH07] opted for exact optimization techniques (CPLEX for instance) to find optimal planning solutions, which make it restricted to medium-sized instance problems. However the work in [AC08] uses heuristics (based on greedy selection) as an optimizer.

The common thread between all these related work regardless of the (fixed/non-fixed) topologies and the (exact/heuristic) optimization methods used is that they all consider a variant of single-objective optimization model. More precisely, the total deployment cost is the sole objective to optimize under other relevant QoS constraints. Perhaps the only promising study that deviates from this trend, found in [HX07], proposes a bi-objective model for the gateway placement problem, where a weighted aggregate objective function is used. Aggregating many objectives into a single fitness functions has been (and is still being) successfully used in many optimization projects. However, the very glaring shortcoming of the aggregate approach, as is widely known in the multi-objective community, is its inability to find potential candidate solutions when the landscape of the objective functions is non-convex [DD97].

The Multi-Objective (MO) optimization approach produces several non-dominated solutions. Optimality in MO optimization problems is redefined by the non-dominance concept, better known as Pareto optimality, where none of the (non-dominated) solutions is better than the rest with respect to all objectives. Moreover, this set of “trade-off” solutions does naturally reflect the multi-criteria decision making used by engineers -who usually prefer multiple non-dominated solutions where each can be used in a different decision making scenario.

Up to date and to the best knowledge of the authors, there has been no attempt to model WMN planning problems using a pure MO optimization approach. Basically, we can argue that a WMN planning problem can be seen as an optimization problem where the two most important objectives are the deployment cost (to minimize) and the network performance (to maximize). Minimizing the deployment cost is mainly achieved by deploying less network devices (routers/gateways), but this will create longer delays in user traffics and induce bottlenecks, which undermine the network performance. Similarly, maximizing network performance can be achieved by strategically placing extra network devices, which fattens the deployment cost budget. Often, as in the previous example, the objectives in a multi-objective optimization problem do conflict with each other in the sense that an increase in one objective dimension undermines another objective. This clearly plays in favor of multi-objective optimizers as they are the best methods to return a spectrum of trade-off solutions.

Our main contributions, mainly stemmed from the above argument, can be summarized as follows.

- We devise a generic MO optimization framework that captures and reflects the essence and the true nature of a WMNs planning problem. The goal is to minimize the cost and maximize the overall network performance. We propose a population-based MO optimizer in order to produce several non-dominated planning solutions, from which the network planner can choose those that better suits his/her budget and resources.
- We do not assume any *a priori* fixed topologies. Our planning WMNs solutions are constructed from scratch and in an incremental way to meet the QoS requirements, taking into consideration interference aware model while meeting the planner's objectives and satisfying the relevant constraints.
- We propose three different metrics for maximizing the network performance. This led us to design three multi-objective WMN planning models.
- We design a hybrid meta-heuristic evolutionary algorithm based on Genetic Algorithms (GAs) and Multi-Objective Particle Swarm Optimization (MOPSO) to solve the three WMNs planning models. A thorough comparative experimental study is then provided by tuning different WMN key-parameter on the three optimization models. Then, a network simulation using OMNET++ is also conducted to actually measure the performance of three specific (same-priced) topologies derived from the three models.

The rest of the paper is organized as follows. Section 3.2 describes the mathematical formulation of the three WMN planning optimization models. The evolutionary meta-heuristic algorithm to solve the proposed bi-objective models is detailed in Section 3.3.

Experimental numerical results and a comparative analysis are presented in Section 3.4. Finally, we conclude the paper in Section 3.5.

3.2 Multi-objective Modeling Approach and Formulation

In this section, we present the terminology and notations used in describing our modeling approach. We then formulate three theoretical bi-objectives optimization models.

3.2.1 Wireless Mesh Network Planning Problem

Figure 3.2 is a simplistic depiction of the terminology explained below.

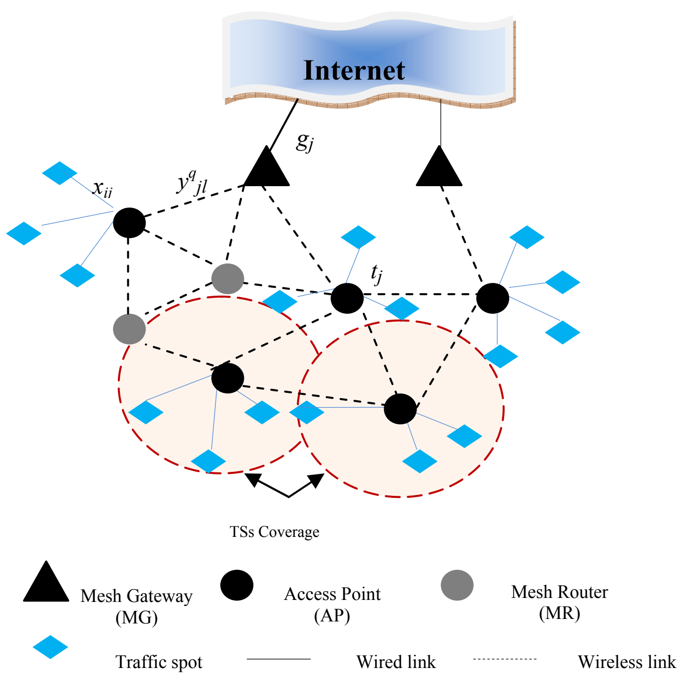


Figure 3.2: WMN Planning Problem- Key parameters and variables.

We define I={1,..,n} as the set of positions of n Traffic Spots (TSs) concentrations in the service area and L={1,..,m} as the set of positions of m Candidate Locations (CLs) where mesh nodes can be installed.

The planning problem aims at:

- Selecting a subset $S \subseteq L$ of CLs where a mesh node should be installed so that the signal level is high enough to cover the considered TSs.
- Defining the gateway set by selecting a subset $G \subseteq L$ of CLs where the wireless connectivity is assured.
- Maintaining the cardinalities of G and S as small as possible to meet the financial and performance requirements.

In the following, unless otherwise stated, i and j belong to I and L respectively. The traffic generated by TS_i is denoted by d_i, while u_{jl} is the traffic capacity of the wireless link between CL_j and CL_l. The capacity of the radio access interface of an access point AP located at CL_j is denoted by v_j . The WMN planning key parameters are e_j the cost associated to installing a mesh node (AP, MR or MG) at location CL_j, and p_j the additional cost required to install a gateway (MG) at that location.

3.2.1.1 Network coverage and connectivity setup.

The network coverage a_{ij} and network connectivity b_{jl} are the two main WMN planning parameters. The network coverage is a binary matrix that states whether a client at TS_i can be covered by one or many locations CL_j .

$$a_{ij} = \begin{cases} 1 & if\ TS_i \text{ cov}ered\ by\ CL_j \\ 0 & otherwise \end{cases}$$

The network connectivity is a binary matrix and indicates whether two locations can be wirelessly connected.

$$b_{jl} = \begin{cases} 1 & if\ CL_j\ and\ CL_l\ can\ be\ wirelessly\ connected \\ 0 & otherwise \end{cases}$$

The main decision vector variables (see Figure 3.2) are the routers installation locations, the gateways installation locations and the assignment of the users TS_i to CL_j.

$$t_j = \begin{cases} 1 & \text{if a device installed at } CL_j \\ 0 & \text{otherwise} \end{cases}$$

$$g_j = \begin{cases} 1 & \text{if a gateway installed at } CL_j \\ 0 & \text{otherwise} \end{cases}$$

$$x_{ij} = \begin{cases} 1 & \text{if } TS_i \text{ assigned to router at } CL_j \\ 0 & \text{otherwise} \end{cases}$$

3.2.1.2 Mesh Node Installation, Radio/Channel and Flow setup.

We suppose initially that mesh nodes operate using the same number of radios R, each with k channels, $(k>R)$ and $k \in C$, where C ={1,..,c} and c can be at most 12 orthogonal channels if IEE802.11a is used.

Other extra installation variables are needed in a Multi-Radio Multi-Channel WMN:

- $z_j^q = 1$ if a mesh node is installed at CL_j and is assigned channel q, $q \leq k$,
- $y_{jl}^q = 1$ if a there is a wireless link from a mesh node installed at CL_j to a mesh node installed at CL_l using channel q, $q \leq k$.
- N_{jl} is the set of links that cannot be simultaneously active with the link y_{jl}^q.

Finally, we define the flow variables f_{jl}^q and F_j. The variable f_{jl}^q denotes the traffic flow routed from a router in CL_j to a router in CL_l using channel q. The variable F_j is the traffic flow on the wired link between a gateway at CL_j and the Internet.

For better readability, Table 3.1 summarizes the notation used in the problem formulation.

Table 3.1: list of symbols used in the WMN design Models.

Symb.	**Description**
AP	Access Point
MR	Mesh Router
MG	Mesh Gateway
N	Number of Traffic Spots (TSs)
M	Number of Candidate Locations (CLs)
d_i	Traffic generated by TS_i
u_{jl}	Traffic capacity of wireless link (CL_j,CL_l)
Vj	Capacity limit for AP radio access interface
e_j	A device cost installation
p_j	A gateway additional cost installation
R	Number of radio interfaces
K	Number of channels
a_{ij}	Coverage of TS_i by CL_j
b_{jl}	Wireless connectivity between CL_j and CL_l
t_j	Installation of a device at CL_j
g_j	Installation of a gateway at CL_j
x_{ij}	Assignment of TS_i to CL_j
z^q_j	Installation of a device at CL_j , assignment of channel *q*, $q<k$
y^q_{jl}	Establishing a wireless communication on channel *q* between (CL_j,CL_l)
f^q_{jl}	Flow on channel q between (CL_j,CL_l)
F_j	Flow on the wired link from CL_j to Internet
N_{jl}	Set of links interfering with the link y^q_{jl}

Next, we propose three instance models that attempt to simultaneously minimize the network deployment cost and maximize the network throughput. They differ, however, in modeling the network throughput objective.

3.2.2 WMN planning Optimization Models

Optimal WMN planning solutions under multi-objective approach are more realistic and much preferred by network planners in that they have to be cost-effective (the deployment cost is minimized while the throughput is maximized). While the deployment cost objective is straightforward, the throughput objective can be viewed from different perspectives. The throughput objective function could be maximized by balancing the loads over network channels, minimizing the aggregation of network interferences, or maximizing the culmination of the flows over the entire network.

3.2.2.1 Load-Balanced Model

It seems plausible to enhance the quality of service by minimizing contentions and traffic bottlenecks. One way to achieve this is to properly balance the loads on the links over the whole network. We formulate the Load-Balanced (optimization) model as follows:

$$\min \sum \left(e_j t_j + p_j g_j \right) \tag{3.1}$$

$$\min \sqrt{\frac{\sum_{j\in L}\sum_{l\in L}\sum_{q\in C}\left(f_{jl}^{q} / u_{jl} \right)^2}{\sum_{j\in L}\sum_{l\in L}\sum_{q\in C} f_{jl}^{q} / u_{jl}}} \tag{3.2.a}$$

Subject to:

$$\sum_{j\in L} x_{ij} = 1 \qquad \forall i \in I \tag{3.3}$$

$$x_{ij} \le a_{ij} t_j \qquad \forall i \in I,\ \forall j \in L \tag{3.4}$$

$$\sum_{i\in I} d_i x_{ij} + \sum_{l\in L}\sum_{q\in C}\left(f_{lj}^{q} - f_{jl}^{q} \right) - F_j = 0 \quad \forall j \in L \tag{3.5}$$

$$\sum_{k,h\in N_{jl}} y_{kh}^{q} \le 1 \qquad \forall q \in C,\ \forall j,l \in L \tag{3.6}$$

$$\frac{f_{jl}^{q}}{u_{jl}} \leq y_{jl}^{q} \qquad \forall q \in C, \forall j,l \in L \tag{3.7}$$

$$\sum_{i \in I} d_i x_{ij} \leq v_j \qquad \forall j \in L \tag{3.8}$$

$$F_j \leq M\, g_j \qquad \forall j \in L \tag{3.9}$$

$$2y_{jl}^{q} \leq b_{jl}\left(z_j^q + z_l^q\right) \qquad \forall q \in C, \forall j,l \in L \tag{3.10}$$

$$g_j \leq t_j \qquad \forall j \in L \tag{3.11}$$

$$\sum_{l \in L} y_{jl}^{q} \leq 1 \qquad \forall q \in C,\ \forall j \in L \tag{3.12}$$

$$\sum_{q \in C} z_j^q \leq R\ t_j \qquad \forall j \in L \tag{3.13}$$

$$x_{ij}, z_j^q, y_{jl}^q, t_j, g_j \in \{0,1\} \quad \forall i \in I, \forall j,l \in L, \forall q \in C \tag{3.14}$$

$$f_{jl}^{q}, F_j \in R \qquad \forall j,l \in L, \forall q \in C \tag{3.15}$$

In this model, the function objective (3.1) minimizes the total cost of the network including installation cost e_j and additional gateway installation cost p_j. The load-balanced objective function (3.2.a) is the minimization of the standard deviation of the ratio of traffic flows over the network links.

Constraint (3.3) and Constraint (3.4) assign a TS_i to an Access Point (AP) installed at location CL_j. Constraint (3.3) makes sure that the TS_i is assigned to exactly one and only one AP installed at CL_j, while constraint (3.4) implies that the TS_i and the assigned AP are within the coverage area.

Constraint (3.5) defines the flow balance for each mesh node at CL_j**.** Constraint (3.6) limits link interferences, while inequalities (3.7) and (3.8) respectively defines the flow-link capacity and the demand-radio access capacity constraints. Constraint (3.9) stipulates that the flow routed to the wired backbone is different from zero only when the mesh node installed is a gateway. We set *M* with a very large number to limit the capacity of the installed gateway.

Constraint (3.10) forces a link between CL_j and CL_l using the same channel *q* to exist only when the two devices are installed, wirelessly connected and tuned to the same channel *q*. Constraint (3.11) ensures that a device can be a gateway only if it is installed.

Constraint (3.12) prevents a mesh node from selecting the same channel more than once to assign it to its interfaces. Constraint (3.13) states that the number of links emanating from a node is limited by the number of its radio interfaces. It also states that if a channel is assigned only once to a mesh node, it is a sufficient condition for its existence.

All the above constraints are called hard constraints with the exception of constraint (3.5) (which is then called a soft constraint). The fact to have only constraint (3.5) violated while other constraints are satisfied can be explained by the inability to find routes to flow the traffic generated by mesh clients. This is mainly caused by the lack of node pairs that are tuned to the same channel to establish wireless communications. Therefore, a reassignment of channels for the same topology in later iterations (using mutation) could help in satisfying all traffic demand (constraint 3.5 will be then fulfilled).

3.2.2.2 Interference Model

Because of the limited number of orthogonal channels, the spatial reuse of channels results in high level of interferences. This naturally degrades the network performance which is reflected by an overall throughput decrease.

Therefore, we may argue that the overall network interference, modeled by constraint (3.6), is sufficiently important for the network performance to be elevated to the status of an objective function that is to be minimized. For this purpose, we propose a novel performance (interference level) metric that we call *Balanced Channel Repartition (BCR).* It is defined as follows:

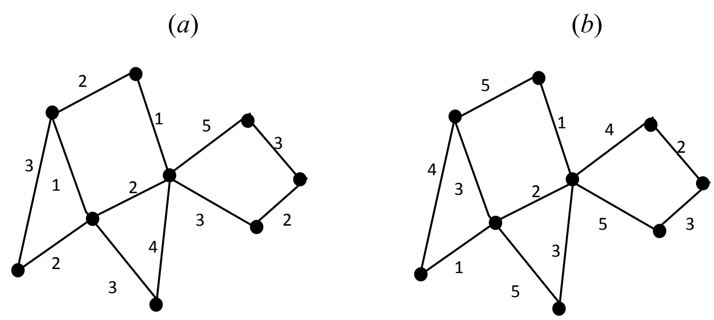
$$\varphi_q = Max\left|O_q - O_{q'}\right| \qquad \forall q, q' \in C \quad , q \neq q'$$

Where, $$O_q = \sum_{j,l \in L} y_{jl}^q \qquad \forall q \in C$$

In other words, the number of occurrences of channel *q*, denoted by O_q, is used to compute the gap between the balanced allocation of channel *q* and the current allocation. Our aim is to minimize this gap.

The second objective function is then defined as $$Min\sum_{q\in C}\varphi_q$$

Figure 3.3 shows that the spatial channel reuse in (b) is better than that in (a). The value of total φ_q in (a) is equal to 14 while total φ_q in (b) is equal to 5. This is caused by the unbalanced reuse of some channels in topology (a) -namely channel 2 and channel 3.



(a) $O_1=2, O_2=4, O_3=4, O_4=1, O_5=1$ ($\varphi_1=2, \varphi_2=3, \varphi_3=3, \varphi_4=3, \varphi_5=3$)

(b) $O_1=2, O_2=2, O_3=3, O_4=2, O_5=3$($\varphi_1=1, \varphi_2=1, \varphi_3=1, \varphi_4=1, \varphi_5=1$)

Figure 3.3: Same topology with two different channel allocations.

The second model is therefore defined as minimizing both the following two objectives:

$$\min\sum\left(c_j t_j + p_j g_j\right) \tag{3.1}$$

$$\min\sum_{q\in C}\varphi_q \tag{3.2.b}$$

subject to the same set of constraints as the one defined in the first model but without constraint (3.6).

Using this new metric (BCR) together with constraint (3.12) prevents local imbalances in channel allocation. While BCR metric tries to balance the number of occurrences of channels over network links (global balance in channel allocation), constraint (3.12) eliminates the possibility to have the same channel allocated many times to the same mesh node through its radio interfaces. As a consequence, each node will have only one of its direct neighbours (one hop away) tuned to the same channel; thus BCR together with constraint (3.12) leads to local and global balance in allocating network channels.

3.2.2.3 Flow-Capacity Model

In this model, the throughput function objective is modeled as maximizing the total throughput by computing the overall flow-capacity ratio (also called link utilization) of the network.

The objectives of the flow-capacity model are given below. The model is subject to the same set of constraints as defined for the Load-Balanced Model.

$$\min \sum \left(c_j t_j + p_j g_j \right) \tag{3.1}$$

$$\max \sum_{j \in L} \sum_{l \in L} \sum_{q \in C} \frac{f_{jl}^{q}}{u_{jl}} \tag{3.2.c}$$

In Section 3.4, an introspective comparative experimental study is conducted on these three instance models.

3.3 The Solution Approach

Our WMN planning optimization is essentially the maximization of the network throughput (depending on which perspective is used) while at the same time ensuring the minimization of the total deployment cost. This is achieved by selecting a minimum number of routers/gateways and adequately choosing their positions so that the network connectivity is ensured while providing full coverage to all mesh clients. It is proven that a WMN planning optimization problem is NP hard [AC08]. Its difficulty lies on the fact that it tries to optimize the conflicting objectives (cost and throughput) simultaneously while addressing all the constraints.

As stated earlier, solving a Multi-Objective Problem (MOP) returns a set of Pareto-optimal solutions. Each Pareto solution represents a different trade-off between the objectives that is said to be "non-dominated", since it is not possible to improve one criterion without worsening another.

3.3.1 Solving a Multi Objective Problem using Evolutionary Algorithm

3.3.1.1 MOP Concepts and definitions.

In the last two decades, there have been growing interests in the field of multi-objective optimization to solve real-world problems. Good introduction to this field of research can be found in [De02] and [Go89].

Without loss of generality, we assume that the various objectives are to be minimized. Then, the optimization of a MOP can be formulated as:

minimize $y = f(x) = [f_1(x)\ , f_2(x), \ldots, f_N(x)]$

where $x = [x_1, x_2, \ldots, x_D] \in$ decision space

and $y = [y_1, y_2, \ldots, y_N] \in$ objective space.

For a constrained problem, the decision variables x are subject to a set of constraints. Every decision variable vector x in the decision space is evaluated through the objective functions. The objective values are then represented as points in the objective value space.

Definition 1 *(Pareto Dominance):* For two decision vectors a and b, a is said to dominate b or $a \prec b$ if and only if: $\forall i \in \{1,\ldots,N\}, f_i(a) \le f_i(b) \wedge \exists i \in \{1,\ldots,N\}, f_i(a) < f_i(b)$.

Definition 2 *(Pareto Optimality):* A decision vector a is said to be Pareto Optimal if and only if a is non-dominated. Formally, $\forall b,\ a \prec b$.

Definition 3 *(Pareto Front):* The Pareto Front is a set of all Pareto Optimal solutions (non-dominated solutions) in the objective value space.

Illustration in Figure 3.4 shows that points *B*, *E*, *F*, and *H* are non-dominated as they do not lie in any of the first quadrant of the other points. Point *D* is dominated by points of *C, E, F,* and *G*.

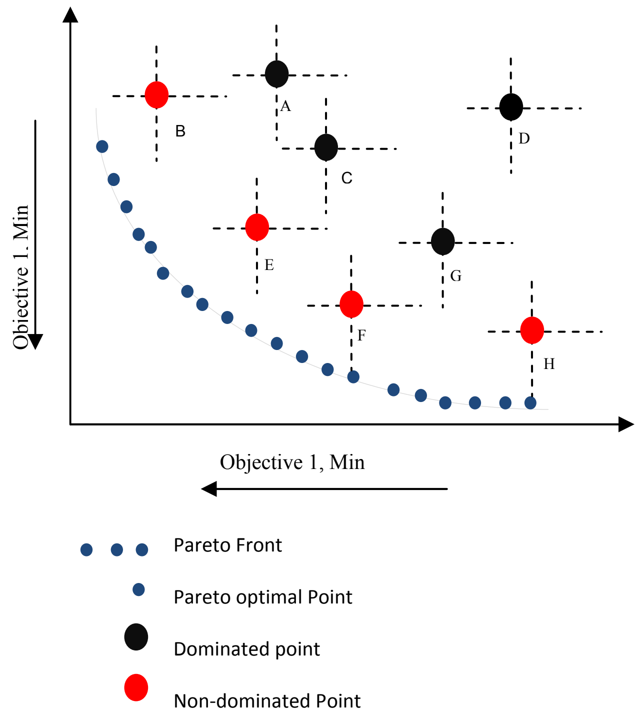


Figure 3.4: Pareto Dominance and Pareto Front for a 2-functions objective space.

3.3.1.2 Evolutionary and Swarm Optimization Algorithms

There are many nature inspired optimization algorithms that have been very successful in solving complex optimization engineering problems. The noteworthy are Genetic Algorithms (GAs) [Go89], Particle Swarm Optimizers (PSO) [KE95], Ant Colony (ACO) [DM96], Simulated Annealing (SA) [KG83], and Tabu Search (TS) [GL97] to name a few.

On the one hand, GAs is a meta-heuristic search technique that is adequate in exploring huge and complex search spaces. It starts off with a set (first generation) of acceptable solutions and goes on mixing their structures (crossover) and/or mutating them through many cycles (generations) until suitable solutions are found. GAs is particularly strong in dealing with discrete search spaces in that they are better explorers. They are also found particularly suited for diverse network optimization problems ([AH05], [CK05], [CP01], [RD04], [RW05]).

On the other hand, Particle Swarm Optimization (PSO) is an optimization technique based on an evolutionary approach introduced by Kennedy and Eberhart [KE95]. It models the dynamic movement or behavior of the particles in a search space. By sharing information across the environment over generations, the search process is accelerated and is more likely to visit potential optimal or near-optimal solutions. PSO do not perform well for discrete search spaces, however it gets better results in a faster and cheaper way. Moreover, it is easy to implement with simple concepts and requires few parameters to adjust.

PSO has been extended to cope with an MOP which mainly consists of determining a local best and global best Potential Solutions (PSs) of a particle in order to obtain a front of optimal solutions. There are some efficient and well-known multi-objective techniques based on PSO algorithms, of which MOPSO [CL02] seems to be the most effective.

We devise a kind of a hybrid optimizer that borrows the mutation operator from GAs (to better explore the search space) and uses the velocity calculation, from PSO, to guide the search towards local and global (sub) optimums. More precisely, our WMN optimization algorithm (called VMOPSO) is a modified version of MOPSO equipped with the Crowding-Distance (CD) technique of NSGA-II [De02] and uses a mutation procedure. The crowding distance value of a solution, as thoroughly studied in [De02] and [RN05], is the average distance of its two neighboring solutions. The boundary solutions with the lowest or the highest objective function value are given an infinite crowding distance values so that they are always selected. This process is done for each objective. The final crowding distance value of a solution is computed by adding the entire individual crowding distance values in each objective value.

Both the mutation procedure and the CD technique strive to enhance the exploration process, though at different levels. The CD technique is applied on the archive, where the final set of solutions would be diverse. The mutation procedure, however, operates at generation level, where the algorithm will have (enough) frequent discrete jumps to allow for escaping the traps of the local-optima issue. We also add a constraint handling mechanism for solving constraints optimization problem, such as WMN design problem. In the following, we provide more details on how the multi-objective models are solved using VMOPSO.

3.3.2 Logical and Physical Modeling of a planning solution

This section describes how our WMN planning solutions are logically and physically modeled.

3.3.2.1 A Grid Topology for a Network Deployment Scheme

The first issue to address is what topology to adopt when constructing a network of mesh node to properly handle users TSs demands.

Robinson and Knightly [RK08] conducted a performance study of deployment factors and concluded the benefits of adopting grid topologies over other topologies. In the same context Li et al. [LW07] studied the gateway placement for throughput optimization in WMNs using a grid-based deployment scheme. Their method of placing exactly *k* gateways has achieved better throughput in the grid scheme than in random schemes.

Based on these findings, we adopt a *square grid* layout as the physical representation of our WMN planning. Each grid cell corner is a CL where a mesh node can be installed. If a mesh node is installed at a given CL, it may establish a wireless communication with its eight direct-neighbors. This assumption will increase the chances of selecting a candidate neighbor among the eight with which a wireless link will be set up in the channel assignment procedure.

3.3.2.2 A Particle in the Swarm: Modeling a WMN planning Solution.

In PSO, a particle (a position in the search space) represents a set of assignments that is a solution to the problem. In our case, a particle is a complex data structure that provides information about user connectivity (x_{ij}), device installation (t_j) and (z^q_j), devices connectivity (y^q_{jl}), gateway existence (g_j), link flows (f^q_{jl}), and gateway/backbone link flows (F_j). Figure 3.5.a depicts different components of a particle data structure. The building blocks of a particle structure are *Positions, Links, Flows* and *Demands*. The block *Positions* is the most important one, as it provides information about user connectivity and the type of devices, as well as their locations and installation. The *mesh nodes* component contains the locations of

APs (represented by IZ vector), the locations of MGs (represented by GW vector) and the list of channels assigned to radio interfaces of every mesh node installed (MR included). Figure 3.5.b illustrates an example of the *mesh nodes* component of a particle.

3.3.3 The VMOPSO Algorithm

Given a set of TSs scattered in a geographical region, the idea is to construct a network of mesh nodes (APs, MRs, MGs) that will best service the users TSs with minimum cost and under the given constraints. The VMOPSO algorithm needs to breed a swarm (collection) of *acceptable* potential planning solutions, i.e. satisfying all the constraints defined in Section 2.2.1. In this Section, we show first how the initial swarm composed of feasible solutions it built, then we describe the VMOPSO algorithm to show how a new swarm of *acceptable* potential planning solutions is bred.

3.3.3.1 Building the initial set of feasible solutions

In continuous optimization problems, getting the initial position and velocity is more straightforward because a simple random initialization is used. However, since the problem of planning a WMN is a constrained optimization problem, the initial positions must represent feasible solutions, and thus, need to be designed carefully.

Constructing an initial set of feasible solutions that satisfy the constraints (3.3) to (3.15) represents the most challenging part in our optimization process. Building such an initial set requires three main design stages, namely coverage insurance, connectivity augmentation and gateway assignment.

Coverage insurance: Recall that a TS_i can be covered by one or many CLs. This stage handles the assignment of each TS_i to one and only one CL_j . We start by selecting randomly a CL_j from the set of CLs that cover that TS_i (Figure 3.6.a). An AP (Access Point) is then installed at this location CL_j only if it has not yet been selected (see Figure 3.6.b). By applying the same procedure to all TSs, we obtain a set S_1 of APs location that provides full coverage to all TSs. More formally, S_1={ $j \in L$, CL_j covers TS_i, $i \in I$ }. At this stage, constraints (3.3) and (3.4) are satisfied and the initial set contains vertices of a disconnected graph as shown in Figure 3.6.b.

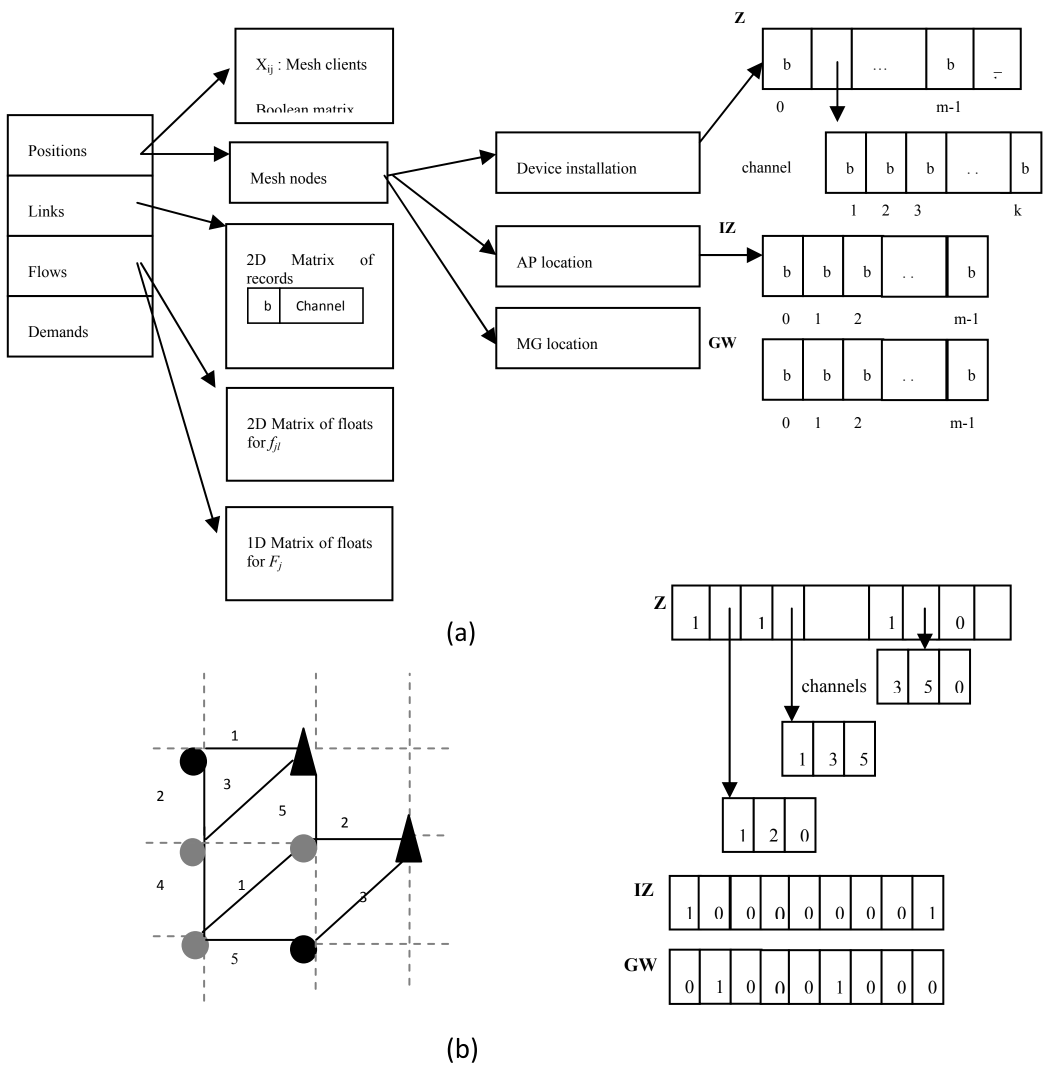


Figure 3.5: Particle encoding (b: stands for Boolean value), (a) Particle data structure, (b) A Particle position example with m=3, R=3, k=5 (right side figure), *mesh nodes* component of the particle position (left side figure).

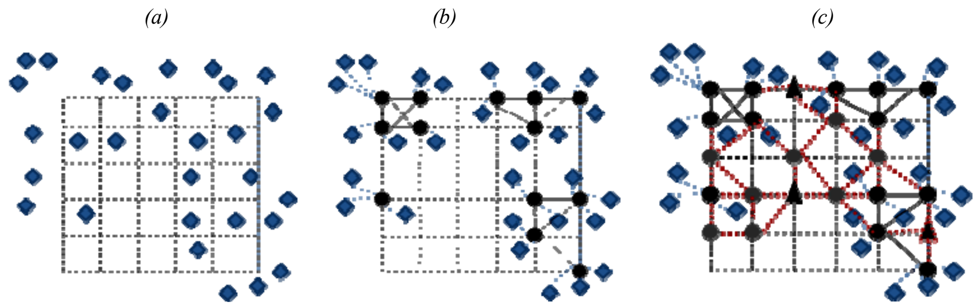


Figure 3.6: A Particle position example:
(a)TSs locations, (b) TSs assigned to CLs (c) S1 augmented, MGs selected.

Connectivity augmentation: Once the coverage is done, there is no guarantee that the graph is connected. Therefore there is a need to augment the set S_1 by adding new MRs (Mesh Routers) to connect the APs together. We apply a neighborhood based selection algorithm to find the next node to be inserted. The augmentation algorithm consists mainly, on choosing the closest neighbor in one component graph to any node of a different component. Then, the path between the two nodes is augmented. The algorithm stops when all nodes belong to the same graph component (see Figure 3.6.c).

Gateway assignment: is based on a random selection from the set of nodes that are eligible to be gateways. However, this last design stage (gateway assignment) could be a subject of further investigation to improve network performance without changing the generic model.

For computational purposes, we use a symmetric adjacency matrix to represent the connectivity graph. We apply the fixed channel assignment algorithm described by Das et al. [DA05] and we implement Edmonds-Karp's max flow algorithm [EK72] to assign a value on each link y_{jl} using channel q to route a flow. All remaining constraints (i.e., 3.5-3.14) are then satisfied.

A feasible solution must satisfy all hard and soft constraints. However, those solutions that violate only the soft constraint (3.5) can be included in the population if space allows. This increases the likelihood of a non-feasible solution to mutate and provide a feasible one in later generations.

3.3.3.2 Breeding Potential Planning Solutions

The very first step in VMOPSO Algorithm (Algorithm 3.1) is to initialize the positions, as described above, initialize the boundary limits and the velocities of each solution *i* (particle) in *Sw*. At this step, only feasible solutions are considered.

Each of these particles would then go through an evaluation process, i.e., an assessment of the quality of the solution, which is nothing but the evaluation of the two objective functions.

During the exploration of the search space, each particle has access to two pieces of information: the best Potential Solution (PS) that it had encountered (*pBest*) and the best PS encountered by its neighbors *(gBest)*. This information is used to direct the search by computing velocities (see Algorithm 3.2): velocity[i] = *iw* * velocity[i] +r_1 * (*pBes*t[i] – position[i]) +r_2* (*Archive*[*gBest*] – position[i]), where r_1, r_2 *are* random numbers in the range of [0,1] and *iw i*s the inertia weight . A large inertia value will cause the particles to explore more of the search space, while a small one directs the particles to a more refined region.

The *Archive* is then updated by inserting into it all the currently non-dominated (fittest) solutions. This insertion process ends up in removing dominated solutions. In the case where the archive is full and there are still non-dominated solutions to be inserted, priority is then given to those particles that would ultimately enhance the diversity of the archive set, which is achieved by using the crowding distance technique (see section 3.3.1.2). When the decision variable exceeds its boundaries, it takes the value of its corresponding boundary and the velocity is changed to the opposite direction.

Algorithm 3.1: VMOPSO Main Algorithm

Input *Sw:* swarm, *gMut: Generational Mutation factor*, *MaxGeneration*
Output *Archive*: External repository

Step 1:

1. Initialize the swarm *Sw*

For each particle *i* in *Sw* *//Build feasible solutions that satisfy all constraints,*

a. Initialize feasible position, *// the three main steps shown in Section* 3.3.3.1

b. Specify *lowerBound*$_i$ and *upperBound*$_i$ *//boundary limits*

c. Initialize velocity *// initially set to Zero*

d. Set the global best guide *gBest* to *pBest*

e. Set the personal best guide *pBest* to that position

End For

2. Initialize the iteration counter *t*=0

3. Evaluate all particles in *Sw* *//compute objective functions f1 and f2*

4. Filter non-dominated solutions from *Sw* and Store them into *Archive*.

Step 2: **Repeat**

1. Process the *Archive*.
   a. Sort the *Archive* in a descending order of one of the *objective functions f1 or f2.*
   b. Compute the crowding distance (*CD*) values for each j∈*Archive*.
   c. Sort the *Archive* in a descending order of CD values*.*
2. Set *gBest[i]* to the randomly selected particle from the top 10% of the sorted *Archive.*
3. **ConstructWMNPlanningSolution** **//** *invoke Algorithm 3.2.*
4. Check for constraints satisfaction
5. Update the *Archive* *// insert non-dominated and feasible particles in the Archive.*
   a. If any particle *k* in *Sw* dominates any particle *l* in *Archive* then:
   Delete *l* from *Archive* and insert *k* in *Archive*.
   b. **If** *Archive* is full and there is non-dominated particle (candidate) in *Sw* then
      1. Compute the crowding distance values for each j∈*Archive*
      2. Select the victim: a Random particle in the bottom 10% of the CD-sorted *Archive (most crowded portion).*
      3. Replace it with the new candidate.
   End If
6. Update pBest
7. Increment t

Until (t>= *MaxGeneration)*

For each particle in the swarm, the iterative algorithm (Algorithm 3.2) consists of constructing a subset S_1 of APs locations to cover all TSs, mutating it, placing gateways and then assigning flows and channels. The most important phase is the repetetive task of constructing the set S_1 and then mutating it over and over until it satisfies at least all hard constraints. Then S_1 is augmented to ensure the connectivity constraints.

After this solution-construction process, the velocities, the positions and the fitnesses (values of the two objective functions) of the particles are computed. Then some of these particles are inserted into the archive provided that they dominate or at least are non-dominated by the previously "archived" non-dominated solutions.

Algorithm 3.2: ConstructWMNPlanningSolution

```
Input   Sw: Swarm, t: generation counter, MaxGeneration,
        gMut: Generational mutation factor,
        sMut: Swarm mutation factor                  //adopted from MOPSO [CL02],
                                                     // sMut = (1-t/MaxGeneration*gMut)^(3/2)
Output  Sw: Swarm

mutateEnabled:= true;
If (t>= MaxGeneration*gMut) then mutateEnabled :=false;
for each particle i in Sw.
        if (mutateEnabled) and (sMut=1)               //Mutation at early generations
           S1 := Mutate(S1)                          // S1 is the subset of APs locations
        endif
        S := Augment(S1);                            // Connectivity augmentation
        Y1:=Construct_connectivity_matrix(S) ;
        Y2:= Assign_channels(Y1) ;
        G := PlaceGateways(Y2);                      //Gateway assignment
        Compute_flows(G) ;
        Construct_New_Particle();          // with the newly generated S,Y2,G and flows
        Compute_Velocities();              // As described in the beginning of this section
        Update_Positions();                // New position= current position + computed velocity
        Check particle boundaries, if violated change particle search direction
        (i.e.,velocity(i)* -1)
        Evaluate_Particles();              // Compute objective functions f1 and f2
endfor
```

A position in the search space is a solution to our planning problem; however, the values, returned by Update_Positions() procedure in Algorithm 3.2 are not guaranteed to be integers (0 or 1). For this purpose, we add a final process that we call *particle filtering* to allow only particles with a considerable progress to change to 0 (respectively 1). If the difference between the two positions (initial and the updated one) of a particle goes beyond a given threshold α (based on experiments, α is set to 0.3), then the final position will be the reverse of the initial one (i.e., 0 if it was 1 and vice-versa); otherwise, the new position is discarded. i.e., the particle remains in its original position for further improvement.

3.4 Numerical Experiments, Simulation and Analysis

In this section, we use the algorithms we devised and described in Section 3.3 to solve the three model problems proposed in Section 3.2 - (*a*) Load-Balanced Model, (*b*) Interference Model, (*c*) Flow-Capacity Model. The obtained results are presented and discussed.

3.4.1 Experiments Setup

Our numerical analysis setup is based on WMN key parameters which are as follows: the number of clients (TSs) n, the number of CL m, the client demands d_i, the gateway factor cost p_j, and the number of radio interfaces R. In this regard, we define the Standard Setting (SS) of the WMN key parameters as the following:

SS=[(n:150), (m:49), (d_i:2Mb/s), (u_{jl}:54Mb/s), (v_j:54Mb/s), (M:128Mb/s), (e_j:200), (p_j:8*e_j), (R:3), (k:11)].

The positions of the n TSs are randomly generated for the first run and kept fixed for the remaining runs. A run of our algorithm involves 100 generations each with a population size and an archive size of 50 and 20 particles respectively. Finally, we set the mutation rate to 50% ($gMut$=0.5), which has proven to lead to the best Pareto front [BH08a]. The algorithm is coded in the Java programming language and all the experiments were carried out on a Pentium M 1.5GHz machine.

We study the performance of our algorithm over grid graphs and under many deployment scenarios. For practical reasons, the throughput objective of the Flow-Capacity Model is rewritten as a minimization of the inverse of the overall network flow-capacity aggregate. Obviously, for the sake of a consistent results' interpretation, the same initial configurations (clients' distribution) are saved and used for the three models. Lastly, for each execution scenario (key parameter variation study), results are reported on 10 runs thus requiring additional filtering process to maintain the non-dominance aspect amongst the resulted Pareto fronts.

3.4.2 Measuring the Performance

Diversity and convergence of the returned set of solutions are the two main characteristics of any multi-objective optimization problem solver. In this subsection we introduce the most widely used metrics of diversity and convergence to compare the contending fronts.

3.4.2.1 Diversity Measure

First, we use the Schott Spacing Metric [Sc95] to measure the range variance of neighboring vectors in the *Archive* (the Pareto Front, PF). It is defined as:

$$S = \sqrt{\frac{1}{(n-1)} \sum_{i=1}^{n} (\bar{d} - d_i)^2}$$

Where n is the number of solutions in the PF,

$$d_i = \min_j (| f_1^i - f_1^j | + | f_2^i - f_2^j |),$$

$\bar{d}$: The mean of all d_i.

A zero value for this metric means that all solutions of the PF are equidistantly spaced, however, in this study we are not interested in how close the metric value is to zero, but on the values of this metric returned by each PF. The lower the value returned by a PF, the better that PF is.

3.4.2.2 Convergence Measure

The coverage and the hyper-area metrics proposed in by Zitzler [39] are powerful metrics that assess the convergence of a given front. The quasi-totality of works in the domain of performance assessment in the realm of MOEA uses at least one of these two metrics.

The convergence metric, γ, proposed by Deb in [De02] assumes the presence of the true Pareto-optimal front. A sample set called *H* of *N* equidistantly-spaced solutions from the true Pareto-optimal front is extracted. Then each point obtained with an algorithm, a minimum Euclidean distance from it to the set *H* is computed. The averages of these values constitute γ.

This metric is misleading and therefore is not used in the experiments. In Figure 3.7, the front *F*2 (a singleton for the sake of simplicity) is deemed to be better than the front *F*1 –as it is closer to the true Pareto front than *F*1. However, *F*2 is strictly dominated by *F*1.

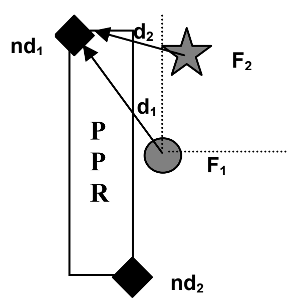


Figure 3.7: Anomaly of the Convergence metric γ.

Authors in [HK06] proposed a new quality indicator that measures the minimum improvement a vector solution (a point) in the objective search space has to undertake in order to reach the non-dominance status. For this purpose, a set of Potential Pareto Regions (SPPRs) is constructed. Each PPR in the SPPRs is a region within which non-dominance status is verified. For each point outside the SPPRs, we can measure its *Expected Improvement* (*EI*) as the length of the segment of the line originating from the point and intersecting the closest PPR. In other words, *EI* is a scalar value that a point in the objective space has to gain in order to reach the status of non-dominance. An illustrative example is depicted in Figure

3.8. For more details on this technique and the algorithms used to compute the EIs, we refer the reader to the lecture notes in [HK06].

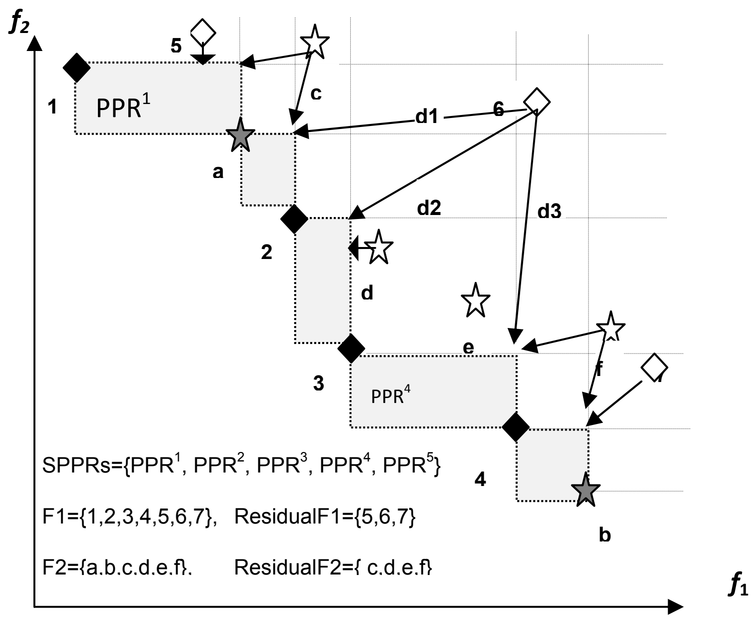


Figure 3.8: Potential Pareto Region (PPR) and the Expected Improvment (EI).

In our experimentations, only inertia (*iw*) value setup and radio (*R*) variation experiments involve contending comparable fronts. To decide on which value of *iw* to choose and which radio variation is optimal, we use the Spacing Metric, the *Expected Improvement EI* metric and some coverage related metrics, such as:

$PF_i^{Pareto} = PF_i \cap CPF$.

- $|PF_i|$: The size of the set of non-dominated vector solutions returned,
- $|CPF|$: The size of the CPF filtered, CPF-size
- $|PF_i^{Pareto}|$: The number of vector solutions inside the CPF, ($PF_i \cap CPF$)
- $|PF_i\text{-}CPF|$: The number of vector solutions outside the CPF,
- %fromCPF : The percentage of each PF_i covering the CPF- $\frac{|PF_i^{Pareto}|}{|CPF|}$,

- %fromPF: The percentage of each PF_i covering the front returned by PF_i in question- $\frac{|PF_i^{Pareto}|}{|PF_i|}$.

It must be noted that some of the above metrics are redundant. However, they are reported for a better contrast.

3.4.3 Plotting and Graphs Interpretation

For each model, the planning solutions (deployment cost against performance) for a given value of each key parameter variation constitute a (Pareto) front of non-dominated solutions that is plotted in a (objective space) graph. On the other hand, only the cheapest solution is considered for plotting the resource utilization graph. For that, we plot the number of MRs, the number of APs, the number of MGs, and finally the number of links to show the network connectivity level.

In this subsection we compare the characteristics of the solutions, which can prove very important in decision making. These characteristics are the number of the solutions, the width of the spectrum of the solutions, and the uniform-distribution of the solutions. In addition, for each scenario we further plot the device utilization graphs in terms of the number of gateways, routers, and links. This makes the comparisons between the three models possible.

3.4.4 Results and Analysis

3.4.4.1 Setting the Inertia value

A large inertia value will cause the particles to explore more of the search space, while a small one directs the particles to a more refined region. The importance of inertia weight was pointed out by Shi and Eberhart [SE98] who reported that 0.4 is the best value. However, for a different type of problem, such as WMN design problem, a different value of *iw* may lead to better exploration and exploitation of a search space. To set an appropriate value of *iw* for our numerical experiments, different runs are carried out for the same model (Load-balanced Model for instance), by changing only the inertia weight *iw,* while maintaining the same SS as defined in Section 3.4.1. In Figure 3.9, the Pareto fronts of ten runs, for different value of *iw* (0.2, 0.4, 0.6, 0.8) are plotted.

It is clear from Figure 3.9, that the solutions in Pareto front corresponding to *iw*=0.8 are almost all dominated by the solutions of the other fronts (i.e., *iw*=0.2, 0.4, 0.6).

Referring to Table 3.2, the size of the non-dominated set (|PF|) for *iw*=0.2 is not as bigger as the size of the non-dominated set when *iw*=0.6, but it is taking around of 55% of the CPF (a merger of the 3 contending fronts) and 66% of the front are non-dominated. The diversity of the solutions is also much better when *iw*=0.2. Based on these results, we set *iw*=0.2 for all remaining numerical experiments.

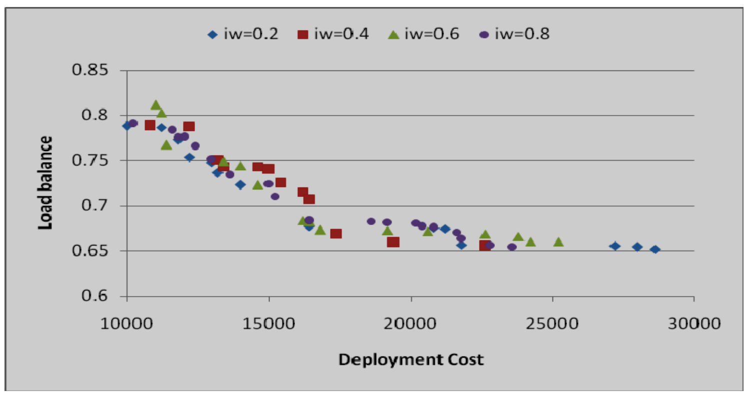


Figure 3.9: Pareto fronts of planning solutions for different value of inertia weight, *iw*.

Table 3.2: Test results of Load-balanced Model for different value of inertia weight.

Inertia weight	iw=0.2	iw=0.4	iw=0.6
Spacing S	**0.0526**	0.1014	0.153
|PF|	15	15	17
|CPF|	18		
|PFi ^{Pareto}|	**10**	3	5
|PFi-CPF|	**5**	12	12
%fromCPF	**0.5556**	0.1667	0.2778
%fromPF	**0.6667**	0.2	0.2942

3.4.4.2 Radio Interfaces (R) Variation

The number of radio interfaces *R* is varied from 2 to 5, and each of these radio interfaces is equipped with 11 channels. In this experiment, to better test the channels we do not use the standard setting SS as defined in section 3.4.1, but choose a heavily loaded and condensed network (*m*=100, *n*=150, d_i=5Mb/s) instead. The Pareto fronts illustrated in Figure 3.10 show that Load-Balanced model provides better, diverse and greater number of solutions than the other two models. In Table 3.3, we choose to perform head-to-head comparisons for a better analysis. For each model, we compare the results of instance models of 2-radios with 3-radios, 4-radios with 3-radios, 5-radios with 3-radios, and finally 5-radios with 4-radios. For all the three models, the 3-radios decision choice always outperforms the 2-radios one, while the 4-radios and 5-radios always outperform the 3-radios instances.

The Load-balanced model gives the larger sets of solutions (|PF|) while Link utilization shows a better diversity. In Load-balanced and Interference models, choosing 4 radios seems the best decision choice since the fronts related to 4-radios, when compared to the 5-radios design choice, make up 62% to 71% of the CPF.

In Link Utilization model, the solutions of the 5-radios decision choice are all in the CPF, though not well-spaced (S= **0.6959**) and as can also be seen in Figure 3.10.c. The 4-radios decision choice, however, end up with a better diverse set of solutions. It must also be noted that all of its solutions that are outside the CPF (see line |PFi-CPF|) actually resides on the limit of the non-dominance status (EI=0).

The more radio interfaces are deployed the more links are established, and the less gateways are needed. This remains true when *R* shifts from 2 to 3 and from 3 to 4 (Figure 3.10). The Load-Balanced Model profits from a radio gain by decreasing the number of APs, relays, and gateways and increasing the number of links. The Interference Model does follow the same pattern as the Load Balanced Model in reducing the number of resources.

On the other hand, all models show a disruption when the number of radios goes from 4 to 5 (see Figure 3.11.a and b). This may be caused by the high level of interferences related to the increase in network links.

We can then stipulate that no gain can be obtained if we deploy more than four radio interfaces, which stands true for all three models, under the same *SS*.

3.4.4.3 Grid Size (m) Variation

The number of candidate locations *m* is gradually increased while all other parameters are maintained fixed. Results (Figure 3.12 and Figure 3.13) show that there is consent in all models that a 7x7-grid is the best in satisfying the Standard Setting *SS*. A very important remark is that the cardinality and the width of the spectrum of the planning solutions are greater in the Load-Balanced Model than they are in the other two models. This fact makes the first model the best to find cheaper planning solutions. On the other hand, Interference-based model seems to generate more and well spaced solutions than the third model does. These observations, drawn from Figure 3.12, suggest that a network planner with 'flexible' requirements would possibly opt for Load-Balanced Model as it offers more and better diverse planning solutions.

When we turn our attention to resource utilization, it is clear from Figure 3.13 that the Load-Balanced Model dominates the flow-capacity model since it uses less network mesh nodes in all types of grids. On the other hand, the interference based model requires fewer routers but more gateways for grids larger than 8x8. One can observe that the Load-Balanced Model is more careful in using the gateways (MG) (Figure 3.13.b) as it rather adds more routers (MR) (Figure 3.13.a) and precisely more access points (AP) as shown in Figure 3.13.b. Notice that in all models, a higher number of candidate locations leads to an increase in the number of routers and gateways even for the same number of users. The first reason is the fact that increasing the number of CLs increases the probability of a TS (Traffic Spot for a client) not being connected to an AP through a multi hop wireless path, which leads to installing more nodes. A larger size of grid can improve the network performance as more flexibility in choosing routing paths is possible, and consequently, the probability to have traffic contention and bottlenecks is very low, but also increases the total deployment cost, which is highly affected by the number of gateways deployed. Therefore, in practice, the network planner has to decide on the appropriate grid size that satisfy both cost and performance requirements.

Table 3.3: Radio Setup results for a heavy condensed network.
(m=100, n=150, d_i=5Mb/s)

Interference Mode								
#Radios	3	2	**4**	3	5	3	5	**4**
|PF|	7	7	**6**	7	5	7	5	**7**
|CPF|	7		**7**		6		7	
|PFi ^{Pareto}|	7	0	**4**	3	4	2	2	**5**
|PFi-CPF|	0	7	**2**	4	1	5	3	**2**
%fromCPF	100	0	**57.14**	42.86	66.67	33.33	28.57	**71.43**
%fromPF	100,0	0,0	**66,7**	42,9	80,0	28,6	40,0	**71,4**
Avg EI	0	860.72	**0**	0.75	0	40.4	0	**0.5**
stdv EI	0	1252.11	**0**	0.83	0	79.81	0	**0.5**
Spacing S	0.4842	0.7970	**0.5145**	0.4842	1.7979	0.4842	1.7979	**0.5145**
Load balanced Model								
#Radios	3	2	**4**	3	5	3	5	**4**
|PF|	18	13	**21**	19	20	19	20	**22**
|CPF|	20		**21**		20		21	
|PFi ^{Pareto}|	18	2	**13**	8	16	4	8	**13**
|PFi-CPF|	0	11	**8**	11	4	15	12	**9**
%fromCPF	90	10	**61.9**	38.1	80	20	38.1	**61.9**
%fromPF	100,0	15,4	**61,9**	42,1	80,0	21,1	40,0	**59,1**
Avg EI	0	1727.28	**0**	127.28	0	880	0	**2822.2**
stdv EI	0	2162.94	**0**	213.58	0	1726.34	0	**3900.4**
Spacing S	0.8143	0.5811	**0.5835**	0.8143	0.4035	0.8143	0.4035	**0.5835**
Link Utilization Model								
#Radios	3	2	4	3	**5**	3	**5**	4
|PF|	7	7	8	7	**10**	7	**10**	9
|CPF|	8		9		**11**		**14**	
|PFi ^{Pareto}|	7	1	7	2	**10**	1	**10**	6
|PFi-CPF|	0	6	1	5	**0**	6	**0**	3
%fromCPF	87.5	12.5	77.78	22.22	**90.91**	9.09	**57.14**	42.86
%fromPF	100,0	14,3	87,5	28,6	**100,0**	14,3	**100,0**	66,7
Avg EI	0	6600	0	1520	**0**	1866.67	**0**	0
stdv EI	0	5938.57	0	1330.26	**0**	1431.39	**0**	0
Spacing S	0.3311	0.5066	0.1431	0.3311	**0.6959**	0.3311	**0.6959**	0.1431

(a) (b) (c)

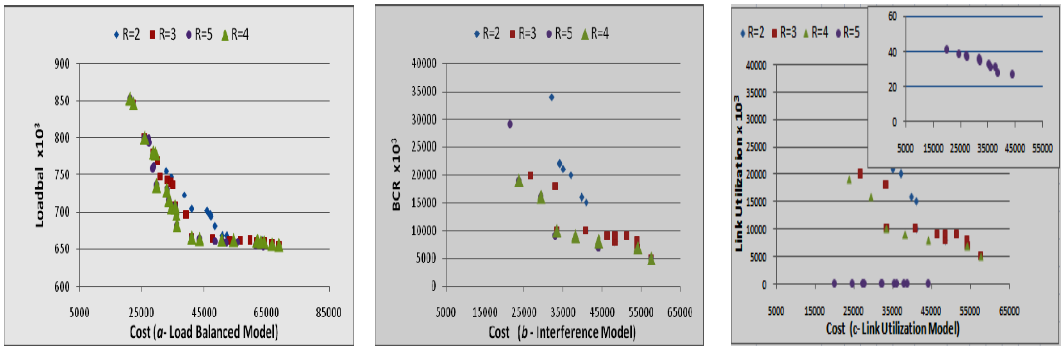


Figure 3.10: Pareto Fronts of Planning Solutions For different radio interfaces:
(a) Load-Balanced Model, (b) Interference Model, (c) Flow-Capacity Model.

(a) (b)

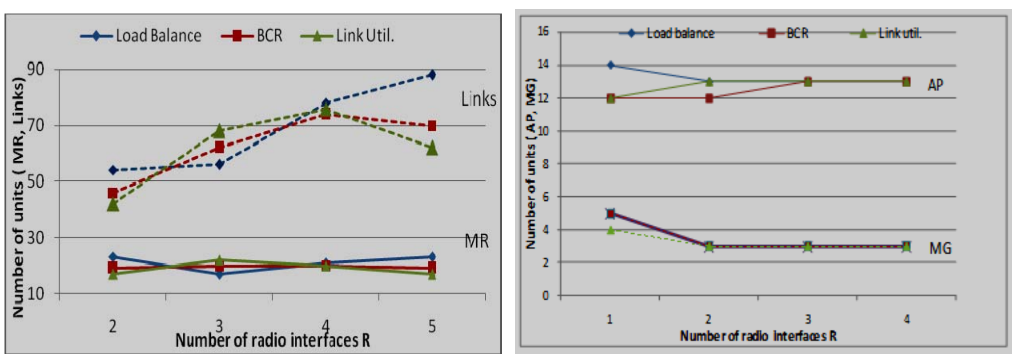


Figure 3.11: Network Devices Utilization For Three Models with Different Radio Interfaces.
(a) Number of MRs-Links, (b) Number of APs- MGs

(a) (b) (c)

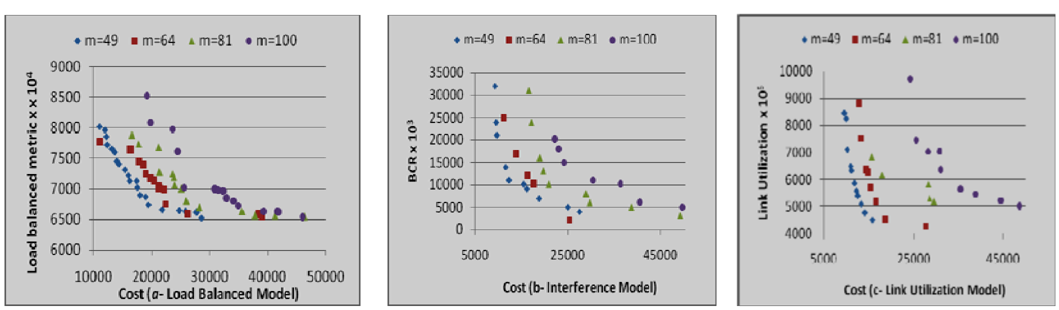


Figure 3.12: Pareto Fronts of Planning Solutions For different Grids.
(a) Load-Balanced Model, (b) Interference Model, (c) Flow-Capacity Model.

(a) (b)

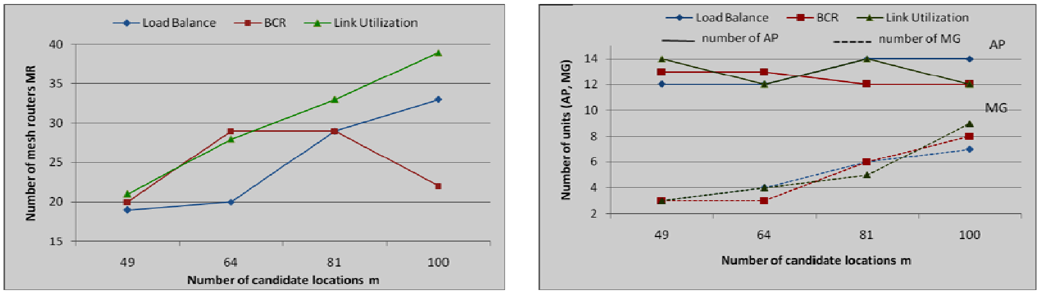


Figure 3.13: Network Devices Utilization For Three Models with Different Grids.
(a) number of MRs, (b) number of APs and MGs

3.4.4.4 Demand (d_i) Variation

Regarding Pareto fronts for d_i =1,2,3,4 and 5Mb/s, the Load-Balanced Model (Figure 3.14.a) returns larger set of planning solutions while the non-dominated planning solutions provided by the Interference Model (Figure 3.14.b) are better stretched and evenly spaced than those of Flow-Capacity Model (Figure 3.14.c).

As can be seen From Figure 3.15.a, when demands increase the number of gateways increases accordingly to satisfy connectivity constraints by creating new routing paths. More relays *MRs* than *APs* are added in order to connect these *APs* to newly added gateways. All models deploy almost the same number of gateways when demand varies, however, Interference Model seems to better handle the increase of demands, as shown in Figure 3.15.b, by using less *APs*.

(a) (b) (c)

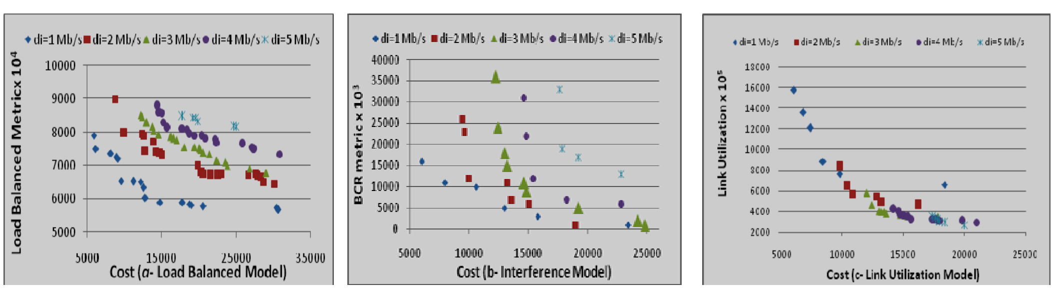


Figure 3.14: Pareto Fronts of Planning Solutions For different demands.
(a) Load-Balanced Model, (b) Interference Model, (c) Flow-Capacity Model.

(a) (b)

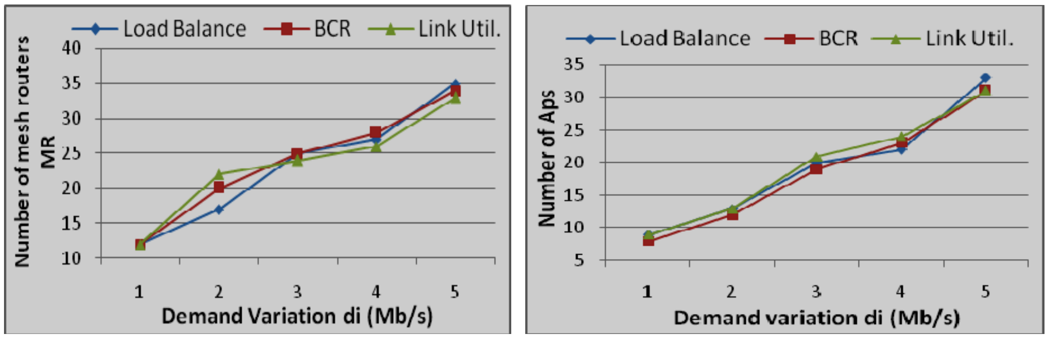


Figure 3.15. Network Devices Utilization For Different Demands. (a) Number of MRs, (b) Number of APs.

3.4.4.5 Traffic Spots (n) Variation

As with previous scenarios, Figure 3.16 shows that more and diverse planning solutions are produced by Load-Balanced Model. Load-balanced and Flow-Capacity models require few gateways, relays, and links to be added when more users are added in, compared to Interference Model which adds more of these devices (see Figure 3.17). On the other side, the Load-Balanced Model deploys less APs than the other models; this suggests that the Load-Balanced Model may be better in handling the scalability issue.

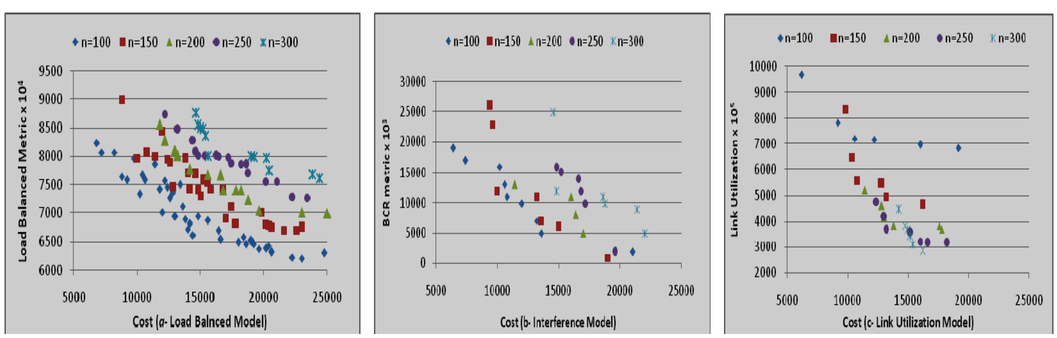


Figure 3.16: Pareto Fronts of Planning Solutions For different Traffic Spots.
(a) Load-Balanced model, (b) Interference model, (c) Flow-Capacity Model.

(a) (b)

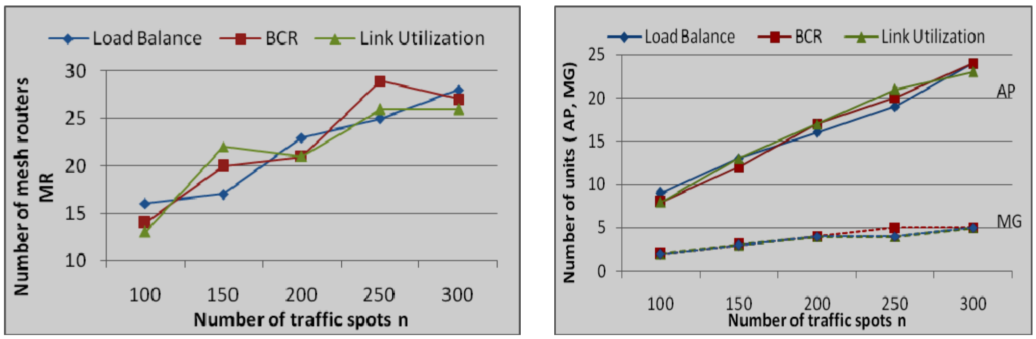


Figure 3.17: Network Devices Utilization For Different Traffic Spots.
(a) Number of MRs , (b) Number of APs and MGs.

3.4.5 A Comparison with Related Work

We introduced three bi-objective models with two conflicting objectives (deployment cost and network performance) that need to be optimized concurrently while satisfying all the QoS constraints. Validating our results against other known models for WMN planning problems turns out to be impossible as it is unpractical to compare a set of Pareto (two-dimension) optimal solutions with a one-dimension optimal solution. Nevertheless, we can at least check the one common objective function (deployment cost) to see whether the results fall in the same range.

We compare our results to the closest related work results obtained by Amaldi et al [3]. We refer to their model as AML and to ours as MOCB (using Load balanced Model). They used the following parameters setup (d_i=3Mb/s, n=100, m=50, R=3 and k=11.) and obtained a “single” planning solution per run. They reported the mean value calculated over the ten runs (#MR=23.65, #MG=3.3, #Links=21.35). Using the same parameters setup, we obtained 15 non-dominated planning solutions (see Table 3.4). We report the two extreme planning solutions (cheapest, most expensive) together with Amaldi et al.’s mean value solution in Table 3.5.

Table 3.4: solution of MOCB (Load-Balanced Model),

d_i=3Mb/s, n=100, m=50, R=3 and ch=11.

MR	*AP*	*MG*	*Links*	*Cost*	*Load balance*
20	13	3	31	9400	0.898454
23	12	3	35	10000	0.811035
18	13	4	30	10800	0.800554
22	13	4	43	11600	0.796620
23	13	4	37	11800	0.790363
25	12	4	40	12200	0.770813
29	13	4	46	13000	0.760068
25	14	5	43	14000	0.728297
21	12	6	35	15000	0.726868
24	13	6	43	15600	0.713449
21	12	7	38	16800	0.683738
29	15	7	50	18400	0.675634
23	14	8	42	19000	0.661046
25	14	11	46	24800	0.648230
26	15	15	57	32200	0.640597

Table 3.5: Two extreme planning solutions of MOCB versus the solution of AML

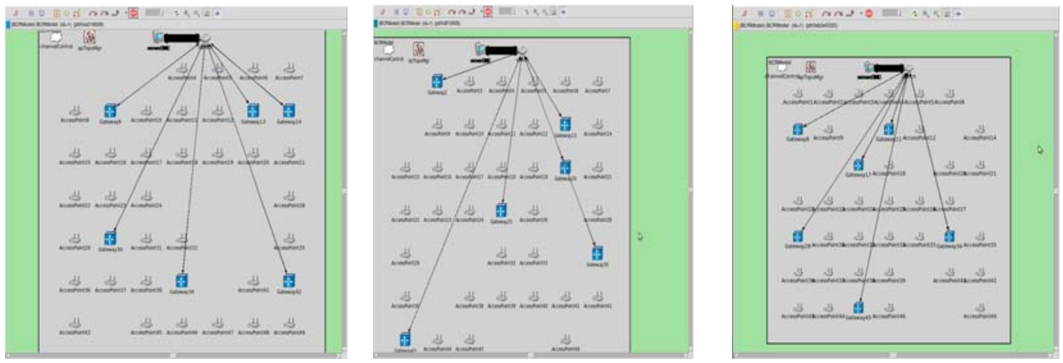
	MR	*MG*	*Links*	*Cost*
AML	23.65	3.3	21.35	10660.0$
MOCB$_{cheapest}$	20	3	31	9400.0$
MOCB$_{expensive}$	26	15	57	32200.0$

Our planning solutions of MOCB are numerous and diverse, ranging from the very cheap planning solution (MOCB$_{\mathbf{cheapest}}$ in Table 3.5) with less balanced channels' load to the very expensive planning solution (MOCB$_{\mathbf{expensive}}$ in Table 3.5) with well-balanced distribution of load over network channels. Results in Table 3.4 show that our approach tends to provide some planning solutions which may be more expensive than that of AML, but guarantee load balanced topologies while others are cheaper. Balancing load over network channels is a desirable QoS metric that increases network performance. Indeed, it minimizes traffic contentions and bottlenecks, which increases global network throughput. The AML model is a single-objective model, which does not consider any QoS metric in the formulation. This fact led us to compare only the common objective (cost objective function) on a single objective basis. Table 3.5 shows that MOCB generates from 12% cheaper planning solutions to 30.2% more expensive planning solutions than the average-value solution generated by the AML model for the same parameters setting.

3.4.6 Performance Evaluation via simulation

The main goal of this section is to evaluate the performance of the three models using a common metric, namely the overall network throughput. The analysis on the results obtained in Section 3.4.4, by varying different key parameters, has shown that Load-Balanced Model always generates broader, diverse and well-dispersed set of non-dominated planning solutions. However a clear conclusion about the performance of the planning solutions could not be drawn without comparing the throughput each model generates. To this end, we have run simulations with the discrete event network simulator OMNET++ and INETMANET framework [OM09] to support the MR-MC topologies.

In order to define the simulation scenario and get more insights on the true performance of the planned WMNs, we consider one solution provided by each model under a specific standard setting SS=[(n:150), (m:49), (d_i:1Mb/s), (u_{jl}:54Mb/s), (v_j:54Mb/s), (M:128Mb/s), (e_j:200), (p_j:8*e_j), (R:3), (k:11)]. The three solutions selected have the same deployment cost (same value of f_1) and are built under the same distribution of clients TSs. Figure 3.18 depicts the three simulated topologies.



(a) (b) (c)

Figure 3.18: Simulated networks. (a): Load-Balanced Model, (b): Interference Model, (c): Flow-Capacity Model.

We feed the simulator with the positions and the types (AP, MR, MG) of mesh nodes, as well as the channel matrix and the routing matrix derived from Edmond's approach [EK72]. We run the simulations with *ftp* traffic on top of TCP application. Each AP is transferring a file (*ftp*) and each gateway is wired (connected by cable) to a switch. Links capacity on these cables is set to 100Mbps and the wireless link capacity is set to 11Mbps. All the simulations are implementing fully the IP stack and all the routing between stations is IP routing (layer 3). Each station must negotiate each ARP with its next hop. This introduces an additional delay at the beginning of each traffic transaction, as normally happen in the real devices. The radio transmission power is set to 100mW and all the radios in the same channel are under mutual interference. Finally we use the wireless propagation model PathLoss with alpha set to 2.

To compare the throughputs, we use the received bytes (or bits) (throughout the simulation time) by each server associated to an AP. The graph presented in Figure 3.19 illustrates the bits/s TCP throughput for all servers (APs) per topology. The higher slopes in the graph indicate bigger throughputs. We can see that in the Interference Model, 64% of the servers have their bits/s values oscillate above 5000bits/s, while 52% of the servers in the Load-Balanced Model and 43% of the servers in the Flow-Capacity Model have their bits/s values above 5000bits/s. This suggests that the Interference Model handles better the initial network loads (users' demand).

We further calculate the overall TCP throughput and standard deviation (Std) of the bytes received by all the gateways of each topology. The results reported in Table 3.6 show that the topology of the Load-Balanced Model performs better as it has the highest overall throughput. Moreover, it is easy to see that the traffic loads are well balanced by this approach, leading also to a fair use of gateways capacity since the gateways are equitably used (better Std value) compared to the other two models.

(a) (b) (c)

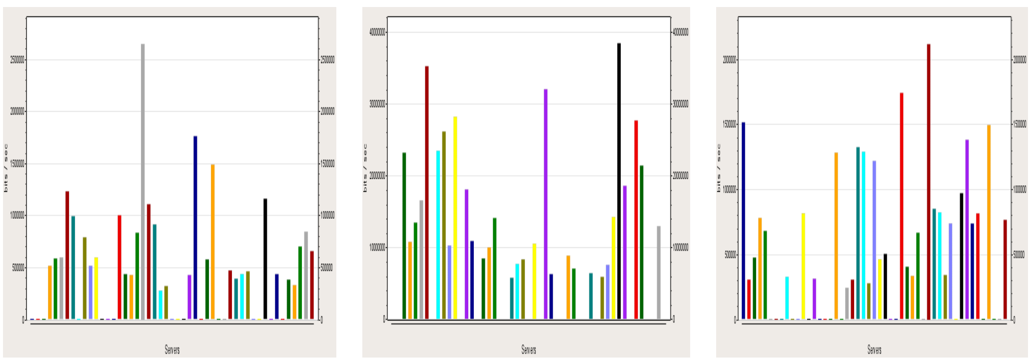


Figure 3.19: Servers (bits/s) TCP throughput. (a): Load-Balanced Model, (b): Interference Model, (c): Flow-Capacity Model.

Table 3.6: Total TCP throughput from the three topologies

Interference Model		**Load-Balanced Model**		**Flow-Capacity Model**	
MG index	Bytes Received /s	MG index	Bytes Received/s	MG index	Bytes Received/s
MG#2	41373.01	MG#9	30946.56	MG#8	15961.60
MG#13	44270.08	MG#13	30292.91	MG#11	18373.12
MG#20	13009.49	MG#14	43300.69	MG#17	31968.85
MG#25	22225.49	MG#30	31813.97	MG#29	38054.83
MG#35	45850.88	MG#39	26081.71	MG#34	44300.37
MG#43	26627.84	MG#42	31375.36	MG#45	33156.69
Tot. TCP Throughput	**32226.13**		**32301.87**		**30302.58**
Std	**13527.67**		**5772.93**		**11089.94**

3.5 Concluding Remarks

The bulk of the contributions in solving the WMNs planning problems assume a fixed topology, are all bounded to medium size instance problems, and optimize a single objective, namely the network deployment cost.

In this paper, we have shown that the optimization of WMN planning problem is naturally multi-objective. We proposed a generic WMN planning model where the two objectives of deployment cost and network throughput are optimized simultaneously. While the deployment cost is trivial, maximizing the throughput can be achieved in three ways: either maximizing the overall flow-capacity ratio, minimizing the network interference or balancing the network links' load. We instantiated three specific WMN planning models, namely Load-Balanced Model, Interference Model, and Flow-Capacity Model.

We conducted some numerical experiments on the three models to study the impacts of some key parameter variations on the network performance. In the light of the results shown in Section 3.4, and from a decision making perspective, Load-Balanced Model always generate a broader set of non-dominated solutions, favors cost-effective solutions, and guarantees a diverse and well dispersed set of solutions than the other two models. This makes this model the better of the three to generate cheaper planning solutions. There is also a tendency in using the costly gateways with care in a sense that it usually adds more links and routers than deploying expensive gateways. On the other side, Interference Model handles better the increase of demands and no more gain can be obtained with more than four radio interfaces.

Finally, the actual performance of our three planning bi-objective models is assessed by a component-based network simulator to derive the actual network throughput. The results clearly show that the Load-balanced Model provides better overall throughput. Equally important, gateways receive better balanced shares of the network traffic due to the inherent design approach which strives to balance the loads all over the network links.

Chapitre 4

Design of Scalable and Efficient Multi-Radio Wireless Networks

D. Benyamina, A. Hafid, M. Gendreau

Abstract

A proper design of Wireless Mesh Networks (WMNs) is a fundamental task that should be addressed carefully to allow the deployment of scalable and efficient networks. Specifically, choosing strategic locations to optimally place gateways prior to network deployment can alleviate a number of performance/scalability related problems. In this paper, we first, propose a novel Clustering based Gateway Placement Algorithm (CGPA) to effectively select gateways positions. Existing solutions for optimal gateway placement using clustering approaches are tree-based and therefore are inherently less reliable since a tree topology uses less links. Independently from the tree structure, CGPA strategically places the gateways to serve as many routers as possible that are within a bounded number of hops. Next, we devise a new multi-objective optimization approach that models WMNs topologies from scratch. The three objectives of deployment cost, network throughput and average congestion of gateways are simultaneously optimized using a nature inspired meta-heuristic algorithm coupled with CGPA. This provides the network operator with a set of bounded-delay trade-off solutions. Comparative empirical and experimental studies with different key parameter settings are conducted to show the effectiveness of CGPA and to evaluate the performance of the proposed model.

Status: This paper is submitted to ACM Wireless Networks Journal**.** A part of this article was presented in *IEEE LCN*, Switzerland, 2009 [BH09b]. The model used as a case study to validate the approach proposed in this article was also presented in *ACM Qshine*, Spain, 2009 [BH09d]. Lately, the paper (*ACM Qshine'*09) has been selected for publication in a *Special Issue of the Journal ACM/Springer Mobile Networks and Applications (ACM MONET)*, to be published in 2010 [BH10].

4.1 Introduction

With the tremendous success of wireless technologies and the high demand of Internet Access, the design of scalable and cost-effective wireless networks is becoming an absolute necessity. In this context, Wireless Mesh Networks (WMNs) have recently been proposed as wireless access networks. In Infrastructure WMNs (IWMNs), Access Points (APs) provide internet access to Mesh Clients (MCs) by forwarding aggregated traffic to Mesh Routers (MRs), known as relays, in a multi-hop fashion until a Mesh Gateway (MG) is reached. MGs act as bridges between the wireless infrastructure and the Internet. WMNs are highly reliable, scalable, adaptable and cost-effective. They are already pervasive in many diverse environments, such as home networking, enterprises, and universities. Nevertheless, users experience a number of problems, such as intermittent connectivity, poor performance and lack of coverage [BH07a]. Essentially, performance is highly impacted by wireless interference and network congestion. In Multi-Radio Multi-Channel (MR-MC) networks, mesh nodes are equipped with multiple network interfaces, thus allowing simultaneous communications over orthogonal channels. However, since the number of available orthogonal channels is limited, interferences happen causing network performance degradation. In WMNs, traffic is mainly routed by IWMN between the mesh clients and the Internet and goes through the MGs. Since all internet traffic has to pass through one of the MGs, the network may be unexpectedly congested at one or more of them, even if every MR provides enough throughput capacity [VH08]. A proper WMN design is a fundamental task; if addressed carefully, it can considerably improve the network efficiency in terms of coverage, throughput, delay and cost.

Basically, the design of WMN involves deciding how many and where to install the network nodes (given a set of candidate locations), which type of nodes to select (AP, MG or simple MR), and which channel to assign for each node interface, while guaranteeing users coverage, wireless connectivity and traffic flows at minimum cost. In fact, the construction cost of IWMNs is highly proportional to the number of deployed MGs.

Basically, the placement of these mesh nodes (MGs) determines the hop-length of the communication paths in the network, the amount of congestion, and the available bandwidth to and from the Internet. When designing wireless networks, network scalability is an important feature to consider. The scalability of WMNs is highly affected by the geographical expansion and/or the increase of aggregated demand (when the demand per user increases and/or the number of users increases). Prior work [AB06] has shown that a network scales better when the traffic pattern is local, which is guaranteed only if each node sends to nearby gateways within a fixed radius, independent of the network size. Therefore, to keep the expected path length almost constant, as the network size grows, one would think on dividing network nodes into groups or clusters. Each cluster is served by one MG, called cluster head; all nodes in the cluster have a bounded distance, in terms of number of hops, to reach the cluster head (MG). Thus, ensuring a minimum number of communication hops bounded by the cluster radius will increase network throughput as reported by Li et al. [LB01]. Moreover, having shorter communication paths is a desired goal when designing multi-radio wireless networks since the impact of inter-path (or co-channel) interference on network performance is reduced.

Problem addressed. In this study, we address the problem of WMN design by exploiting the trade-offs among network deployment cost, network throughput, gateways' congestion level, the number of communication hops between sources and gateways, and users' coverage. Indeed, minimizing the cost requires stingy resources utilization (deploying fewer routers and/or gateways) which impacts the network performance. With few routers deployed, the traffic is routed on longer paths to get to its destination, thus increasing communications delays. With few gateways deployed, congestion may happen (since all traffic traverse gateways to and from the internet) affecting network throughput. Conversely, deploying more resources (higher deployment cost) helps in providing shorter paths and less congested gateways; however, this may cause high interference levels and thus degrade network performance. In fact, optimizing one of these criteria will affect/undermine other(s) criteria(s); therefore, it is difficult, if not impractical, to have a solution that is optimal in all criteria. Thus, a multi-objective approach is definitely recommended for such problems.

WMN design problem belongs to the set of Multi-commodity capacitated network design problems (MCNDPs). They are known to be hard combinatorial optimization problems for which several solution strategies have been developed. Several of these strategies involve the relaxation of some problem constraints and the strengthening of the model through the addition of valid inequalities [Co06]. In this study, we propose a multi-objective model to search for the near-optimal set of non-dominated planning solutions. This set of trade-off solutions is very much welcomed by engineers who prefer to have several solutions in hand before taking decisions. An efficient and multi-objective meta-heuristic is then needed to solve the proposed model.

Contribution. In this paper, we focus first, on the problem that given the locations of APs and MRs with their traffic demands, determine which routers are selected as gateways under connectivity, bounded delay, and financial constraints. For this purpose, we propose a Clustering Based Gateway Placement Algorithm (*CBGPA*) that: (1) Ensures strategic placement of MGs. The position of a candidate MG is selected based on a cluster radius and on the expected path length from the selected MG to all APs belonging to the same cluster; (2) Guarantees network scalability by forcing each node to send traffic to its nearby gateway; and (3) Deploys a smaller number of MGs, thus resulting in cost effective topologies. Briefly, the clustering technique (see Section 4.4) ensures a proper placement of MGs leading to less deployment cost while providing enough network throughput capacity.

Next, we propose a multi-objective optimization model for designing WMNs from scratch (all mesh nodes locations are not decided). We consider deployment cost, total network throughput, and the level of congestion of MGs, as the three objectives to minimize simultaneously.

Finally, to solve the multi-objective model, we adopt the Multi-Objective Particle Swarm Optimizer (MOPSO) that we tailor for WMN design problem solving. Obviously, such optimizers necessarily return a set of near-optimum solutions that are non-dominated with each other, i.e., none is better than the rest with respect to all objectives. Through the proposed model, we show how CBGPA is coupled with the multi-objective optimizer to complement the design model. The goal would be then, the design of scalable, bounded delay and cost-effective WMN (cost and congestion are minimized while throughput is maximized) infrastructures.

The key contributions of the paper can be summarized as follows:

- A clustering technique for optimal placement of MGs that guarantees bounded delays, better throughput and less deployment cost;
- A *novel* multi-objective optimization model;
- A meta-heuristic algorithm to solve the model.

To the best of our knowledge, there has been so far no real attempt to model WMN design problems using a pure multi-objective approach. The only work worth mentioning is presented in [HX07]; it concerns only gateways placement problem where locations of other mesh nodes are known *a priori*. Bing et al. [HX07] use a multi-objective approach but then aggregate the many objectives into a single one representing a weighted sum of objectives values. This is a classical approach to handle Multi-Objective Problems (MOPs); however, the biggest problem with this approach is the inability to find solutions in non-convex fronts [DD97]. Moreover, the setting of the relative weights for the different objectives is subjective and often leads to favoring some and penalizing others.

Paper organization. The rest of the paper is organized as follows. We start by presenting related work in Section 4.2, followed by network model description given in Section 4.3. Section 4.4 presents the Clustering Based Gateway Placement Algorithm *CBGPA*. The multi-objective model to design scalable, bounded delay and cost-effective WMN infrastructures is given in Section 4.5. Section 4.6 presents the solution approach and the meta-heuristic adopted to solve the proposed model. In Section 4.7, we present and discuss the simulation results. Finally, we conclude the paper in Section 4.8.

4.2 Related Work

In this study, we address two complementary problems: the topology design problem and the optimal gateway placement problem. Existing related research for the topology design problem concerns mainly partial topology design where either routers location or gateways location are fixed *a priori* [AB06], [CQ04], [Hw08], [HX07], [LB01], [RU08], [SR07]. The only close related work that proposes WMN planning schemes where the locations of routers and gateways are not fixed, is found in [AC08], [BH07]. Nevertheless, these studies consider in a way or another minimization of a single objective based on the deployment cost. In [BH07], the authors propose a unified model for WMN design formulated as an ILP problem. Their objective is to minimize the total installation cost by tuning all the network parameters; the delay is considered as constraint in their formulation but users' coverage is not considered in their model. Because of the exponential number of constraints and variables, the problem is solved for only small size networks. The authors in [AC08] construct and formulate the planning model as an ILP problem based on user-coverage satisfaction. QoS requirements, such as the delay and throughput are not considered in their formulation. We stress the point that none of these approaches tackle the issue of "optimal" gateways placement, gateways congestion level, and/ or network scalability.

Due to the impact of MGs placement on network performance and network scalability handling, there has been a recent surge of interest in optimal placement of gateways in WMNs

[AB06], [CQ04], [HW08], [HX07], [LB01], [RU08]; however, only few use the clustering approach [AB06], [CQ04], [HW08] for scalability analysis. The authors in [AB06] and [CQ04] propose different clustering techniques to divide the WMN into clusters represented by trees routed by the MGs. Although, these techniques have a number of benefits (e.g., low routing overhead and efficient flow aggregation), they suffer from reliability degradation known in tree-based structures (A tree topology uses, theoretically, less links). Furthermore, if the topology is restricted to a tree, under the link capacity constraint, a large number of gateways may be needed [HW08], thus increasing the network deployment cost. Figure 4.1 shows how a tree-based topology tends to deploy more gateways than a mesh topology (2 MGs Vs. 1 MG). Every potential link (a dashed line) is associated to a capacity link (the value between brackets) and a traffic demand is associated to every node.

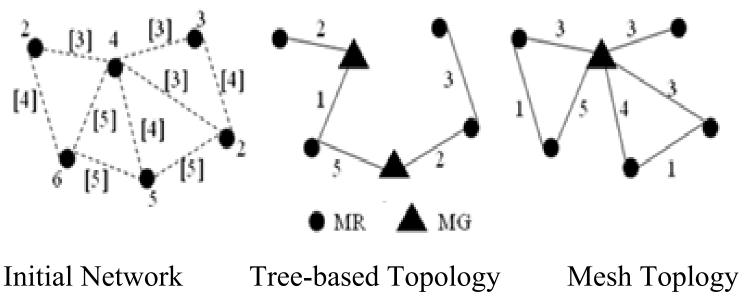


Figure 4.1: Impact of network topology in gateways deployment

Without the restriction of tree topology, Hsu et al [HW08] model the gateway placement problem by a combinatorial optimization problem where they propose two algorithms; Self-Constituted Gateway Algorithm (SCGA) and Predefined Gateway Set Algorithm (PGSA). Both algorithms use genetic search algorithm to search for feasible configurations and use a modified version of Dijkstra algorithm to look for paths with bounded delays. In PGSA, the number of gateways, initially set to one, is increased by one iteratively until a feasible configuration is obtained. While in SCGA, the number of gateways is set up dynamically, when needed. The PGSA may converge, but very slowly, to find a feasible solution in a real-size network (large number of mesh nodes). A minimum number of gateways, g, required to support the traffic demand, is obtained after (g-1) iterations, whereas many iterations could be avoided if the information of ingress traffic demand is exploited to compute the initial value of g. In SCGA, the dynamicity of gateways allocation may lead to premature convergence of the search algorithm (converges to local minima); consequently, non-optimal solutions are found. Moreover, the design problem solved by both search algorithms does not consider bounded delay in terms of communication hops but in terms of the ratio packet size over link capacity; this does not have any impact on the required optimal number of gateways to deploy.

4.3 Network Model

In this study, we consider a multi-radio multi-channel (MR-MC) WMN and we suppose initially that the mesh nodes operate using the same number of radios *R*, each with *k* channels, *(k>R)* and $k \in C$, where *C* = {1,.., *c*} and *c* can be at most 12 orthogonal channels (if IEEE 802.11a is used).

We represent a WMN as an undirected graph *G(V,E),* called a connectivity graph, mathematically represented by a two dimensional matrix (connectivity matrix) . Each node *v* represents a mesh node which can be an access point (AP), a relay (MR) or a gateway (MG) (see Figure 4.2.a). The neighborhood of *v,* denoted by *N(v*), is the set of nodes residing in its transmission range. A bidirectional wireless link exists between *v* and every neighbor *u* in *N(v)* and is represented by an edge *(u,v).*

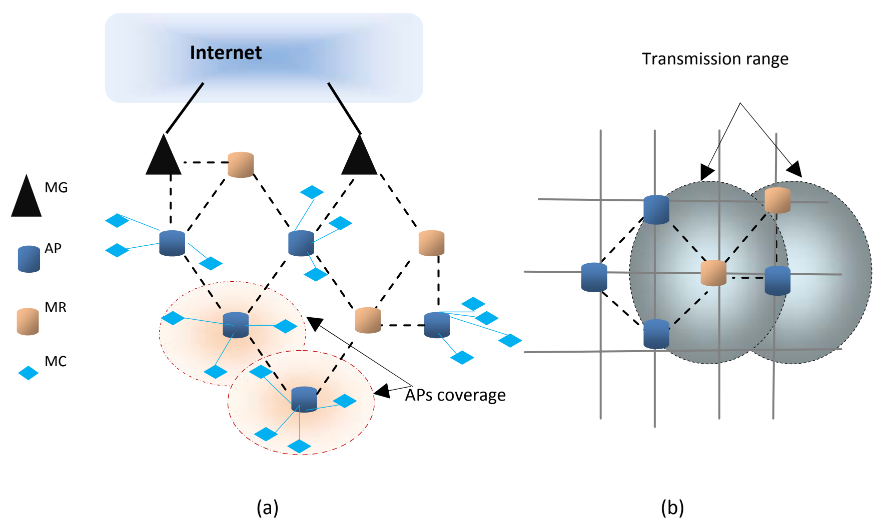


Figure 4.2: WMN design problem. (a): network model. A MC covered by many APs (overlapping APs' coverage) is assigned to only one AP. (b): WMN grid-like layout.

A number of studies on WMN performance [LW07], [RK08], have shown the benefits of grid topologies over random topologies where coverage, connectivity, average fair capacity, and network throughput are better in grid topologies, especially square grid topologies, than random topologies. In this study, we adopt a *square-grid-like* layout as the physical representation of our WMN infrastructure. Each mesh node, if installed, may establish a wireless communication with its eight direct neighbors (Figure 4.2.b). This assumption increases the chances of selecting a candidate neighbor among the eight with which a wireless link will be set up in the channel assignment procedure. The maximum degree of *G* denoted by Δ is bounded by the number of radio interfaces, *R.*

4.4 Clustering Approach and MG Placement

In this section, we suppose that the locations of APs and MRs are a priory known and only MGs locations are left to be decided.

4.4.1 Algorithm Description

The aim of our clustering approach is to guarantee an upper bound length for every potential path between any mesh node and its nearby MG. Once the set of APs is defined and the whole graph is fully connected, the cluster construction procedure, implemented by *CBGPA*, starts by placing a MG at a half way position between two APs. For each not yet visited AP, its peer AP is selected as the closest one among all its AP neighbors; an immediate neighbor (within one hop distance) is not a candidate AP.

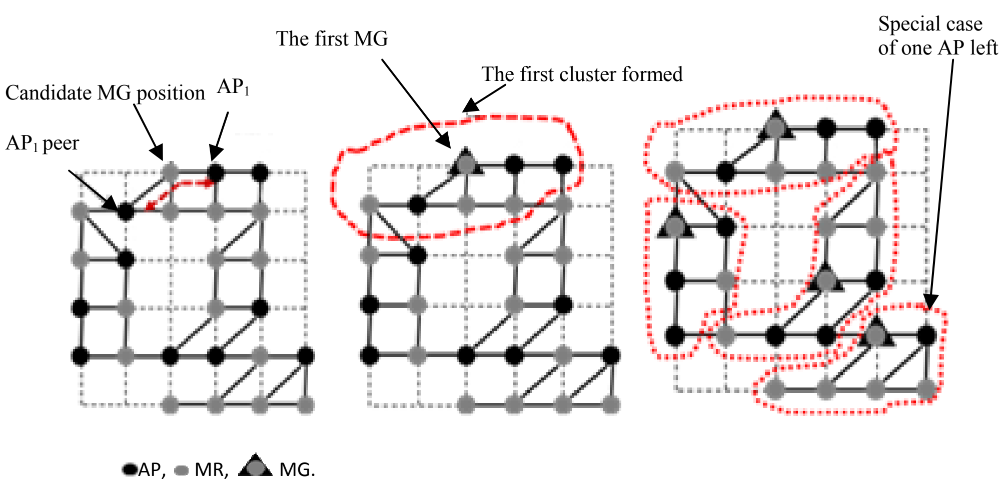


Figure 4.3: Different stages in clusters construction and gateways placement in 6x6 grid based WMN with *R*=3 and *H*=2.

We use Breadth First Search (BFS) algorithm [Ca98] to select the peer AP since all graph links have the same cost (equal to one). The set of mesh nodes that are far away from the newly placed MG by at most *H* hops are included in the same cluster and marked as visited. *H* is set by the network planner to limit the maximal distance, in terms of number of hops, of the MR-MG communication paths. The algorithm is iterative and stops when all mesh nodes are marked. In some situations, where there is one AP left (no peer AP is found), its parent in the routing path (its predecessor) is selected as MG; when the algorithm terminates, all nodes belong to disjoint clusters, each headed by one MG. The total number of formed clusters represents then, the minimal number of MGs that guarantees the required delay with a minimum deployment cost.

Algorithm 4.1 describes the clustering based gateways placement algorithm (CBGPA) while Figure 4.3 illustrates the main *CBGPA* operations.

Algorithm 4.1: Clustering algorithm *CBGPA*

Input *Y*: Connectivity matrix, *APnumber:* number of placed APs.

Output *GW*: MGs positions

j=0; *APleftTobeClustered*=*APnumber*;

totalApClustered=0;

shortestPathLength= largeValue;

While (j<*APnumber*) and (*APleftTobeClustered* >1) **do**

While (exist $k \in$ list of non clustered APs) **do**

pathLength = BreadFirstSearch (AP_j , AP_k)

if (*pathLength*< *shortestPathLength*) **then** *index*=*k*; **End if**

k=*k+1*;

End while

Mark (AP_j); Mark (AP_{index});

totalApClustered = *totalApClustered*+2;

AP*leftTobeClustered*= *APnumber*- *totalApClustered*;

indexGate= GoBackHalfWay(AP_j , AP_{index});

Set *GW*[*indexGate*] to 1;

BuildOneCluster(*indexGate, H*);

Update (*totalApClustered*);

j=*j*+1;

End while

If (*leftTobeClustered*=1) **then**

Set *indexGate* to index of pathParent of AP left;

Set *GW*[*indexGate*] to 1;

End if

GoBackHalfWay() returns the position of the candidate MG, *indexGate*, which is equidistantly located between AP_j and AP_{index}. All mesh nodes that are located within a radius of *H* hops from *indexGate* are included in the same cluster (BuildOneCluster()). APs included in that cluster are marked and the total number of clustered APs is then updated (Update()).

4.4.2 Algorithm Correctness

Lemma 1: *The clustering algorithm CBGPA terminates within a finite number of iterations.*

PROOF: The clustering process requires a number of iterations, which we denote N_{iters}. *CBGPA* stops when N_{iters} is equal to the number of formed clusters including the cluster which is added when there remains one isolated access point (does not belong to any of the formed clusters). In Multi-Radio Multi-Channel (MR-MC) networks, the number of simultaneous communications allowed between any two nodes, is bounded by the number of radio interfaces *R*, assigned to the communicating nodes. Therefore, each node in the cluster (including MG) has at most *R* direct neighbors. Starting from MG node, each of its direct neighbors is interconnected with at most (*R*-1) neighbors (two hops away from MG); the same applies for neighbors 3 hops away and so on. Let NC_{clus} be the average number of nodes per cluster. Then, given the cluster radius *H*, and the total number of mesh nodes installed *n*, we have:

$$NC_{clus} \leq R\prod_{i=1}^{H-1}(R-1) \leq R^H \tag{4.1}$$

The number of iterations (formed clusters) is then given by the following equation:

$$N_{iters} = n / NC_{clus} \tag{4.2}$$

Using (1) and (2), we obtain a lower bound on the number of iterations of *CBGPA*, expressed by inequality (4.3):

$$N_{iters} \geq \left\lfloor \frac{n}{R^H} \right\rfloor \tag{4.3}$$

Note also that the worst case scenario occurs when each cluster is formed by only one couple of access points. In the case when "*APleftTobeClustered*=1" after terminating the main loop (see Algorithm 4.1), an additional cluster is formed, which gives an upper bound on the total number of formed clusters. Therefore,

$$N_{iters} \leq \left\lceil \frac{N_{AP}}{2} \right\rceil + 1 \tag{4.4}$$

Where, N_{Ap} is the total number of APs. Using (4.3) and (4.4), we get (4.5):

$$\frac{n}{R^H} \leq N_{iters} \leq \left\lceil \frac{N_{AP}}{2} \right\rceil + 1 \quad \square \tag{4.5}$$

Lemma 2: *The distance between any two MGs has a lower bound of (H+1)* (*Cluster heads are well distributed).*

PROOF: Consider the following worst case scenario (situation where two MGs are too close to each other). Assume that v_1 and v_2 are two cluster heads, each located at the border of a cluster (which we refer later as a border-cluster node). A border-cluster node is either a border node on one of the four grid borders or a middle node as shown in Figure 4.4. Three cases are possible:

Case 1: v_1 and v_2 are border nodes. Executing BuildOneCluster(*indexGate, H*) (see Algorithm 4.1) creates one cluster that groups all nodes that are *H* hops away from *indexGate*th node (MG). Hence, v_1 and v_2 are at least (2 x *H*) hops apart.

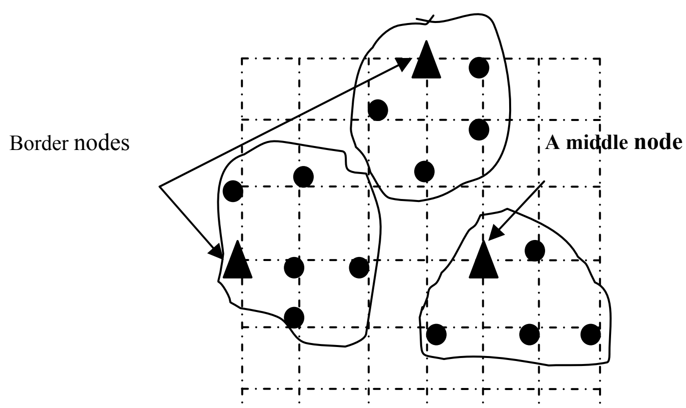


Figure 4.4: Situations when a MG node is a border –cluster node in 7x7 grid based WMN with R=3 and H = 2.

Case 2*:* Only one of them is a border node, let's say v_1. The second node, v_2, is a middle node. Let us consider the worst case scenario where v_2 node is elected as a cluster head after the execution of the conditional instruction "*APleftTobeClustered* =1" (see Algorithm 4.1). In this case, v_2 is the first predecessor of the isolated access point node. The minimum distance to the closest cluster head (v_2) could not be smaller than H hops; otherwise, the isolated access point would have joined the closest cluster and no AP is left (condition “leftTobeClustered=1” is set to false). Therefore, v_1 and v_2 are at least (H+1) hops apart.

Case 3: v_1 and v_2 are middle nodes. Each cluster has a small diameter bounded by the number of communication hops H. For the same reason as in case 2, we determine that the middle nodes v_1 and v_2 are at least (H+1) hops apart. □

Lemma 3: *At the end of the clustering process, each cluster is headed by one MG.*

PROOF: We prove this lemma by contradiction. Assume that a cluster is formed without placing an MG at the center of the cluster as cluster head. This implies that GoBackHalfWay(AP_j ,AP_{index}) does not return any node to be elected. In this case, executing BreadFirstSearch (AP_j ,AP_k) would not find a path between AP_j and AP_k which later becomes AP_{index} as the closest peer. This means that $AP_{j,}$ and AP_{index} belong to two disconnected graphs whereas the graph is connected. This proves that our assumption is false; thus, Lemma 3. □

One of the goals of *CBGPA* is to have few MGs covering (serving) large areas of the network. The following lemma sets an upper bound on the largest area that can be covered by a single MG.

Lemma 4: *Let Ł be the cell side length and H the number of communication hops. There exists at least one MG (cluster head) in any 4(H Ł)^2 area.*

PROOF: Figure 4.5 shows an illustration where one MG serves all nodes within two hops (H=2) in a 2Łx2Ł area. Given that (2Ł)(2Ł)≤ (2HŁ)(2HŁ) ∀ H≥1, we conclude that at least one MG can serve *a 4*(H Ł)^2 area. □

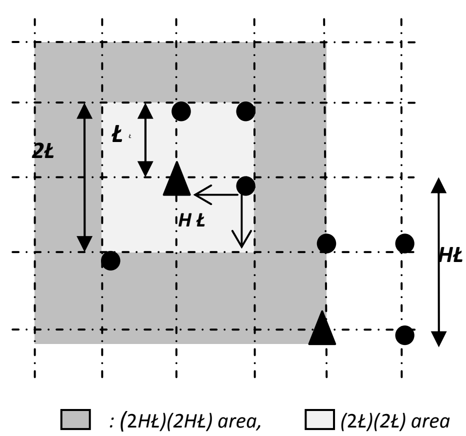


Figure 4.5: Minimum number of MGs in a 4(HŁ)^2 area with H=2.

4.4.3 Complexity study of CBGPA

The clustering algorithm *CBGPA* complexity is dominated by the shortest paths checking function. Let n_0 (resp. m_0) be the number of nodes (resp. edges) in the graph and let n_1 ($n_1 < n_0$) be the number of APs. We need to check for the shortest path between AP_j and every AP_l ($j \neq l$); this takes at most $O(n_1 m_0 \log n_0)$. Except the particular situation when only one unvisited AP is left at the completion of the main loop (first loop) of Algorithm 4.1, every cluster is formed by at least two APs. Then, for at most $n_1/2$ unvisited APs, the shortest path checking is performed. Then, the overall worst case complexity is $O(½\, n_1^2\, m_0 \log n_0)$ (or simply $O(n_1^2\, m_0 \log n_0)$).

4.5 Multi-objective Model to Design WMNs

In Section 4.4, we presented *CBGPA* that provides an optimal placement of gateways, given a selected set of candidate locations. Among a large set of candidate locations only a subset, where mesh nodes (MRs) are installed, is selected as the set of candidate locations to place a MG. This means that APs and MRs placements are known. Each AP j sends its traffic (i.e., generated by its mesh clients) on a path $\pi^k_{j,l}$ to gateway l, where the length $\pi^k_{j,l}$, in terms of the number of communication hops, is smaller than a fixed bound H. It has been reported in [AB06] that APs which have a higher number of hops to a mesh gateway, have lower capacity paths. Thus, lowering hop count generally increases capacity.

Kodialam et al. [KN05] report that there exist multiple design criteria for WMNs; their proposal allows optimizing a single objective function at a time; however, no generic method for dealing with the multiple metrics is provided. The work in [VH08], propose a model (within a tool) to measure the performance of a designed WMN prior to its deployment. The main idea is to define: (1) a set of metrics that work as evaluation criteria for WMNs; and (2) a weighted combination of the metrics for a simultaneous use of multiple evaluation criteria in WMNs optimization. In this section, we propose a multi-objective optimization model to design WMN topologies (to obtain optimal APs and MRs locations); then, we show how *CBGP* algorithm is used to select optimal MGs locations among the obtained MRs locations. A part of this section was already introduced in Chapter 3, but repeated in this section for the sake of clarity and completeness.

4.5.1 Problem Description

Let I={1,..,n} be the set of positions of traffic concentrations in the service area (Traffic Spots: TSs) and L={1,..,m} the set of positions where mesh nodes can be installed (Candidate Locations, CLs). From this section onward, we denote by n the number of TSs and m the number of CLs.

The WMN design problem aims at:

- Selecting a subset $S \subseteq L$ of CLs where a mesh node should be installed so that the signal level is high enough to cover the considered TSs.
- Defining the gateway set by selecting a subset $G \subseteq L$ of CLs where the wireless connectivity is assured so that all traffic generated by TSs can find its way to reach a node in G.
- Maintaining the cardinalities of G and S small enough to satisfy the financial and performance requirements of the network planner.

In order to describe the problem formally, we introduce the following notation:

The traffic generated by TS_i is denoted by d_i, while u_{jl} is the traffic capacity of the wireless link between CL_j and CL_l. The capacity of the radio access interface of an access point AP located at CL_j is denoted by v_j. The parameters c_j and p_j are respectively the cost associated to installing a mesh node (AP, MR or MG) at location CL_j and the additional cost required to install a gateway (MG) at that location. The network coverage a_{ij} and network connectivity b_{jl} are the two main WMN planning parameters. The network coverage is a binary matrix that states whether a client at TS_i can be covered by one or many locations CL_j .

$$a_{ij} = \begin{cases} 1 & \textit{if } TS_i \text{ cov}\textit{ered by } CL_j \\ 0 & \textit{otherwise} \end{cases}$$

The network connectivity is a binary matrix and indicates whether two locations can be wirelessly connected.

$$b_{jl} = \begin{cases} 1 & \textit{if } CL_j \textit{ and } CL_l \textit{ can be wirelessly connected} \\ 0 & \textit{otherwise} \end{cases}$$

The main decision vector variables (see Figure 4.6) are the routers (APs, MRs) and gateways installation locations, and the assignment of TS_i to CL_j.

$$t_j = \begin{cases} 1 & \textit{if a device installed at } CL_j \\ 0 & \textit{otherwise} \end{cases}$$

$$g_j = \begin{cases} 1 & \textit{if a gateway installed at } CL_j \\ 0 & \textit{otherwise} \end{cases}$$

$$x_{ij} = \begin{cases} 1 & \textit{if } TS_i \textit{ assigned to router at } CL_j \\ 0 & \textit{otherwise} \end{cases}$$

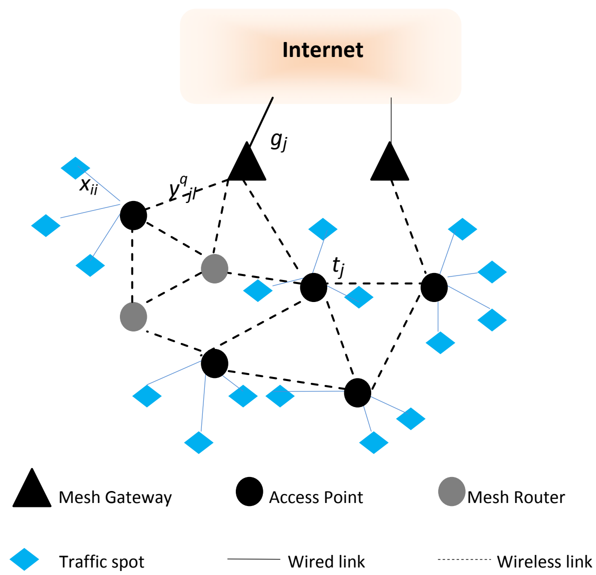


Figure 4.6: WMN Planning Problem.

We suppose initially that mesh nodes operate using the same number of radios *R*, each with *k* channels, *(k>R)* and $k \in C$, where *C* ={1,..,*c*} and *c* can be at most 12 orthogonal channels if IEEE802.11a is used.

Other extra installation (0-1) variables are needed in a multi-radio multi-channel WMN: z^q_j =1 if a mesh node is installed at CL_j and is assigned channel *q*, $q \leq k$, y^q_{jl} =1 if a there is a wireless link from a mesh node installed at CL_j to a mesh node installed at CL_l using channel *q*, $q \leq k$.

Finally, we define the flow variables f^q_{jl} and F_j. The variable f^q_{jl} denotes the traffic flow routed from a router in CL_j to a router in CL_l using channel *q*. The variable F_j is the traffic flow on the wired link between a gateway at CL_j and the Internet. Table 4.1 summarizes the notation used in the problem formulation.

Table 4.1: List of Main Parameters/Variables used in Model Formulation

Par./Var.	***Description***
n	Number of Traffic Spots (TSs)
m	Number of Candidate Locations (CLs)
d_i	Traffic generated by TS_i
u_{jl}	Traffic capacity of wireless link (CL_j,CL_l)
vj	Capacity limit for AP radio access interface
c_j	A device cost installation
p_j	A gateway additional cost installation
R	Number of radio interfaces
k	Number of channels
H	Maximal number of hops on a routing path
a_{ij}	Coverage of TS_i by CL_j
b_{jl}	Wireless connectivity between CL_j and CL_l
t_j	Installation of a device at CL_j
g_j	Installation of a gateway at CL_j
x_{ij}	Assignment of TS_i to CL_j
z^q_j	Installation of a device at CL_j , assignment of channel q, $q<k$
y^q_{jl}	Establishing a wireless communication on q Between (CL_j,CL_l)
f^q_{jl}	Flow on channel q between (CL_j,CL_l)
F_j	Flow on the wired link from CL_j to Internet
N_{jl}	Set of links interfering with the link y^q_{jl}
P_{jl}	Set of paths between AP *j* and MG *l* with at most *H* hops
π^k_{jl}	K^{th} path from P_{jl}

4.5.2 Formulation

In the following, we describe the main criteria considered in our problem formulation.

Deployment cost. Minimum installation cost is a fundamental issue in deploying WMNs. Increasing the number of MGs may increase the network throughput and may lead to a smaller number of gateway bottlenecks. Thus, we need to determine the right places of APs and MGs that result in: (1) a minimum number of APs that provides full coverage; and (2) a minimum number of MGs that provides enough throughput while satisfying QoS constraints. The first objective function to optimize computes the total cost of the network including installation cost c_j and additional gateway installation cost p_j.

$$Min\sum\left(c_j t_j + p_j g_j\right) \tag{4.6}$$

Network throughput. Because of the limited number of orthogonal channels, the spatial reuse of channels results in high level of interferences; this degrades the network performance by lowering its overall throughput. We optimize the network throughput by favoring topologies with well balanced channel reuse. The number of occurrences of a channel *q'*, denoted by $O_{q'}$, is used to compute the gap between the balanced allocation of channel q and the current allocation.

$$\varphi_q = Max\left|O_q - O_{q'}\right| \qquad \forall q,q' \in C$$

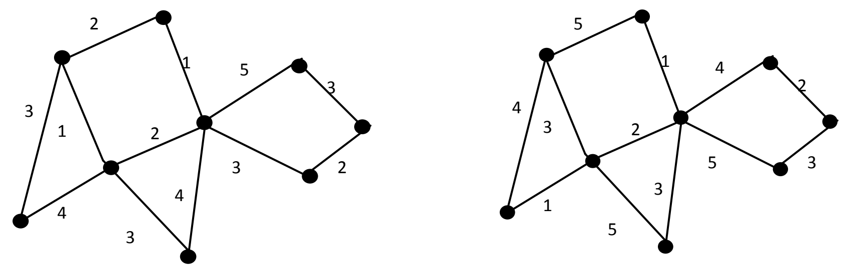
Where,

$$O_q = \sum_{j,l \in L} y_{jl}^q \qquad \forall q \in C$$

Our aim is then to minimize this gap; this is the second objective function of our model.

$$Min \sum_{q \in C} \varphi_q \tag{4.7}$$

Illustration in Figure 4.7 shows that, spatial channel reuse is better in (b) than in (a). The value of $\sum \varphi_q$ in (a) is equal to 11 while $\sum \varphi_q$ in (b) is equal to 5. This is caused by the unbalanced reuse of some channels (i.e. 2 and 3) in (a).



(a) *(b)*

Figure 4.7: Same topology with two different channel allocations.
(a) $O_1=2$, $O_2=3$, $O_3=4$, $O_4=2$, $O_5=1$ ($\varphi_1=1$, $\varphi_2=2$, $\varphi_3=3$, $\varphi_4=2$, $\varphi_5=3$),
(b) $O_1=2$, $O_2=2$, $O_3=3$, $O_4=2$, $O_5=3$ ($\varphi_1=1$, $\varphi_2=1$, $\varphi_3=1$, $\varphi_4=1$, $\varphi_5=1$).

Congested MGs. When all traffic to or from mesh clients (through APs) traverse a subset of network gateways, it may make these gateways congested; this leads to unfair/unbalanced use of gateways (i.e., some gateways are congested while others are barely used). In this paper, we consider fairness, in using gateways, as another performance metric to be optimized.

One of the conflicting objectives we plan to optimize is to minimize this unfair use of MGs, measured by the standard deviation of flows entering network gateways, as given below.

$$Min\sqrt{\sum_{l\in G} F_l^2 \Big/ \sum_{l\in G} F_l} \tag{4.8}$$

Full Coverage criterion. The coverage is defined as the size of the physical area where TS has a route to the core network (Internet). The area depends on the locations of APs but more importantly on the amount of APs that have a route to the core network. APs have partially overlapping coverage areas as shown in Figure 4.1. The APs should be located such that all TSs are covered. Constraint (4.9) is used to make sure that a given TS *i* is assigned to only one CL *j*. Inequality (4.10) implies that a TS *i* is assigned to an installed and covering mesh node *j*.

$$\sum_{j \in L} x_{ij} = 1 \qquad \forall i \in I \tag{4.9}$$

$$x_{ij} \leq a_{ij} t_j \qquad \forall i \in I, \forall j \in L \tag{4.10}$$

Bounded Delay. The aim of the proposed model is providing low-cost connection and full coverage to mesh clients that satisfy QoS constraints. In this paper, we consider delay as a QoS constraint to be satisfied, given in the form of a bounded number of communication hops. *H* hops is the maximum path length between any mesh node and its nearby gateway. In Section 4.4, we presented a clustering approach to achieve this requirement. Each AP *j* sends its traffic (i.e., generated by its mesh clients) on a path $\pi^{k}_{j,l}$ to gateway *l*. Constraint (4.11) ensures that if mesh node *j* is installed as AP, and mesh node *l* is installed as MG then the expected path length between them cannot exceed *H* hops.

$$2\, \pi^{k}_{j,l} \leq H\,(t_j + t_l) \quad \forall\, j \in S,\, l \in G \tag{4.11}$$

Co-channel Interference. A key issue impacting any multi-hop network performance is the co-channel interference. It is known, from [HW08] and [HX07] that the packet drop rate of a multi-hop path increases sharply as the number of traversed hops increases. This can be improved by limiting the number of hops from any AP to a MG [VH08]. In this model, the impact of co-channel interference is translated into a threshold *H* on the MR-MG hop count.

The optimization model is also subject to other constraints given as follows:

$$\sum_{i \in I} d_i x_{ij} + \sum_{l \in L} \sum_{q \in C} \left(f^{q}_{lj} - f^{q}_{jl} \right) - F_j = 0 \quad \forall j \in L \tag{4.12}$$

$$\frac{f^{q}_{jl}}{u_{jl}} \leq y^{q}_{jl} \qquad \forall q \in C, \forall j, l \in L \tag{4.13}$$

$$\sum_{i\in I} d_i x_{ij} \le v_j \qquad \forall j \in L \tag{4.14}$$

$$F_j \le M g_j \qquad \forall j \in L \tag{4.15}$$

$$2y_{jl}^q \le b_{jl}\left(z_j^q + z_l^q\right) \qquad \forall q \in C, \forall j, l \in L \tag{4.16}$$

$$g_j \le t_j \qquad \forall j \in L \tag{4.17}$$

$$\sum_{l\in L} y_{jl}^q \le 1 \qquad \forall q \in C,\ \forall j \in L \tag{4.18}$$

$$\sum_{q\in C} z_j^q \le R\, t_j \qquad \forall j \in L \tag{4.19}$$

$$x_{ij}, z_j^q, y_{jl}^q, t_j, g_j \in \{0,1\} \qquad \forall i \in I, \forall j, l \in L, \forall q \in C \tag{4.20}$$

$$f_{jl}^q, F_j \in R \qquad \forall j, l \in L, \forall q \in C \tag{4.21}$$

Constraint (4.12) defines the flow balance for each mesh node at CL_j. Constraints (4.13) and (4.14) respectively define the flow-link capacity and the demand-radio access capacity constraints. Constraint (4.15) stipulates that the flow routed to the Internet is different from zero only when the installed mesh node is a gateway. We assign *M* a very large number to limit the capacity of the installed gateway. Constraint (4.16) forces a link between CL_j and CL_l using the same channel *q* to exist only when the two devices are installed, wirelessly connected and tuned to the same channel *q*. Constraint (4.17) ensures that a device can be a gateway only if it is installed. Constraint (4.18) prevents a mesh node from selecting the same channel more than once to assign it to its interfaces. Constraint (4.19) states that the number of links emanating from a node is limited by the number of its radio interfaces; it also states that if a channel is assigned only once to a mesh node, it is a sufficient condition for its existence. Constraints (4.20) and (4.21) define 0-1 and real decision variables.

All the above constraints are called hard constraints with the exception of constraint (4.12) which is called a soft constraint. The WMN planning system attempts to optimize the three objectives and satisfy all hard and soft constraints as defined above.

4.6 Multi-objective Solution Approach

The rationale behind our planning is:

1) The maximization of the network throughput, by minimizing the level of interferences;
2) The minimization of gateways congestion level;
3) The minimization of the total deployment cost by selecting a minimum number of routers/gateways and choosing their positions so that the network connectivity is ensured while providing full coverage and bounded delay to all mesh clients.

WMN planning is a fairly complex problem; its difficulty lies in the fact that it tries to simultaneously address all the criteria. Joint optimization of the above criteria is defined as a multi-objective search problem. As stated earlier, solving a Multi-Objective Problem (MOP) returns a set of Pareto-optimal solutions. Each solution represents a different trade-off between the objectives that is said to be "non-dominated".

4.6.1 Solving Multi Objective Optimization Problem (MOOP)

In the last two decades, there have been growing interests in the field of multi-objective optimization to solve real-world problems. Good introduction to this field of research can be found in [De02] and [CL02].

Without loss of generality, we assume that the various objectives are to be minimized. Then, the optimization of a MOP can be formulated as:

Minimize $y = f(x) = [f_1(x), f_2(x), \ldots, f_N(x)]$

where $x = [x_1, x_2, \ldots, x_D] \in$ decision space and

$y = [y_1, y_2, \ldots, y_N] \in$ objective space.

One of the most difficult parts encountered in practical network design optimizations is constraints handling. For a constrained problem, the decision variables x are subject to a set of constraints. Every decision variable vector x in the decision space is evaluated through the objective functions. The objective values are then represented as points in the objective value space (Figure 4.8).

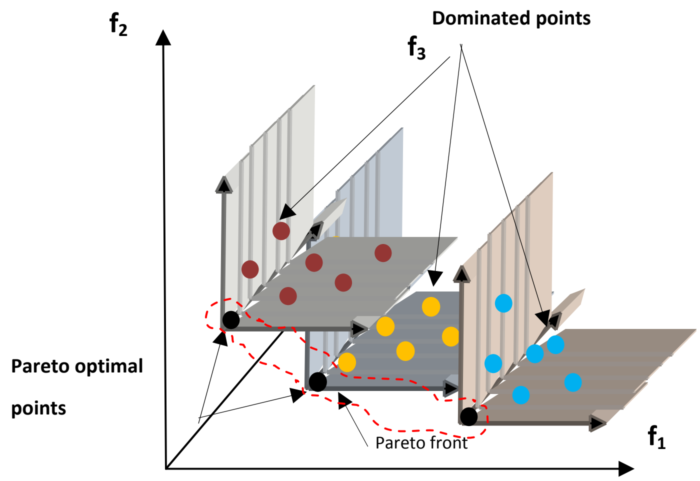


Figure 4.8: Pareto Dominance, Optimality and the Front for three objective functions

Definition 1 *(Pareto Dominance):* For two decision vectors *a* and *b*, *a* is said to dominate *b* or $a \prec b$ if and only if: $\forall i \in \{1,\ldots,N\}$ $f_i(a) \leq f_i(b)$ and,

$\exists i \in \{1,\ldots,N\}$ $f_i(a) < f_i(b)$.

Definition 2 *(Pareto Optimality):* A decision vector *a* is said to be Pareto Optimal if and only if *a* is non-dominated.

Definition 3 *(Pareto Front):* The Pareto Front is a set of all Pareto Optimal solutions (non-dominated solutions) in the objective value space.

Illustration in Figure 4.8 shows that points that lie in the three dimensional area are dominated by the origin point (dotted point) of that area.

We use a variant of MOPSO, Multi-Objective Particle Swarm Optimization, as the optimization technique [CL02], to solve the model. We call the proposed technique VMOPSO-C. Apart from finding the non-dominated solutions, achieving a well-diverse Pareto solution front is the primary goal of the MOOP. We propose to use a crowding distance mechanism in order to maintain diversity of Pareto front solutions and to incorporate a mutation factor (*fmut*) to boost the exploration capability of the standard MOPSO [CL02]. In the following, we provide more details on how the multi-objective generic model is solved using VMOPSO-C.

4.6.2 VMOPSO-C Algorithm

Besides the crowding distance to maintain solutions diversity, we propose a constraint handling mechanism for solving constraints optimization problem.

The crowding distance value of a solution, as thoroughly studied in [RN05], is the average distance of its two neighboring solutions. The boundary solutions with the lowest or the highest objective function value are given an infinite crowding distance values so that they are always selected. This process is done for each objective. The final crowding distance value of a solution is computed by adding the entire individual crowding distance values in each objective value. Personal best solution (*pBest*) (also known as local best potential solution) and global best solution (*gBest*) are the most important parameters of a particle that the optimizer determines to guide the swarm, in order to obtain a front of optimal solutions.

The particles in the swarm at a given iteration cycle constitute a generation. Each generation evolves (by means of mutation and position update) a different swarm of particles that is (on the average) better than the predecessors. Algorithm 4.2 describes VMOPSO-C main algorithm using a maximum number of generation *MaxGeneration*.

During the exploration of the search space, each particle has access to two pieces of information: the best Potential Solution (PS) that it has encountered and the best PS encountered by its neighbors. This information is used to direct the search by computing velocities: velocity[i] = *iw* * velocity[i] +r_1 * (*pBest*[i] – position[i]) +r_2* (*REP*[*gBest*] – position[i]), where r_1, r_2 *are* random numbers in the range of [0,1]. *iw i*s the inertia weight. A large inertia value will cause the particles to explore more of the search space, while small one directs the particles to a more refined region. The importance of inertia weight was pointed out by Shi and Eberhart [SE98] who reported that 0.4 is the best value. The repository *REP* is then updated by inserting into it all the currently non-dominated (fittest) solutions. This insertion process ends up removing dominated solutions. In the case where the archive is full and there are still non-dominated solutions to be inserted, priority is given to those particles that would ultimately enhance the diversity of the archive set, which is achieved by using the crowding distance technique. When the decision variable exceeds its boundaries, it takes the value of its corresponding boundary and the velocity is changed to the opposite direction.

Algorithm 4.2: VMOPSO-C Main Algorithm

Input *fmut*: Mutation factor, *MaxGeneration*
Output *REP*: External repository to contain Pareto solutions

1: Initialize the swarm (Build feasible solutions that satisfy all the constraints defining the optimization problem)
   For each particle *i* in the swarm
   a. Initialize feasible position,
   b. Set the personal best guide *pBest* to that position
   c. Initialize velocity *// Initialized to zero*
   d. Specify *lowerBound*$_i$ and *upperBoundi* *// 0-1 for integer variables*
   e. Set the global best guide *gBest* to *pBest*
   End For
2: Initialize the iteration counter *t*=0
3: Evaluate all particles in the swarm //evaluation of objective functions
4: Store non dominated solutions found in step 1 into *REP*.
5: **Repeat**
   a. Compute the crowding distance values for each j∈ *REP*
   b. Sort *REP* in descending crowding distance values
   c. **For** each particle *i* in the swarm
      i. Set *gBest[i]* to the randomly selected particle from the top 10% of the sorted *REP.*
      ii. Compute new velocity, position of particle *I* *// see velocity computation below*
      iii. Check particle boundaries, if violated change particle search direction *(i.e.,velocity(i) * -1)*
      iv. If (*t*< *MaxGeneration*fmut) then mutate*
      v. Evalute particle *i*
      End For
   d. Check for constraints satisfaction
   e. Check for non dominance of all particles in the swarm, insert non-dominated and feasible solutions into *REP* and delete dominated solutions from *REP*
   f. **If** *REP* is full **then**
      i. Compute the crowding distance values for each j∈ *REP*
      ii. Randomly selected particle from the bottom 10% of the sorted *REP (most crowded portion).*
      iii. Replace it with the new solution.
      End If
   g. Update *pBest*
   h. Increment *t*
Until (*t*= *MaxGeneration)*

4.6.3 Solving the WMN Planning Problem Using VMOPSO-C

Particles Encoding. In Particle Swarm Optimization, a particle (a position in the search space) represents a set of assignments that is a solution to the problem. In our case, a particle is a complex data structure that provides information about user connectivity (x_{ij}), device installation (t_j) and (z^q_j), device connectivity (y^q_{jl}), gateway existence (g_j), link flows (f^q_{jl}), and gateway/backbone link flows (F_j). A feasible solution must satisfy all hard and soft constraints. During the search, non-feasible solutions that violate only the soft constraint (12) can be included in the population. This increases the likelihood of a non-feasible solution to mutate and provide a feasible one in later generations. The followings are the phases involved in the resolution of the proposed model.

Building Initial Feasible Solutions. WMN planning problem is a constrained optimization problem; therefore, the initial positions must represent feasible solutions, and thus, need to be designed carefully. Constructing an initial set of feasible solutions that satisfy the constraints (4.9) to (4.21) represents the most challenging part in our optimization process.

First, we start by selecting randomly a CL_j from the set of CLs that cover a given TS_i (Fig 4.9.a). An AP is then installed at this location CL_j only if it has not yet been selected. By applying the same procedure to all TSs, we obtain the set S_1 of APs locations that provide full coverage to all TSs. More formally, S_1={ $j \in L$, CL_j covers TS_i, $i \in I$ }. At this stage, constraints (4.9) and (4.10) are satisfied and the initial set contains vertices of a disconnected graph as shown in Figure 4.9.a.

Once the coverage is done, the set S_1 is augmented by adding new MRs (mesh Routers) to connect the APs together. We apply a neighborhood based selection algorithm to find the next node to be inserted. The augmentation algorithm consists, mainly, of choosing the closest neighbor in one component graph to any node of a different component. Then, the path between the two nodes is augmented. The algorithm stops when all nodes belong to the same graph component (see Figure 4.9.b).

Finally, gateways are placed optimally according to MGs placement algorithm (see Section 4.4) which consequently satisfies Constraint (4.11).

For computational purposes, we use a symmetric adjacency matrix to represent the connectivity graph. We apply the fixed channel assignment algorithm described by Das et al. [DA05] and we implement Edmonds-Karp's max flow algorithm [EK72] to assign a value on each link y_{jl} using channel q to route a flow. All remaining constraints (i.e., 4.12-4.21) are then satisfied.

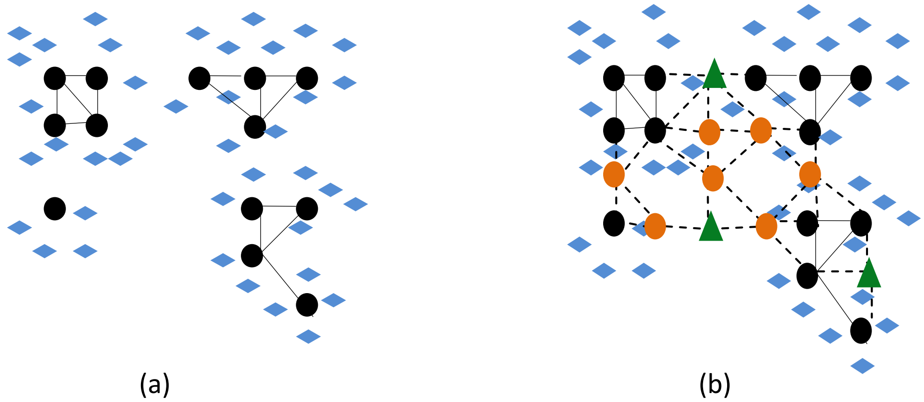


Figure 4.9: A Feasible Particle position example: (a) TSs assigned to CLs and a subset S_1 is formed (b) S_1 is augmented and MGs are selected.

Breeding Potential Planning Solutions: the WMN Planning Algorithm - We propose an iterative Network Planning Solution Algorithm (*NPSA*) that consists of constructing, for each particle in the swarm, a subset S_1, mutating it, placing gateways and then assigning flows and channels. The most important phase is the repetitive task of constructing the set S_1 of APs locations to cover all TSs and then mutating it over and over until it satisfies at least all hard constraints. Then, S1 is augmented to ensure the connectivity. After this solution-construction process, the velocities, the positions and the fitness (values of the three objective functions) of the particles are computed. Then, some of these particles are inserted into the external repository *REP* provided that they dominate or at least are non-dominated by the previously “archived” non-dominated solutions. Algorithm 4.3 describes *NPSA*.

A position in the search space is a solution to our planning problem; however, the values, returned by Update_Positions() procedure, are not guaranteed to be integers (0 or 1). For this purpose, we add a final process that we call *particle filtering* to allow only particles with a considerable move (to the new position) to change to 0 (respectively 1). If the difference between the two positions (initial and updated one) that a particle gets in the search space goes beyond a given threshold α (based on experiments, we set α to 0.3), then the final position is the reverse of the initial one (i.e., 0 if it was 1 and vice versa); otherwise, the new position is discarded (the particle remains in its original position). Consequently, all retained positions are then 0-1 integers.

Algorithm 4.3: Network Planning Solution Algorithm, ***NPSA***

Input *fmut*: Mutation factor, *MaxGeneration*

Output *REP*

```
t=0;
Construct_Initial_Soft&Hard_feasible_solutions();
While (t<MaxGeneration)
 For each particle in the swarm
    S1 ← Mutate(S1,fmut) ;
    S ← Augment(S1);                         //Connectivity augmentation
    Y1 ← Construct_connectivity_matrix();
    Y ← Assign_channels(Y1);
    G ← invoke CBGPA                         //See Section 4.4
   Compute_flows() ;                         //using Edmonds algorithm [EK72]
   Construct_New_Particle()
 Endfor
Compute_Velocities();                        //as described in Section 4.6.2
Update_Positions();                          //Newposition=current position+velocity
Evaluate_Particles();                        //compute objective functions
REP ← Insert_feasibleNonDominated_Solutions();
Update_ParticuleBest();
 t++ ;
Endwhile
```

4.6.4 *Complexity study of* NPSA

Let the number of objective functions to be optimized be M, and the size of the swarm and the repository be n and N, respectively. In Algorithm 4.3, the complexity is mainly influenced by checking for feasible non-dominated solutions and the diversity computation operation. However, the cardinality of the set of feasible solutions generated iteratively is much lower than the size of the repository, due to the number of constraints a solution has to satisfy. Consequently, the diversity computation function, based on a crowding factor calculation, is very rarely performed. For checking a particle for its non dominance within N+n particles, M(N+n) comparisons are needed. Therefore, the worst case complexity of this function will be $O(M(n+N)^2)$. If we consider the worst case complexity (by assuming that the repository truncation is possible), sorting on the basis of each objective will have a complexity of O(MNlog(N). Then, the worst case complexity (with n+N elements in the repository) is $O(M(N+n)\log(N+n))$. Thus, the overall worst case complexity of Algorithm 4.3 is $O(M(N+n)^2)$.

4.7 Experimentation Results and Analysis

In this section, we use the algorithms we proposed in the previous sections (Sections 4.4 and 4.6) to solve the WMN design model described in Section 4.5. The purpose of our experimental approach is to evaluate the performance of the proposed design model and to show the effectiveness of *CBGPA* through the same model, by varying one WMN key-parameter at a time while maintaining others fixed.

4.7.1 Experiments setup

We consider the following key parameters of WMNs: the number of TSs n, the number of CLs m *(the grid size)*, the client demands d_i, the maximal number of communication hops H, and the number of radio interfaces R. In this regard, we define the Standard Setting (SS) of the WMN as the following: SS=[(n:150), (m:49), (d_i:2Mb/s), (u_{jl}:54Mb/s), (vj:54Mb/s), (M:128Mb/s), (c_j:200), (p_j:8*c_j,), (H:3), (R:3), (k:11)]. The algorithm is coded in the Java programming language and all the experiments were carried out on a Pentium M 1.5 GHz.

A run of our algorithm involves 200 generations each with a population size and an archive size of 30 and 20 particles respectively. It must be noted that in our recent experiments [BH08a], we came to a conclusion that mutating at a rate of 50% of the population (*fmut*=0.5) leads to the best Pareto front.

4.7.2 Performance evaluation

To study the effectiveness of *CBGPA*, we run twice the same set of experiments, for the key parameters (m, n, d_i), using first, *NPSA* coupled with *CBGPA,* then *NPSA* without CBGPA; instead, we use random selection of gateways, and we call it *RGPA*. Additionally, we study the performance of the proposed design model when R and H vary (only *CBGPA* is coupled with *NPSA*). The same random starting distribution of Mesh Clients (MCs) has been used for each execution scenario. Lastly, for each key parameter variation study, results are reported on 10 runs thus requiring additional filtering process to maintain the non-dominance aspect amongst the collected Pareto planning solutions. The positions of the n TSs are randomly generated for the first run and kept fixed for the remaining runs (9 runs) to ensure valid results. For a scaling purpose, the second and third objective values are multiplied by 10^3.

Measuring the Performance. In our experimentations, only the number of hops (H) value setup and the radio interfaces (R) variation experiments involve contending comparable fronts. The variation of *m, n*, and *di* generates different Pareto fronts that are plotted in the same graph using the commercial software Origin [Or09]. Studying the effect of varying *m, n*, and *di* shows how well the scalability issue is handled when *CBGPA* is applied. To decide which value of H to choose and which radio variation is optimal, we use the Spacing Metric and the performance/convergence related metrics, given bellow:

- First, we use the Schott Spacing Metric [Sc95] to measure the range variance of neighboring vectors in the *Archive* (the Pareto Front, PF). It is defined as:

$$S=\sqrt{\frac{1}{(n-1)}\sum_{i=1}^{n}(\bar{d}-d_i)^2}$$

Where n is the number of solutions in the PF,

$d_i = \min_j(| f_1^i - f_1^j | + | f_2^i - f_2^j | + | f_3^i - f_3^j |)$, and

$\bar{d}$ is the mean of all d_i.

A zero value for this metric means that all solutions of the PF are equidistantly spaced; however, in this study we are not interested in how close the metric value is to zero, but in the values of this metric returned by each PF. The lower the value returned by a PF, the better that PF is.

- The fronts are unified and the Common Pareto Front (*CPF*) is derived as follow:

$$CPF = \bigcup_{i=2}^{n} PF_i$$

where n is the number of contending fronts

- $PF_i^{Pareto} = PF_i \cap CPF$.
- $|PF_i|$: The size of the set of non-dominated vector solutions returned, PFsize.
- $|CPF|$: The size of the *CPF* filtered, CPFsize.
- $|PF_i^{Pareto}|$: The number of vector solutions inside the *CPF*, InCPF.
- $|PF_i\text{-}CPF|$: The number of vector solutions outside the *CPF*, OutCPF.
- The percentage of each PF_i covering the CPF $\frac{|PF_i^{Pareto}|}{|CPF|}$, %fromCPF.
- The percentage of each PF_i covering the front returned by PF_i in question- $\frac{|PF_i^{Pareto}|}{|PF_i|}$,%fromPF.

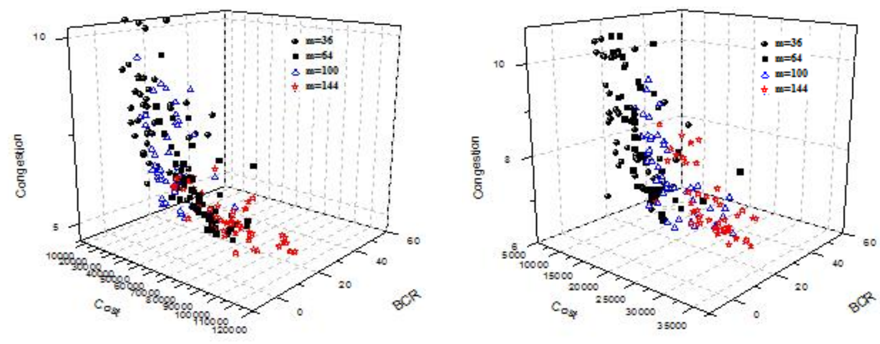
It must be noted that some of the above metrics are redundant. However, they are reported for a better contrast.

Key Parameters Variation. First, we start by varying, gradually, the grid size from 6x6 to 12x12, while the other parameters are maintained fixed. For sake of clarity, only Pareto front solutions found when *m*=36, 64, 100 and 144, are plotted in the same graph (Figure 4.10). It is clear, from Figure 4.10.a, that the 100-grid topology is the best in satisfying the Standard Setting (SS) when *RGPA* is applied, while Figure 4.10.b (with *CBGPA*) shows that 64-grid provides the best Pareto front since most of the 8x8 grid trade-off solutions dominate almost all the rest.

Observe that when using *CBGPA*, the width of the spectrum of the planning solutions (diverse solutions) is better, compared to the planning solutions, using *RGPA*. Notice also that the deployment costs of topologies planned using *CBGPA* are less expensive (a maximum cost of $3x10^4$\$) compared to topologies planned using *RGPA* (a maximum cost of 10^6\$), with almost the same interference and congestion level. There is consent from both set of experiments, that a larger size of grid can improve the network performance (congestion of gateways decreases), but also increases the total deployment cost, which is highly affected by the number of gateways deployed. Therefore, in practice, the network planner has to decide on the appropriate grid size that satisfies both cost and performance requirements.

The number of gateways deployed, for different grids, is shown in Figure 4.11. Only cheapest planning solutions are considered. The clustering approach (*CBGPA*) is shown to be very effective in selecting the strategic position to place MGs. Notice, from Figure 4.11, that *CBGPA* minimizes the number of MGs required to satisfy Internet connectivity which has an upper bound of five MGs to support an aggregated traffic of 2 Mb/s, under delay constraint and, independently from any grid size.

Next, we vary *n* to study how our algorithms would behave when the number of mesh clients increases. Table 4.2 shows the cheapest planning solutions that support the traffic demand of 150, 300, 400, and 450 mesh clients. Notice that in both cases (*RGSA* and *CBGPA*) the same number of gateways is deployed when comparing the cheapest solutions. This can be explained by the efficiency of *NPSA* in placing APs and MRs. However, for almost the same amount of congestion level of gateways, solutions found using *CBGPA,* seem to be more cost-effective solutions than those found using *RGSA,* since they are cheaper and guarantee AP-MG paths with at most *H* hops *(H*=3 in *our SS*). The same observation is derived from the Pareto fronts plotting, as shown by Figure 4.12. Also, conversely to *CBGPA* (Figure 4.12.b), when *n* increases, the production of planning solutions using *RGSA*, is getting harder, especially for *n*>300 and no solution was found when *n* is bigger than 400.



(a) (b)

Figure 4.10: Pareto Fronts of Planning Solutions for different Grids. (a) with *RGPA*, (b) with *CBGPA*

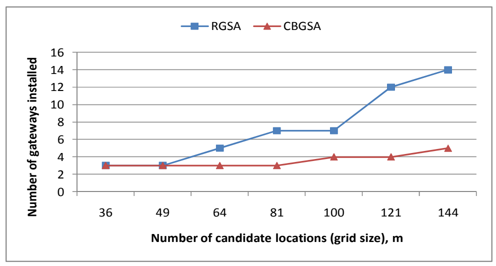


Figure 4.11: Number of gateways deployed when *m* varies

Table 4.2: Cheapest solutions when *n* varies

n	**RGSA**						**CBGSA**					
	MN	**AP**	**MG**	**Cost($)**	**BCR**	**Cong.**	**MN**	**AP**	**MG**	**Cost($)**	**BCR**	**Cong.**
150	19	13	3	8600	40	10,477	19	9	3	8600	22	10,088
300	33	25	5	14600	24	10,990	31	20	5	14200	29	11,006
400	38	30	7	18800	30	10.784	32	24	7	17600	30	10,805
450	No solutions found						34	26	8	19600	44	10,807

MN: total number of mesh nodes (AP, MR, MG), AP: number of access points, MG: number of gateways, Cost: deployment cost, BCR: channel interference metric, Cong.: amount of congestion of gateways.

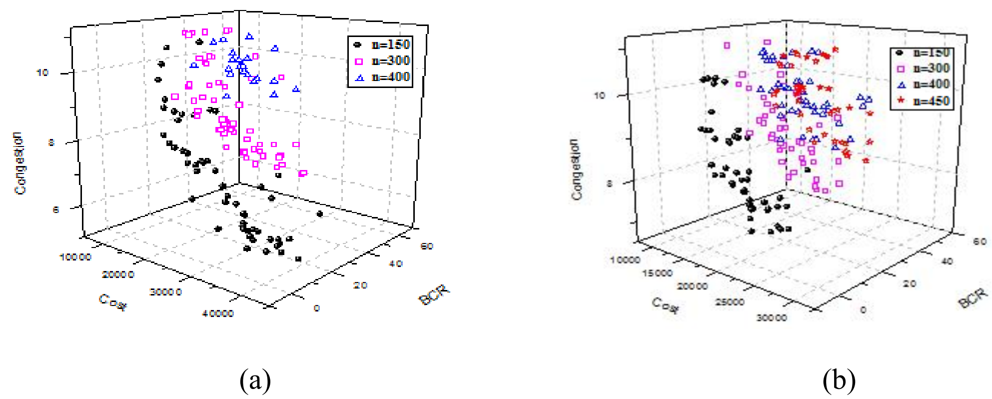


Figure 4.12: Pareto Fronts of Planning Solutions for different Traffic Spots, *n*. (a) with *RGPA*, (b) with *CBGPA*.

We further study network scalability under traffic demand variation. The results reported in Table 4.3 show that when increasing demand d_i from 1 to 5Mb/s, the number of APs increases in both sets of experiments. This is as expected; new APs are added to guarantee coverage to all mesh clients under capacity constraints. Notice also that the number of MGs increases accordingly to satisfy connectivity constraints by creating new paths to the newly added APs. However, when clustering is not considered, the random selection of MGs locations (*RGPA*) leads to deploy more expensive topologies (very large number of MGs are installed) to support the traffic demand, as can be seen in Figure 4.13.a. Higher cost solutions with almost the same interference and congestion levels, compared to solutions plotted in Figure 4.13.b, are found when d_i is bigger than 3Mb/s.

Choosing the appropriate number of radio interfaces is also an important issue. The logical and usual scenario is that increasing the number of radio interfaces *R* per mesh node improves the network performance. To investigate the impact of *R* on our approach effectiveness, we vary *R* from 2 to 5 for the two set of experiments. The Pareto fronts found are plotted in Figure 4.14.

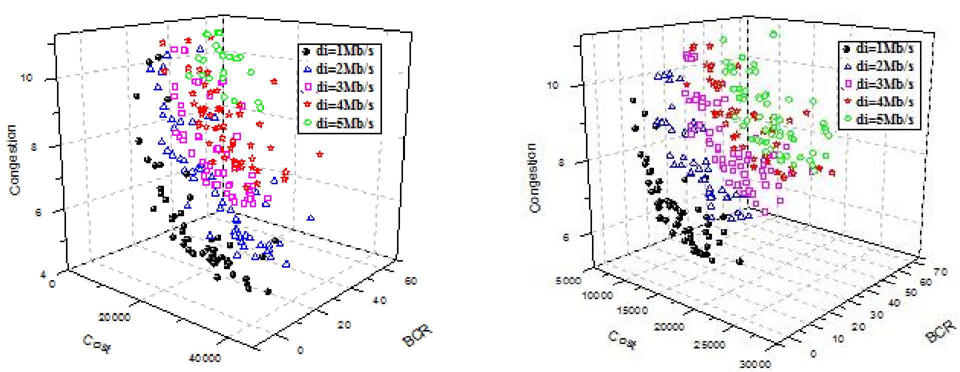
It is clear from Figure 4.14.b that *CBGPA* along with *NSPA* provide a larger set of planning solutions for different values of *R*, compared to Pareto fronts plotted in Figure 4.14.a. We can also see that the Pareto front when *R*=3 (Figure 4.14.b), looks to be the best; however, we cannot decide on the value of *R* setup based only on visual observations, especially in three dimension plotting.

Table 4.4 shows that *R*=4 gives the larger sets of solutions (PFsize) and shows a better diversity (Spacing S). However, choosing 2 radios seems the best decision choice since the fronts related to 2-radios, when compared to the 4-radios design choice, make up 35% of the CPF and 58% of the PF are in the CPF (versus 21%, 25%). The solutions of the 3-radios are also better than the 4-radios, though not well spaced (S=0.503).

Table 4.3: Cheapest solutions when d_i varies

d_i	**RGSA**						**CBGSA**					
(Mb/s)	**MN**	**AP**	**MG**	**Cost($)**	**BCR**	**Cong.**	**MN**	**AP**	**MG**	**Cost($)**	**BCR**	**Cong.**
d_i=1	15	8	2	6200	24	10,344	17	7	2	6600	16	9,025
d_i=2	19	13	3	8600	40	10,477	19	9	3	8600	22	10,088
d_i=3	28	18	4	12000	26	10.640	27	18	4	11800	23	10,665
d_i=4	32	23	5	14400	34	10,991	29	20	5	13800	17	11,006
d_i=5	39	32	6	17400	26	11,196	36	26	6	16800	20	11,196

MN: total number of mesh nodes (AP, MR, MG), AP: number of access points, MG: number of gateways, Cost: deployment cost, BCR: channel interference metric, Cong.: amount of congestion of gateways.

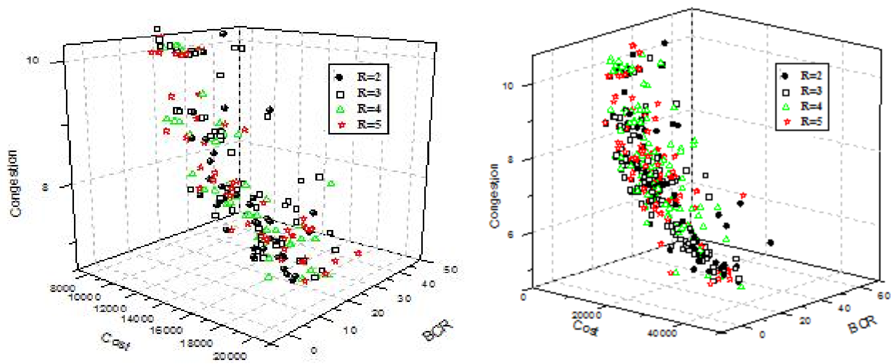


(a) (b)

Figure 4.13: Pareto Fronts of Planning Solutions for different Traffic demand. (a) with *RGPA*, (b) with *CBGPA*.

Table 4.4: Performance/convergence metrics for *R* variation

CPFsize=71	*R=2*	*R=3*	*R=4*	*R=5*
PFsize	43	47	57	51
InCPF	25	18	15	13
OutCPF	18	29	42	38
%fromCPF	**0.35**	*0.25*	0.21	0.18
%fromPF	**0.58**	*0.39*	0.26	0.25
Spacing S	0.449	0.503	**0.411**	0.479



(a) (b)

Figure 4.14: Pareto Fronts of Planning Solutions For different value of *R*. (a)with *RGPA*, (b) with *CBGPA*.

Finally, we study the impact of changing *H* on network performance. Notice, from Figure 4.15, that some of Pareto solutions when *H*=4 (square shapes), dominate most of other Pareto solutions, except few of them, that are dominated by planning solutions when *H*=3 (triangle shapes). Referring to Table 4.5 (%fromCPF and %fromPF lines), results support our claims that were based on visual observation from Figure 4.15. Additionally, the *H*=3 solutions are not as well spaced as the *H*=4 solutions (0.502 v.s. 0.301). Also, notice that only a difference of two solutions is making the *H*=3 front, to be the best. So, the task of deciding on the value of *H* setup (*H*=3 or 4), returns to the network planner decision, who has to be very careful in setting *H* based on his/her preferences and performance requirements.

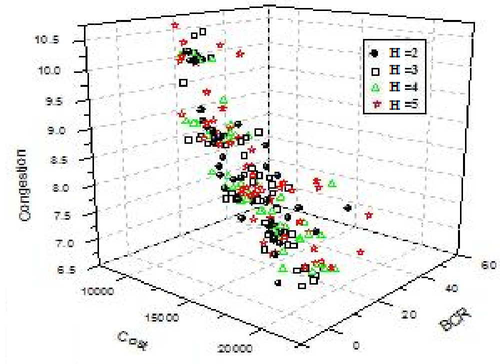


Figure 4.15: Pareto Fronts of Planning Solutions For different number of Hops.

Table 4.5: Performance/convergence metrics for *H* variation

CPFsize=68	*H=2*	*H=3*	*H=4*	*H=5*
PFsize	49	47	47	53
InCPF	18	20	19	11
OutCPF	31	27	28	42
%fromCPF	0.26	**0.29**	*0.27*	0.16
%fromPF	0.36	**0.42**	*0.40*	0.20
Spacing S	0.568	0.502	**0.301**	0.638

.

4.7.3 Comparison with related work

We introduced a multi-objective model with three competing objectives (deployment cost, network throughput, and congestion of gateways) that need to be optimized concurrently while satisfying all the QoS constraints. Validating our results against other known models for WMN planning problems turns out to be impossible for two key reasons;

1) There was no close related work that considers optimal placement of gateways when designing WMN from scratch. The existing contributions in this context, assume that the network topology is known, and only gateways locations have to be decided. Moreover, the gateways congestion and communication delays issues were not considered in such contributions.
2) It is unpractical to compare a set of Pareto (three-dimension) optimal solutions with a one-

dimension optimal solution. Nevertheless, we can at least check the one common objective function (deployment cost) to see whether the results fall in the same range.

Table 4.6: 10 solutions of MOBD, under SS.

MR	AP	MG	Links	Cost	BCR	S.D.
23	15	4	74	11800	14	10.72
25	15	4	78	12200	13	10.75
27	15	4	80	12600	6	10.90
28	18	4	86	12800	8	10.66
29	16	4	90	13000	15	10.64
21	13	5	70	13200	16	9.88
21	14	5	70	13200	19	9.76
22	16	5	72	13400	8	9.94
23	15	5	76	13600	7	9.85
34	17	9	124	23000	10	7.25

Only the first 9 solutions and the last (71TH) solution are shown

Table 4.7: solutions of MOBD versus the solution of AML (c_j=200$, p_j=8* c)

	MR	MG	Links	Cost
AML	23.65	3.3	21.35	10660.0$
MOBD1	23	4	74	11800.0$
MOBD2	34	9	57	23000.0$

We compare our results, after running *NSPA* coupled with *CBGPA,* to the (only one) closest related work reported in [AC08] that considers WMN design from scratch. We refer to the model in [AC08] as AML and to ours as MOBD. The authors in [AC08] used the following Parameters Setup SPS: d_i=3Mb/s, n=100, m=50, R=3 and k=1, and obtained a “single” planning solution (#MR=23.65, #MG=3.3, #Links=21.35) which is the average of 10 runs. Using the same parameters setup SPS we obtained 71 non-dominated planning solutions (see Table 4.6). We report our cheapest and most expensive planning solutions together with the single solution of AML in Table 4.7. The solutions of MOBD are numerous and diverse, ranging from very cheap solution (MOBD1 line in Table 4.7) to very expensive solution (MOBD2 line in Table 4.7) differing mainly by the measured performance indicators; BCR: interferences over network channels and S.D: Gateways congestion level.

Results in Table 4.6 show that our approach tends to provide some solutions which may be more expensive than that of AML, but guarantee that all AP-MG communications are within three hops (the number of hops *H* is set to 3 in the experimentation standard setting SS). The network performance is increased by increasing overall network throughput (by minimizing network interferences) and by minimizing network bottlenecks (a smooth flow passing through MG nodes). None of such performance considerations is thought-out in AML model formulation, which is essentially a single-objective model. This fact leaded us to compare only the common objective (cost objective function) on a single objective basis. Table 4.7 shows that MOBD generates from 11% more expensive solution to almost double-price solutions when compared to AML generated solution for the same parameters settings.

4.7.4 Simulation via OMNET

The aim of this sub-section is to show by means of simulation, the effect of placing MGs using *CBGPA* on the final network performance. For this end, the discrete event simulator OMNET++ V.4.0 in conjunction with the INETMANET networking model [OM09] is used. The simulator is fed up with two networks, having the same deployment cost and covering the same area with the same distribution of MCs. In the first network, referred as “NoCL” in the text, *NSPA* is paired with *RGBA* to place all mesh nodes and define their characteristics, while in the second network, called “WithCL”, *NSPA* is coupled with *CBGPA*. In other words, NoCL is compared against WithCL by comparing their relative performance metrics which are Average bandwidth, TCP Round Trip Time delay and packet loss at MAC layer.

In the simulation scenario, the APs and MRs nodes in both networks are equipped with multiple IEEE802.11b radios, while the MGs nodes are equipped with multiple radios as well as an additional Ethernet device (to uplink to an external network). All nodes include a full IP network stack and AP nodes include a TCP traffic generator (for an *ftp* application) in order to inject traffic to the WMN.

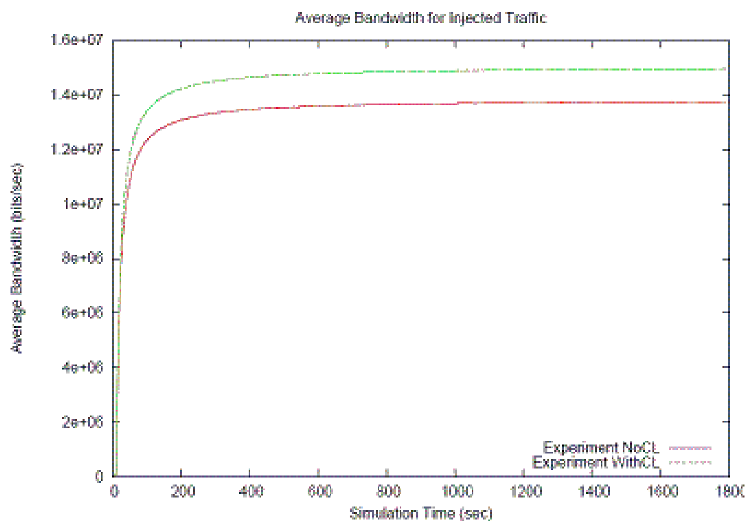


Figure 4.16: Average bandwidth in the two simulated networks (NoCL and WithCL).

Figure 4.16 shows that WithCL network performs better than NoCL network when contrasting the average bandwidth of the whole network. We apply the Tukey's Honest Significance Test (Tukey HSD) [Mo05] with 5% of tolerable estimated error, to contrast the average bandwidths within the models (NoCL and WithCL). A clear picture about the difference is shown in Figure 4.17, where a difference between 1.172 Mbps and 1.180 Mbps, always in favor of the WithCL model is depicted.

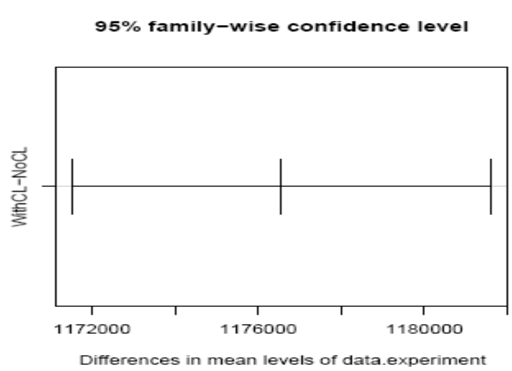
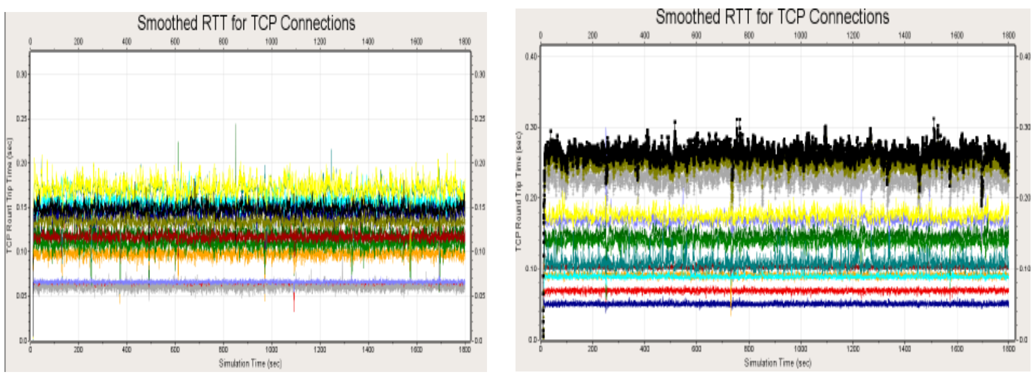


Figure 4.17: Turkey HSD showing the difference in average bandwidth between NoCL and WithCL.

Figure 4.18: Turkey HSD showing the difference in Packet losses between NoCL and WithCL.



(a) (b)

Figure 4.19: TCP Round Trip Time delay; (a): WithCL network, (b): NoCL network

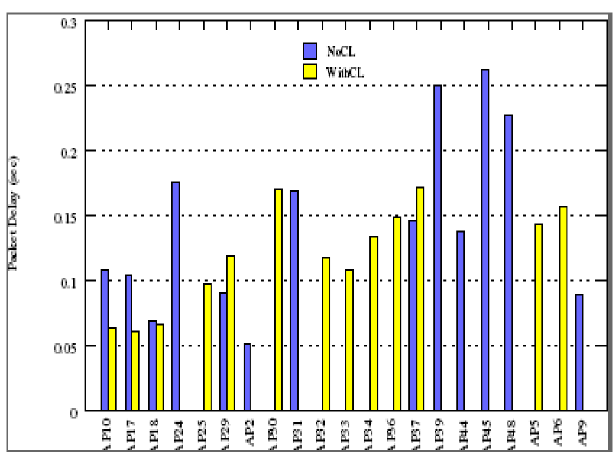


Figure 4.20: Packet Delay per node in both networks

We further measure the packet loss at MAC layer using the GivenUp packets due to excessive retransmission. When observing simulation results, we noticed that both topologies have, in average, between 0 and 4 packets lost by node. However, a variance analysis on packet losses within models (NoCL and WithCL) shows that WithCL model drops fewer packets than the NoCL model. Figure 4.18 shows always a negative difference when both models are contrasted (mean(WithCL)-mean(NoCL)).

Finally, we study TCP packets delay. Figure 4.19.a and Figure 4.19.b show that NoCL model has a higher delay than WithCL model. More precisely, when examining Figure 4.20, we observe that AP39, AP45 and AP48, which are MGs in the NoCL topology, are registering an average delay more than twice the average delay registered by WithCl model (0.246 vs. 0.119).

Summarizing, the network model using the clustering algorithm *CBGPA*, the "WithCL" model, shows clearly a better performance than the "NoCL" model, at least, in average bandwidth, packet loss and delay.

4.8 Conclusion

In this paper, we address two complementary sub-problems: (1) the problem of efficient gateways placement to provide Internet connectivity while guaranteeing a bounded communication delay; and (2) the problem of WMNs design where the locations of all mesh nodes are not decided. For the first problem, we presented a tree-independent clustering approach (*CBGPA*) to select, from a set of candidate locations, strategic locations for MGs placement. The radius of each formed cluster is bounded by the maximal number of hops, *H*, between cluster nodes and the placed MG. For the second problem, we presented a multi-objective optimization model to design WMN topologies from scratch. In this model, the three objectives of deployment cost, interferences over network channels, and congestion of gateways are simultaneously minimized while guaranteeing full coverage to mesh clients. Experiments results have shown that, when the clustering solution (*CBGPA)* is coupled with the solution algorithm of the WMN design model (*NPSA*), it does not provide only scalable and bounded delay planning solutions, but also, the solutions found are guaranteed to be cost-effective.

Chapitre 5

On Providing Reliability in Multi-radio Multi-channel Networks

D. Benyamina, A. Hafid, M. Gendreau and, J. C. Maureira

Abstract

In the design of Wireless Mesh Networks (WMNs), one of the fundamental considerations is the reliability and availability of communication paths between network pairs in the presence of nodes failure. The reliability and deployment cost are important and are largely determined by network topology. In fact, adding redundant network components increases the reliability of a network, but also increases the cost substantially. Usually, network performance and reliability are considered separately. In this paper, we propose a new algorithm based on ear decomposition for constructing reliable WMN infrastructure that resists the failure of a single mesh node and ensures full coverage to all Mesh Clients (MCs). Via a case study, we show the tight relationship between network deployment cost, performance and reliability in a simultaneous optimization in terms of cost and traffic load balancing over network channels. The proposed multi-objective optimization model is solved using meta-heuristics which provides the network operator with a set of reliable tradeoff solutions.

Keywords: Wireless Mesh Network, Network design, Reliability, Multi-objective optimization, Cost-effective topology.

Status

This paper is submitted to Elsevier Computer networks. The preliminary results were published and presented in *IEEE GLOBECOM* 2009, Hawaii [BH09c].

5.1 Introduction

Wireless Mesh Networks (WMNs) are highly reliable, scalable, adaptable and cost-effective which makes them suitable for a large number of applications. They can provide large coverage area, reduce “dead-zones” in wireless coverage and lower cost of backhaul connections. Basically, WMNs consist of robust infrastructure of interconnected access points (APs), relays (MRs) and gateways (MGs). Mesh Clients (MCs) connect directly to APs to access the Internet; MGs act as bridges between the wireless infrastructure and the Internet while MRs relay the traffic. A simultaneous communications is possible over orthogonal channels if the communicating mesh nodes are equipped with multiple network interfaces (the case of Multi Radio Multi Channel, MR-MC, networks).

It is relatively easy to place such nodes to form a WMN infrastructure and to forward packets from sources (MCs) to destinations (MGs - Internet) or vice versa; however, it is very complex to achieve a desirable performance while ensuring full coverage and reliable services to MCs under financial constraints. Moreover, when a router fails to route the traffic, an alternative path should exist for routing the affected traffic. This is the well known survivability problem, which is composed of: (1) defining network restoration policy; and (2) designing robust (survivable) topology. In this paper, we consider the design of robust and cost-effective WMN infrastructure. To guarantee a reliable communication, extra nodes are placed to tolerate single router failures with acceptable overhead and without deteriorating the network performance. Indeed, we deploy the minimum number of mesh nodes, necessary to construct a single node fault-tolerant WMN infrastructure with the provision of full coverage and balanced load over network channels. The challenge is to improve the reliability and the network performance at a minimal cost.

Regarding WMNs design, many studies with different goals have been carried out in the last decade. Examples of these studies include design of topology control scheme [LZ08 and construction of networks’ virtual backbones [SK06], [WT09]. The objective of the topology control study is to identify a subset of possible wireless links that provide connectivity for wireless networks, with certain design criteria (e.g., maximize throughput, minimize delay). The main purpose of virtual backbone construction is to alleviate the Broadcasting Storm Problem by reducing the communication overhead and simplifying the connectivity management. Other studies were conducted with the aim of providing optimized protocols [BI00], [DP04], [RC05]. It has to be noted, that all these studies consider a pre-deployed network where the location and characteristics of network nodes have already been decided.

Another category of studies consider topologies where only gateways or routers are positioned *a priori* [AB06], [SR07]. They propose techniques to place optimally either gateways or access points to satisfy some QoS constraints; Sen et al. [SR07] consider bandwidth and delay as the two QoS requirements to satisfy while the three constraints of throughput, power and interference have to be satisfied in the optimization model presented in [AB06].

From the bulk of contributions that address WMN design problem where the locations of all mesh nodes are not *a priori* decided ([AC08] and [BH08c]), there is only one contribution [BH08c] that considers network reliability in their proposed design approach. They define a reliability cost function that allows maximizing the reliability of WMNs. The proposed approach is based on an iterative policy that is performed endlessly until a reliable and satisfactory solution (cost-effective solution) is found. However, in constraint optimization problem (i.e., WMN design problem) it is very difficult, if not impossible, to compute a good feasible solution that is also reliable when using an iterative design approach; the exception is when the approach/algorithm is proved to converge (within a finite number of iterations, the desired solution is obtained). Moreover, the reliability of the network has to be jointly considered with network QoS requirements while designing WMNs. Our focus in this paper is to construct reliable networks while designing cost-effective WMNs. Guaranteed robust infrastructures are obtained in a finite number of iterations, providing multiple paths to gateways.

In this study, we consider the design of single-node fault tolerant WMNs. There are many protection schemes proposed either to prevent or to recover from node failures [RD07], [LW07]. Most of them are converted to survivable routing problems which assume that a bi-connected network is *already deployed*. In this paper, we propose an efficient algorithm based on ear decomposition theoretical approach to construct a bi-connected WMN infrastructure; such infrastructure is able to accommodate the failure of one mesh node (the most common network failure scenario [TD07]). To the best of our knowledge, this paper is the first to address the design of bi-connected WMNs infrastructure from scratch with a minimum number of mesh nodes.

The rest of the paper is organized as follows. Section 5.2 describes our network model. Section 5.3 presents the bi-connectivity construction algorithm. A case study of designing a reliable and cost-effective WMN infrastructure is given in Section 5.4. In Section 5.5, we show the simulation results. Finally, we conclude the paper in Section 5.6.

5.2 Network Model

We consider a multi-radio multi-channel WMN and we suppose initially that the mesh nodes operate using the same number of radios *R*, each with *k* channels, $(k>R)$ and $k \in C$, where $C = \{1,..,c\}$ and *c* can be at most 12 orthogonal channels if IEEE 802.11a [C03] is used.

We represent a WMN as an undirected graph *G(V,E),* called a connectivity graph. Each node *v* represents a mesh node which can be an access point (AP), a relay (MR) or a gateway (MG) (see Figure 5.1.a). The neighborhood of *v,* denoted by *N(v*), is the set of nodes residing in its transmission range. A bidirectional wireless link exists between *v* and every neighbor *u* in *N(v)* and is represented by an edge *(u,v).*

A number of studies on WMN performance have shown the benefits of grid topologies over random topologies [RK07], [LW07]. In this paper, we adopt a *grid-like* layout as the physical representation of our WMN infrastructure. Each mesh node, if installed, may establish a wireless communication with its eight direct-neighbors (Figure 5.1.b). This assumption increases the chances of selecting a candidate neighbor among the eight with which a wireless link will be set up in the channel assignment procedure. The maximum degree of *G* denoted by Δ is bounded by the number of radio interfaces, *R.*

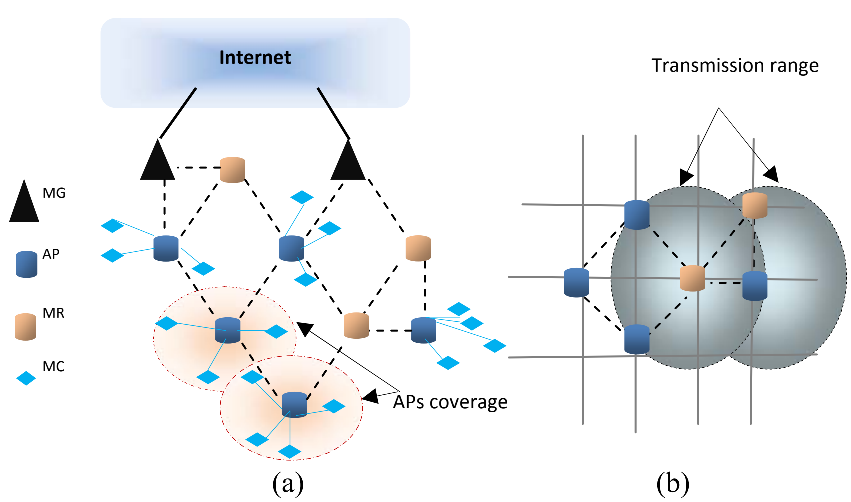


Figure 5.1: WMN design problem. (a): network model, (b): WMN grid-like layout

5.3 Construction of a bi-connected infrastructure

In this section, we present a new algorithm for constructing a bi-connected WMN infrastructure. We first present some definitions; then, we present the detailed algorithm.

5.3.1 Ear Decomposition: Definitions

The technique of ear decomposition has been successfully used in connectivity, bi-connectivity and outer-planarity testing problems ([BI00] and [KR00]). This technique has also been used to restore Wavelength Division Multiplexing (WDM) networks ([LL05] and [SK01]) in order to find the protected routing paths.

Definition1*:* An *ear decomposition P* of a connected undirected graph G*(V,E)* is a partition of the graph's edge set *E* into an ordered collection of paths P_0, P_1, ..,P_k , called ears, such that the following properties hold:

1. P_0 is a cycle called the *root ear*.
2. Each endpoint of P_i, (i>0), is contained in any P_j, for j<i.
3. No internal vertex of P_i, (i>0), is contained in any P_j, for j<i.

An ear P_i is open if the endpoints of P_i do not overlap (i.e., are different), otherwise P_i is closed.

Definition2*:* An open ear decomposition of a graph G is an ear decomposition of G in which every ear P_i, (i>0), is open.

Observations: some observations, which are true for both opened and closed ear decomposition, follow from the above definitions:

1. An edge is contained in exactly one ear.
2. A vertex is contained in one or more ears.
3. A vertex is an internal vertex of exactly one ear, where we consider the root ear's internal vertices to be all its vertices.

The following definition shows that ear decomposition can be used to solve the bi-connectivity testing problem.

Definition3*:* A connected graph G*(V,E) is bi-connected if and only if G has an open* ear decomposition.

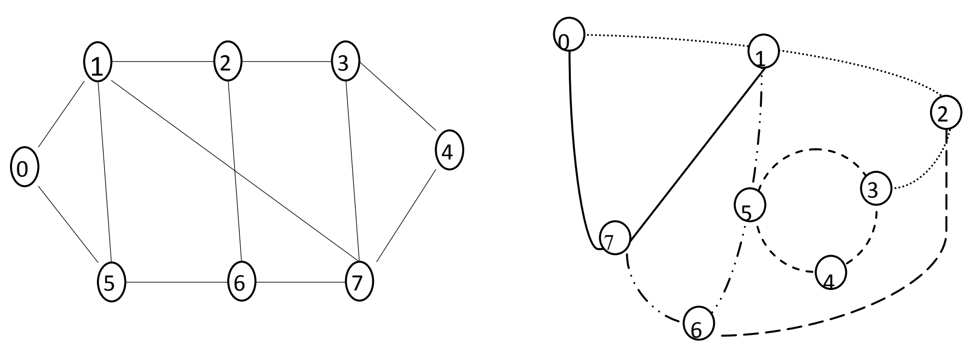
The method of decomposing a graph G into ears is mainly based on spanning tree construction and Euler tour to complete the partition of the graph. The simplest way is that each ear starts by any unused edge from an already-explored vertex, and continue by a shortest path back to another already-explored vertex. The time complexity of the sequential algorithm for the ear decomposition problem [KR00] is $O((m+n)logn)$, where $n=|V|$ and $m=|E|$, while the parallel shared-memory algorithm complexity is $O((n+m)/p\ log\ n)$ [BI00], where p is the number of processors. Figure 5.2 shows an example of ear decomposition on a bi-connected graph with eight vertices. The graph is partitioned into five paths, resulting in P= {P_0, P_1 P_2, P_3, P_4} with P_0={3-4-5}, P_1={3-2-1-0}, P_2={1-5-6-7}, P_3={2-6}, and P_4={0-7-1}.

5.3.2 Construction of a Bi-connected Network

The usual use of ear decomposition is to determine and establish survivable routing paths, assuming that the graph representing the network is bi-connected. Compared to existing survivable network studies using ear decomposition, our approach is *original* in (1) its assumption that the network is not necessarily bi-connected; and (2) in the way the ear decomposition concept is applied to obtain a bi-connected network.

We present, in this paper, a new algorithm, which starts from a disconnected graph and by the completion of the decomposition of the graph in ears; the graph becomes bi-connected.

In the following, we present the main steps involved in constructing a bi-connected WMN infrastructure from scratch. We pass over the details of placing APs in a way that guarantees full coverage to all MCs; we call this process *coverage insurance*; it will be described in detail in Section 5.4.3.



(a) (b)

Figure 5.2: Example of ear decomposition. (a)- The original graph G. (b)- G is decomposed in 5 ears, each is shown in a different line style.

We suppose that the algorithm of constructing robust[1] network starts from the dedicated (placed) APs which will automatically be a part of the final infrastructure.

The basic idea of the algorithm is to construct, by augmentation, a small-sized connected set as a starting infrastructure and iteratively augment the infrastructure by adding new nodes to construct network ears. The algorithm terminates when all APs are included in the constructed ears. The resulting infrastructure is proved to be bi-connected; it can further be improved to satisfy performance and financial requirements.

Given an initial set of APs located on a grid-like layout, let P_k be the k^{th} ear, N_k be the set of nodes in P_k, and T_k be the set of edges in P_k. We call the algorithm to construct a bi-connected network "*BCN algorithm", which* consists of five main steps as shown in Algorithm 5.1.

Algorithm 5.1: *BCN* algorithm

---

1) Use any traversal algorithm to connect, by adding new nodes, a leaf node to the closest neighbor node. We use a modified version of Breadth First Search algorithm [Ca98] (which we call ABFS), embeding an augmentation component, to obtain an initial small-sized connected graph. Figure 5.3 illustrates the augmentation process.

2) Select a node v_0, with the highest degree, d, to be the starting point. Apply the shortest path algorithm, starting from the source v_0 to find a minimal cycle. Let this cycle be the first ear P_k, k=0. If such a cycle does not exist, then apply ABFS to have the required nodes that compose the cycle and update *G(V,E)*.

3) Update the degree of each node $v_j \in N_k$ as follows: $d(v_i) = d(v_i) - 1$ and $d(v_j) = d(v_j) - 1$ for each edge $(v_i, v_j) \in T_k$. Let *EP* be the set of nodes, s.t :

$$EP = \left\{ v_i \in \bigcup_{s \le k} N_s \ / \ d(v_i) > 0 \right\}$$

---

[1] the terms: robust network, reliable network, fault-tolerant network and bi-connected infrastructure are used interchangeably in this paper.

4) **If** all APs are included in previous ears **then** STOP **else** k=k+1 and continue.

Let *SP* be the set of all shortest paths with their end-points pairs $\in$ *EP* and internal nodes $\notin$ *EP,* as defined below.

$$SP = \bigcup_{v_i, v_j \in EP} ShortestPaths(v_i, v_j)$$

If *SP*=Ø (disconnected nodes), then call ABFS to temporally add the necessary nodes for connectivity constraint and back to step 4.

5) A new ear P_k is defined as the longest path among the paths in *SP*.

$$P_k = LongestPath(l_i) \,/\, l_i \in SP, i \in N$$

From new nodes added in step 4), keep only nodes that are in N_k. Update *G(V,E) and g*o to step 3. The algorithm terminates when all APs are included in ears. Figure 5.4.a depicts steps 2, 3, 4 and 5.

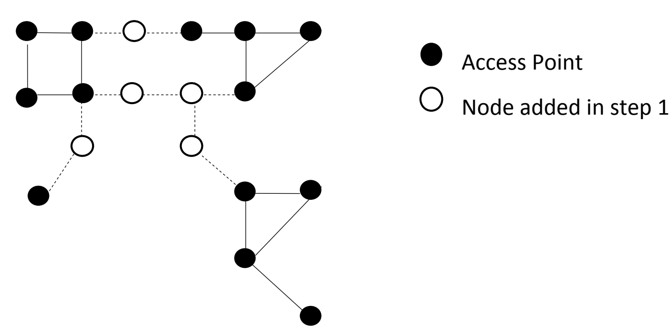


Figure 5.3: Connect the starting APs nodes, using ABFS (step 1). A total of five nodes are added to produce a connected graph.

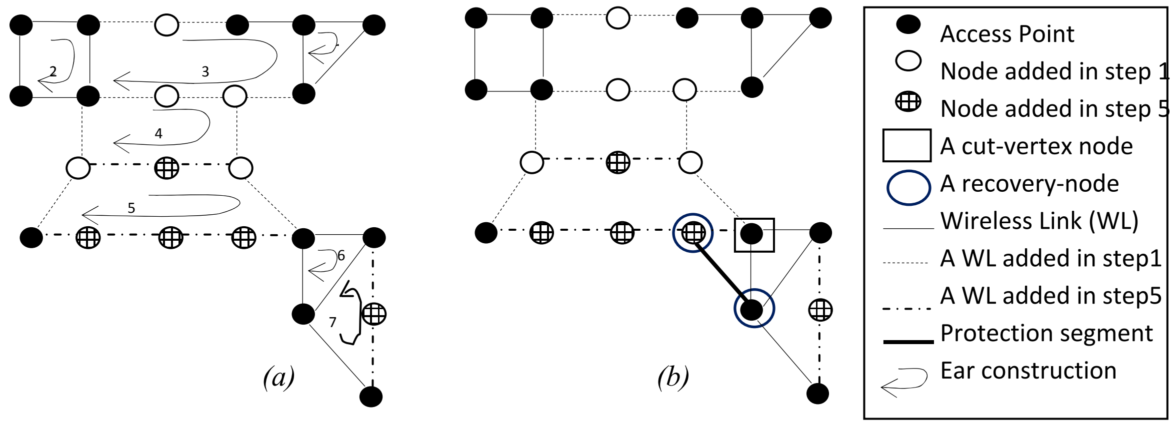


Figure 5.4: Constructing a bi-connected WMN infrastructure with 7 ears. (a) steps 2, 3,4 and 5- a total of 5 nodes are added to a connected infrastructure of 18 nodes. (b) step 6- to recover from a cut vertex failure.

Lemma1: *The steps, shown in Algorithm 5.1, to construct network ears (steps 2 to 5) are not sufficient to construct a bi-connected network.*

Proof: According to *definitions* 2 and 3, a graph is bi-connected if and only if the graph has open ear decomposition. However, the way ears are constructed in steps 3, 4 and 5 of *BCN* algorithm, may form cycles (excluding the starting cycle) and consequently the obtained ear decomposition may not be open. A new ear is formed, by choosing the start and end points as vertices included in previous ears and all other vertices in that ear should be new (not yet included in ears). If the start and end points overlap in one node to form a cycle, then the removal of that node will disconnect the graph since vertices of the newly formed ear are disconnected from vertices of previous ears (node in square, see Figure 5.4.b); this is the well known characteristic of a cut-vertex. Thus, we can argue that the existence of inclusively more than one cycle proves the non bi-connectivity of the network. □

A modification/enhancement of the algorithm to alleviate the problem posed by *Lemma 1* is then required. The condition to only accepting distinct end-points of a composed ear P_k , when constructing *SP*, can be imposed. However, this condition may lead to premature termination of the algorithm. During the iterative execution of the algorithm, we may have a situation where $|EP|$=1. In this case, the algorithm will stop without further discovery of new ears; consequently, some APs are left unvisited (do not belong to any ear) and the resulting network is not robust. In

Step 6, we complete the algorithm by proposing a simple solution that guarantees a fault-tolerant network without adding new nodes.

6) For all cut-vertex u_k, elect two candidate nodes, that we call *recovery-nodes* (u_i,u_j), as follows: u_i is the direct neighbor of u_k in P_k and u_j is the direct neighbor of u_i *in* P_{k-1} and (u_i,u_j) are within the transmission range of each other.

The role of *recovery-nodes* pair, associated with every cut-vertex u_k, is to apply the segment protection policy [14] to recover the network from cut-vertex failures. In such protection policy, the segment between *recovery-nodes* is activated (bold segment in Figure 5.4.b), only when the failure occurs; consequently, spare resources are saved, thus reducing channel interferences.

Lemma 2: *The number of nodes added by BCN algorithm is optimal.*

Proof: The total number of constructed ears is largely dependent on the number of network nodes. The cardinality of any ear decomposition *P*, for a bi-connected network *G(V,E)*, is equal to $m+n-1$ [KR00], where $m=|E|$ and $n=|V|$. When a new node is added, the number of wireless links is kept small enough to minimize the number of edges in *E*. This is achieved by assigning, for each added node, only one predecessor (a tree-like graph). The benefit of selecting the longest "shortest path" in step 5 is to construct a minimum number of ears which results in small number of nodes added to transform a connected graph into a bi-connected one. □

Theorem 1: *Suppose n (resp. m) is the number of nodes (resp. edges) of the final graph, the time complexity of constructing WMN robust infrastructure using BCN Algorithm is* $O(n^3m^2logn)$.

Proof: Let n_0 (resp. m_0) be the number of nodes (resp. edges) in the original graph (composed only with APs). Let n_1 (resp. m_1) be the number of nodes (edges) in the connected graph (result of step 1), and let n (resp. m) be the number of nodes (resp. edges) in the final graph (after completion of *BCN* algorithm). We have the following relationship $n_0<n_1<n$ (resp. $m_0<m_1<m$). The time complexity of constructing a connected graph is $O(n_0^2)$. The number of leaf-nodes is at most (n_0-1). Thus the first step needs $O(n_0^2)$ which is bounded by $O(n^2)$. The time complexity of finding the first cycle using shortest path algorithm, is $O(m_1+n_1logn_1)$ bounded by $O(m+nlogn)$. The running time of step 3 is $O(n)$. Next, in step 4 and 5, checking for all shortest paths with augmentation process, takes at most $O(n^2mlogn)$. Finally step 6 has at most $O(n^2)$ running time. At the completion of Algorithm 5.1, we have $(m+n-1)$ constructed ears (see proof of *lemma* 2), thus the total running time of constructing WMN robust infrastructure using *BCN* Algorithm is $O(n^3m^2logn)$. □

BCN algorithm is composed of two parts. The first part (step 1) consists of adding nodes to connect network APs; the outcome of the first part is then to have a connected network with few links[2]. The second part starts from step 2 to step 6 with the purpose of transforming the connected network into a robust (bi-connected) network. The *BCN* algorithm could also be run on a given infrastructure to enhance its reliability in case of single node failure (step 1 is omitted). However, the number of added nodes in step 5 is not guaranteed to be optimal since it is highly dependent on the number of links in the original infrastructure.

5.4 Case Study: Simultaneous optimization

The purpose of *BCN algorithm* is to place a minimum number of mesh nodes that construct a robust WMN infrastructure and provide full coverage to network MCs. However, the resulting infrastructure after running *BCN* algorithm does not have one of the fundamental features of WMN which is its mesh topology (layout) due to the small number of links established when constructing the infrastructure. In fact, the *BCN* algorithm is run while designing the WMN infrastructure, where many links are added in when assigning channels (the number of links is bounded by *R*), thus allowing robust infrastructure design while restoring all WMN characteristics with optimal number of mesh nodes.

In this section, we will show how the resulting infrastructure is improved to meet other performance constraints (i.e., load balancing over network links) in a simultaneous optimization framework. Throughout this case study, we first present the formal description of the WMN design problem and how to solve the formulated problem; then, we show the tight relationship between reliability and the design of cost-effective WMNs.

5.4.1 WMN Design Problem formulation

Let *I* be the set of positions of traffic concentrations in the service area (Traffic Spots: TSs) and *L* the set of positions where mesh nodes can be installed (Candidate Locations, CLs). From this section onward, we denote by *n* the number of TSs and *m* the number of CLs.

[2] The number of links when connecting the network is kept small enough, to construct a minimum number of ears and thereafter to place a minimum number of nodes that are required to make the infrastructure robust.

The WMN design problem aims at:

- Selecting a subset $S \subseteq L$ of CLs where a mesh node should be installed so that the signal level is high enough to cover the considered TSs.
- Defining the gateway set by selecting a subset $G \subseteq L$ of CLs where the wireless connectivity is assured so that all traffic generated by TSs can find its way to reach a node in *G*.
- Maintaining the cardinalities of *G* and *S* small enough to satisfy the financial and performance requirements of the network planner.

In order to describe the problem formally we introduce the following notation - Let *I*={1,..,*n*} and *L*={1,..,*m*}. In the following, unless otherwise stated, *i* and *j* belong to *I* and *L* respectively. For better readability, Table 5.1 summarizes the notation used in the problem formulation.

Table 5.1: list of symbols used in the WMN design Model.

Param. /Var.	**Description**
n	Number of Traffic Spots (TSs)
m	Number of Candidate Locations (CLs)
d_i	Traffic generated by TS_i
u_{jl}	Traffic capacity of wireless link (CL_j,CL_l)
vj	Capacity limit for AP radio access interface
c_j	Device cost installation at location j
p_j	Gateway additional cost installation at location j
R	Number of radio interfaces
k	Number of channels per interface
a_{ij}	Coverage of TS_i by CL_j , $a_{ij} \in N$ *and* $a_{ij} \in [0,1]$
b_{jl}	Wireless connectivity between CL_j and CL_l, $b_{jl} \in N$ *and* $b_{jl} \in [0,1]$
t_j	Installation of a device at CL_j, $t_j \in N$ *and* $t_j \in [0,1]$
g_j	Installation of a gateway at CL_j, $g_j \in N$ *and* $g_j \in [0,1]$
x_{ij}	Assignment of TS_i to CL_j, $x_{ij} \in N$ *and* $x_{ij} \in [0,1]$
z_j^q	Device installation at CL_j, assignment of channel *q*, $q<k$, $z^q_j \in N$ *and* $z^q_j \in [0,1]$
y_{jl}^q	Wireless link on *q Between* (CL_j,CL_l), $y^q_{jl} \in N$ *and* $y^q_{jl} \in [0,1]$
f_{jl}^q	Flow on channel q between (CL_j,CL_l), $f_{jl}^q \in R$
F_j	Flow on the wired link from CL_j to Internet, $F_j \in R$
N_{jl}	Set of links interfering with the link y^q_{jl}

Load balancing is a desirable feature to have in a wireless mesh network. It reduces congestion in the network, increases network throughput, and prevents service disruption in case of failure [RB05]. We formulate the WMN design problem as a multi-objective optimization model. WMN planning solutions under multi-objective approach are more realistic and much preferred by network planners in that they have to be cost-effective (the deployment cost is minimized while the throughput is maximized). A substantial throughput increase can be obtained if a fair distribution of traffic among a set of diverse paths is performed [RB05]. Thus, we consider balancing loads over network channels in order to increase overall network throughput as the second objective to optimize. The formulation of the optimization problem is given below.

$$Min \sum \left(c_j t_j + p_j g_j \right) \tag{5.1}$$

$$Min \sqrt{\frac{\sum_{j \in L} \sum_{l \in L} \sum_{q \in C} \left(f_{jl}^{q} / u_{jl} \right)^2}{\sum_{j \in L} \sum_{l \in L} \sum_{q \in C} f_{jl}^{q} / u_{jl}}} \tag{5.2}$$

Subject to:

$$\sum_{j \in L} x_{ij} = 1 \qquad \forall i \in I \tag{5.3}$$

$$x_{ij} \le a_{ij} t_j \qquad \forall i \in I,\ \forall j \in L \tag{5.4}$$

$$\sum_{i \in I} d_i x_{ij} + \sum_{l \in L} \sum_{q \in C} \left(f_{lj}^{q} - f_{jl}^{q} \right) - F_j = 0 \quad \forall j \in L \tag{5.5}$$

$$\sum_{k,h \in N_{jl}} y_{kh}^{q} \le 1 \qquad \forall q \in C,\ \forall j,l \in L \tag{5.6}$$

$$\frac{f_{jl}^{q}}{u_{jl}} \le y_{jl}^{q} \qquad \forall q \in C, \forall j,l \in L \tag{5.7}$$

$$\sum_{i\in I} d_i x_{ij} \le v_j \qquad \forall j \in L \tag{5.8}$$

$$F_j \le M\, g_j \qquad \forall j \in L \tag{5.9}$$

$$2y_{jl}^q \le b_{jl}\left(z_j^q + z_l^q\right) \qquad \forall q \in C, \forall j, l \in L \tag{5.10}$$

$$g_j \le t_j \qquad \forall j \in L \tag{5.11}$$

$$\sum_{l\in L} y_{jl}^q \le 1 \qquad \forall q \in C,\ \forall j \in L \tag{5.12}$$

$$\sum_{q\in C} z_j^q \le R\ t_j \qquad \forall j \in L \tag{5.13}$$

$$x_{ij}, z_j^q, y_{jl}^q, t_j, g_j \in \{0,1\} \qquad \forall i \in I, \forall j, l \in L, \forall q \in C \tag{5.14}$$

$$f_{jl}^q, F_j \in R \qquad \forall j, l \in L, \forall q \in C \tag{5.15}$$

In this model, the objective function (5.1) minimizes the total cost of the network including installation cost c_j and additional gateway installation cost p_j. The load-balancing objective function (5.2) minimizes the standard deviation of the ratio of traffic flows over the network links. Constraint (5.3) makes sure that the TS_i is assigned to exactly one and only one AP installed at CL_j, while constraint (5.4) implies that the TS_i and the assigned AP are within the coverage area. Constraint (5.5) defines the flow balance for each mesh node at CL_j. Constraint (5.6) limits link interferences, while inequalities (5.7) and (5.8) respectively define the flow-link capacity and the demand-radio access capacity constraints. Constraint (5.9) states that the flow routed to the wired backbone is different from zero only when the installed mesh node is a gateway. We assign *M* a very large number to limit the capacity of the installed gateway. Constraint (5.10) forces a link between CL_j and CL_l using the same channel *q* to exist only when the two devices are installed, wirelessly connected and tuned to the same channel *q*. Constraint (5.11) ensures that a device can be a gateway only if it is installed. Constraint (5.12) prevents a mesh node from selecting the same channel more than once to assign it to its interfaces. Constraint (5.13) states that the number of links emanating from a node is limited by the number of its radio interfaces; it also states that if a channel is assigned only once to a mesh node, it is a sufficient condition for its existence.

All the above constraints are called hard constraints with the exception of constraint (5.5) which is then called a soft constraint. The fact to have constraint (5.5) violated while all other constraints are satisfied, can be explained by the inability to find routes to flow the traffic generated by mesh clients. This is mainly caused by the lack of node pairs that are tuned to the same channel to establish wireless communications. Therefore, a reassignment of channels for the same topology in later iterations (using mutation) could help in satisfying all traffic demand (constraint 5.5 is then fulfilled). To construct fault-tolerant topologies, we add two more constraints to guarantee two disjoint paths based networks.

$$\sum_{l \in L} \sum_{q \in C} y_{jl}^{q} \geq 2 \qquad \forall \ j \in L \tag{5.16}$$

$$\sum_{l \in L} \sum_{q \in C} y_{lj}^{q} \leq 1 \qquad \forall \ j \in L - G \tag{5.17}$$

There must be at least two node-disjoint paths from each node $j \in S$ to some gateway in G, as shown by constraint (5.16); the idea we use to ensure node disjoint paths is that for a node *j*, there can be at most one incoming flow originating from node $l \in S$ (Equation 5.17). This condition is sufficient and necessary to guarantee vertex disjoint paths. Note that (5.17) automatically prevents flows from forming cycles at the intermediate nodes on the way to the gateway(s). In the following, we show how *BCN* algorithm operates to satisfy the constraints (5.16) and (5.17) when designing the network.

5.4.2 Solving the WMN Design Problem

WMN design is a fairly complex problem; its difficulty lies in the fact that it tries to simultaneously address many criteria (i.e., minimize deployment cost, maximize throughput by balancing traffic load, full coverage to MCs and, robust infrastructure with minimum nodes installed). Joint optimization of the above criteria is defined as a Multi-Objective search Problem (MOP). Solving a MOP returns a set of Pareto optimal solutions [De02]. Each solution represents a different trade-off between the objectives that is said to be "non-dominated". We devise a kind of a hybrid optimizer that borrows the mutation operator from Genetic Algorithms GAs [De02] (to better explore the search space) and uses the velocity calculation, from Particle Swarm Optimization PSO

[KE95], to guide the search towards local and global (sub) optimums. More precisely, our WMN optimization algorithm (called VMOPSO-R) is a modified version of MOPSO equipped with the Crowding-Distance (CD) technique of NSGA-II [De02] and uses a mutation procedure. The crowding distance value of a solution, as thoroughly studied in [De02] and [RN05], is the average distance of its two neighboring solutions. The boundary solutions with the lowest or the highest objective function value are given an infinite crowding distance values so that they are always selected. This process is done for each objective. The final crowding distance value of a solution is computed by adding the entire individual crowding distance values in each objective value.

Both the mutation procedure and the CD technique strive to enhance the exploration process, though at different levels. The CD technique is applied on the archive, where the final set of solutions would be diverse. The mutation procedure, however, operates at the generation level, where the algorithm will have (enough) frequent discrete jumps to allow for escaping the traps of the local-optima issue. We also add a constraint handling mechanism for solving constraints optimization problem, such as WMN design problem. In the following, we provide more details on how the multi-objective models are solved using our proposed VMOPSO-R.

In PSO, a particle (a position in the search space) represents a set of assignments that is a solution to the problem. In our case, a particle is a complex data structure that provides information about user connectivity (x_{ij}), device installation (t_j) and (z^q_j), devices connectivity (y^q_{jl}), gateway existence (g_j), link flows (f^q_{jl}), and gateway/backbone link flows (F_j). The building blocks of a particle structure are *Positions, Links, Flows* and *Demands*. The block *Positions* is the most important one, as it provides information about user connectivity and the type of devices, as well as their locations and installations. The *mesh nodes* component contains the locations of APs (represented by IZ vector), the locations of MGs (represented by GW vector) and the list of channels assigned to radio interfaces of every mesh node installed. Figure 5.5 illustrates an example of the *mesh nodes* component of a particle. Vector Z represents the placement of each mesh node (MR included) and its assigned channel per radio interface; More specifically, Z contains m^2 records (grid size is m), one for each potential position in the grid, and assign “1” to every positioned node showing the R channels selected from a set of k channels. If the number of channels is less than R, then the empty cells are filled with “0”. Vector IZ represents the positions (value equal to 1) of the two APs as depicted in (a) while vector GW represents the positions of MGs (value equal to 1) based on the grid size.

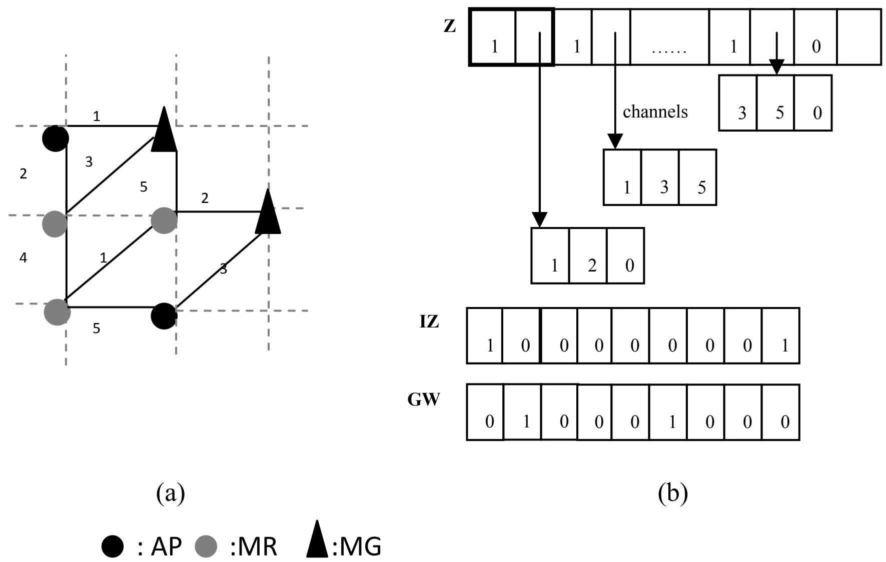


Figure 5.5: Particle encoding, (a) A Particle position example with *m*=3, *R*=3, *k*=5. *(b) mesh nodes* component of the particle position.

5.4.3 The VMOPSO-R Algorithm

Given a set of TSs scattered in a geographical region, the idea is to construct a network of mesh nodes (APs, MRs, MGs) that will best service the users TSs with minimum cost and under the given constraints. The VMOPSO-R algorithm needs to breed a swarm (collection) of *acceptable* potential planning solutions, i.e. satisfying all the constraints defined in sub-section 5.4.1.

5.4.3.1 Building initial solutions

Constructing an initial set of feasible solutions that satisfy the constraints (5.3) to (5.17) represents the most challenging part in our optimization process as it needs to be designed carefully. To handle the assignment of each TS_i to one and only one CL_j , we start by selecting randomly a CL_j from the set of CLs that cover that TS_i (Figure 5.6.a). An AP is then installed at this location CL_j only if it has not yet been selected. By applying the same procedure to all TSs, we obtain a subset S_1 of APs to cover all TSs (*coverage insurance design stage* that satisfies Constraints 5.3 and 5.4). Next *BCN* algorithm, given in Section 5.3, is invoked to construct the bi-connected infrastructure, and finally gateways are placed based on a random selection from the set of nodes that are eligible to be gateways.

For computational purposes, we use a symmetric adjacency matrix to represent the connectivity graph. We apply the fixed channel assignment algorithm described by Das et al.

[DA05] and we implement Edmonds-Karp's max flow algorithm [EK72] to assign a value on each link y_{jl} using channel q to route a flow. All remaining constraints (i.e., 5.5-5.17) are then satisfied.

A feasible solution must satisfy all hard and soft constraints. However, those solutions that violate only the soft constraint (5.5) can be included in the population if space allows. This increases the likelihood of a non-feasible solution to mutate and provide a feasible one in later generations.

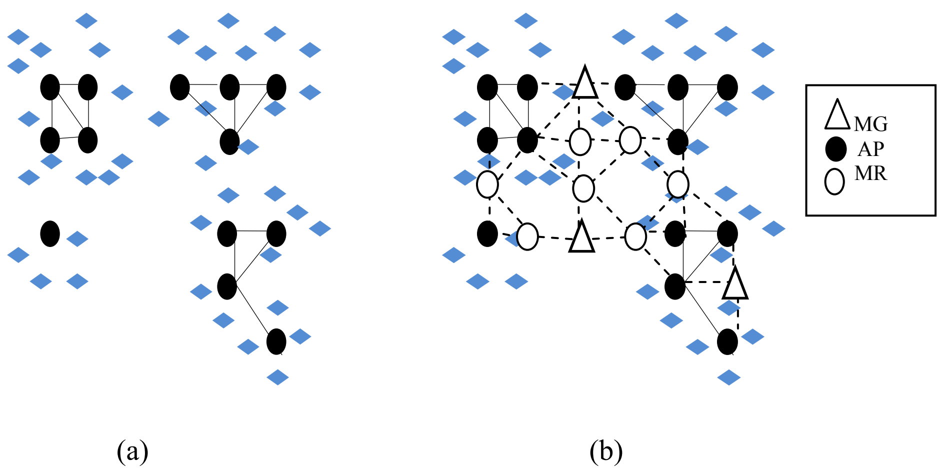


Figure 5.6: A Feasible Particle Position: (a) TSs assigned. (b) S_1 augmented, MGs selected.

5.4.3.2 Breeding Potential Planning Solutions

The very first step in VMOPSO-R Algorithm (see Algorithm 5.2) is to initialize the positions, as described above, initialize the boundary limits and the velocities of each solution *i* (particle) in *Sw*. At this step, only feasible solutions are considered.

Each of these particles would then go through an evaluation process, i.e., an assessment of the quality of the solution, which is nothing but the evaluation of the two objective functions.

During the exploration of the search space, each particle has access to two pieces of information: the best Potential Solution (PS) that it had encountered (*pBest*) and the best PS encountered by its neighbors *(gBest)*. This information is used to direct the search by computing velocities (see Algorithm 5.3): velocity[i] = *iw* * velocity[i] +r_1 * (*pBest*[i] – position[i]) +r_2* (*Archive*[*gBest*] – position[i]), where r_1, r_2 *are* random numbers in the range of [0,1] and *iw is* the inertia weight . A large inertia value will cause the particles to explore more of the search space, while a small one directs the particles to a more refined region.

The *Archive* is then updated by inserting into it all the currently non-dominated (fittest) solutions. This insertion process ends up in removing dominated solutions. In the case where the archive is full and there are still non-dominated solutions to be inserted, priority is then given to those particles that would ultimately enhance the diversity of the archive set, which is achieved by using the crowding distance technique (see section 5.4.2). When the decision variable exceeds its boundaries, it takes the value of its corresponding boundary and the velocity is changed to the opposite direction.

For each particle in the swarm, and based on the initial feasible solutions and *BCN* algorithm, the iterative algorithm (Algorithm 5.3) goes on mutating planning solutions in the swarm from generation to generation, with a bias towards selecting the fittest solutions. After this solution-construction process, the velocities, the positions and the fitness (values of the two objective functions) of the particles are computed. Then, some of these particles are inserted into the archive provided that they dominate or at least are non-dominated by the previously “archived” non-dominated solutions.

Algorithm 5.2: VMOPSO-R Main Algorithm

Input *Sw:* swarm, *gMut: Generational Mutation factor*, *MaxGeneration*

Output *Archive*: External repository

Step 1: Initialize the swarm *Sw*

For each particle *i* in *Sw* *//Build feasible solutions that satisfy all constraints,*

Initialize feasible position, // See sub-section 5.4.3.1

Specify *lowerBound*$_i$ and *upperBound*$_i$; *//boundary limits*

Initialize velocity; *// initially set to Zero*

Set the global best guide *gBest* to *pBest*;

Set the personal best guide *pBest* to that position;

End For

Initialize the iteration counter *t*=0;

Evaluate all particles in *Sw*; *//compute objective functions f1 and f2*

Filter non-dominated solutions from *Sw* and Store them into *Archive*;

Step 2: **Repeat**

- Process the *Archive*.
  - *a.* Sort the *Archive* in a descending order of one of the *objective functions f1 or f2*;
  - *b.* Compute the crowding distance (*CD*) values for each j∈*Archive*;
  - *c.* Sort the *Archive* in a descending order of CD values ;
- Set *gBest[i]* to the randomly selected particle from the top 10% of the sorted *Archive*;
- **ConstructWMNPlanningSolution**; **//** *invoke Algorithm 5.3*
- Check for constraints satisfaction;
- Update the *Archive*: *// insert non-dominated and feasible particles in the Archive*

  If any particle *k* in *Sw* dominates any particle *l* in *Archive* **then** Delete *l* from *Archive* and insert *k* in *Archive*;

  End If

  If *Archive* is full and there is non-dominated particle (candidate) in *Sw* then

  1. Compute the crowding distance values for each j∈*Archive*;
  2. Select the victim: a Random particle in the bottom 10% of the CD-sorted *Archive* (most crowded portion);
  3. Replace it with the new candidate;

  End If
- Update pBest;
- Increment t;

Until (t ≥ *MaxGeneration)*

A position in the search space is a solution to our planning problem; however, the values, returned by Update_Positions() procedure in Algorithm 5.3 are not guaranteed to be integers (0 or 1). For this purpose, we add a final process that we call *particle filtering* to allow only particles with a considerable progress to change to 0 (respectively 1). If the difference between the two positions (initial and the updated one) of a particle goes beyond a given threshold α (based on experiments, α is set to 0.3), then the final position will be the reverse of the initial one (i.e., 0 if it was 1 and vice-versa); otherwise, the new position is discarded. i.e., the particle remains in its original position for further improvement.

Algorithm 5.3: ConstructWMNPlanningSolution

Input *Sw*: Swarm, t: generation counter, MaxGeneration*,*

gMut: Generational mutation factor,

sMut: Swarm mutation factor *//adopted from MOPSO* [24]*,sMut=(1-t/MaxGeneration*gMut)*$^{3/2}$

Output *Sw*: Swarm

---

mutateEnabled:= true;

If (t>= *MaxGeneration*gMut) then* mutateEnabled*:=false;*

for each particle *i* in *Sw*.

  if (mutateEnabled) and (*sMut*=1) //*Allow mutation at early generations*

   S_1 := Mutate(S_1) ; // S_1 *is the subset of APs locations*

  endif

  S := Augment-BiConnect(S_1); // ***Invoke BCN Algorithm***

  Y_1:=Construct_connectivity_matrix(S) ;

  Y_2:= Assign_channels(Y_1) ; // as in [DA05]

  G := PlaceGateways(Y_2); //*Gateways assignment*

  Compute_flows(G) ;

  Construct_New_Particle(); // *with the newly generated S,Y_2,G and flows*

  Compute_Velocities(); // *As described in the beginning of this section*

  Update_Positions(); // *New position= current position + computed velocity*

  Check particle boundaries, if violated change particle search direction *(i.e.,velocity(i) * -1)*

  Evaluate_Particles(); // *Compute objective functions f1 and f2*

endfor

5.5 Performance Evaluation

In this section, we evaluate the performance[3] of Algorithm 5.2 (coupled with Algorithm 5.3 and *BCN* algorithm) under many deployment scenarios. We carry out four set of simulations, where we vary one key parameter at a time (*m*, *n*, *R*, d_i) while maintaining others fixed. We define the Standard Setting (SS) of the WMN as the following: SS=[(n:150), (m:49), (d_i:2Mb/s), (u_{jl}:54Mb/s), (vj:54Mb/s), (M:128Mb/s), (c_j:200), (p_j:8*c_j,), (R:3), (k:11)]. The algorithm is coded in the Java programming language and all the experiments were carried out on a Pentium M 1.5 GHz. Unless stated otherwise, we use the standard setting SS. The positions of the *n* TSs are randomly generated. A run of our main algorithm (Algorithm 5.2) involves 100 generations each with a population size and archive size of 50 and 30 particles respectively.

We take a mutation factor (*fmut*) of 0.5 as our standard setting based on our recent experiments [BH08a] (mutating at a rate of 50% of the population leads to the best Pareto front).

Results are reported after 10 runs. Additional filtering process is required to maintain the non-dominance aspect of the collected Pareto fronts.

For each simulation set, we plot the resources utilization (APs, total nodes added by *BCN* algorithm, Links and, MGs) where only cheapest solutions are considered. We mean by added nodes, the number of nodes required to connect the network and additional nodes necessary to bi-connect the infrastructure (i.e., actual number of relays and gateways composing the final infrastructure; see Figure 5.6.b).

The number of added nodes on connected infrastructure to make it robust is not shown, as the design and the construction of the infrastructure are done from scratch. We also plot optimal planning solutions (deployment cost against load balance) as Pareto points in the objective space graph (Pareto optimal solutions).

[3] The *BCN* algorithm is invoked by Algorithm 5.3 to design robust WMN infrastructure upon the aforementioned multiple criteria satisfaction. The evaluation of *BCN* algorithm could not be done solely without evaluating design solutions after running topology design Algorithms.

5.5.1 Effect of varying number of candidate locations m.

In this set of simulations, we perform four different experiments by varying the grid-size (*m=49, 64, 81, 100*). All Pareto optimal solutions found are plotted in the same graph. Figure 5.7.b shows that the best Pareto front is obtained when *m*=49, and the grid-size of 7x7 is largely sufficient to construct a robust and cost effective WMN infrastructures given the standard setting SS.

As expected, the increase in the number of candidate locations leads to an increase in the number of added nodes, the number of links and the number of gateways (Figure 5.7.a). The number of APs remains relatively stable, since neither the number of MCs nor the traffic demand change. The first reason behind the increase of network resources (except APs) is that increasing the number of CLs increases the probability of a MC not being connected to Internet through a multi-hop wireless path (disconnected mesh nodes), leading to install more nodes and establishing more wireless links to satisfy connectivity constraints. Even if the network is connected, additional nodes and links are also added in order to construct a robust infrastructure, which is performed by *BCN* algorithm.

5.5.2 Effect of changing the number of mesh clients n.

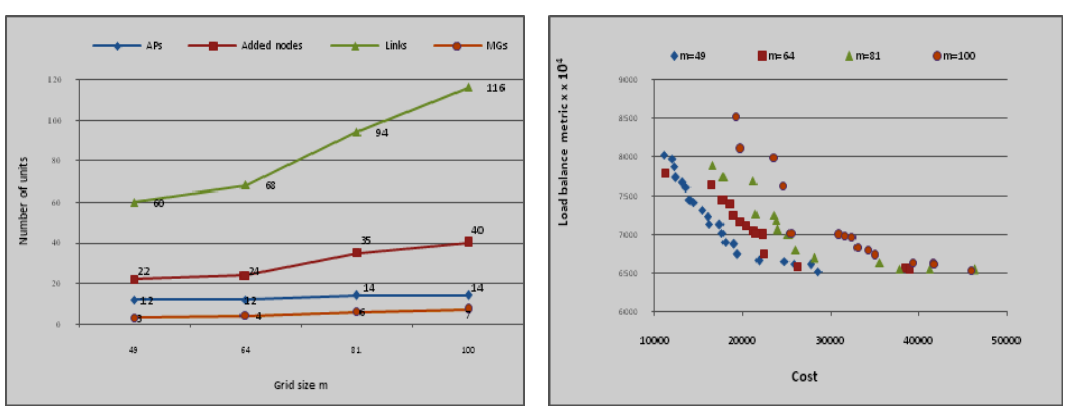
We also study how our algorithm would behave when the number of MCs varies. Notice that the remarkable increase in the number of deployed APs (see Figure 5.8.a) is more related, in the first place, to the increase of users that need to be covered and connected to Internet, then in the second place, to fulfill the load balancing requirement. Compared to the number of added nodes and links, the number of added gateways is not significant (at most one gateway is added for every 50 new MCs). The main reason behind this noticeable gain is that diverse disjoint paths are available to connect all MCs to Internet through MGs (robust infrastructure), hence deploying few gateways are enough to continue providing reliable services to MCs. As shown by Figure 5.8.b, the more MCs are added the more network planner has to pay for robust topologies that are load-balancing guaranteed.

5.5.3 Effect of changing the number of radio interfaces R.

Another performed endeavor to evaluate the performance of our algorithm consists of varying the number of radio interfaces *R* from 2 to 5. A slight decrease in the number of gateways and APs followed by a significant decrease in the number of added nodes is noticed when *R* shifts from 2 to 3 (Figure 5.9.a). However, when *R* shifts from 3 to 4 then from 4 to 5, the number of gateways remains fixed, while the number of added nodes to construct a robust infrastructure, increases. This can be explained by interferences caused when the number of wireless links increases, which leads to place new nodes so that alternative paths could be found to route the traffic. Notice also, from Figure 5.9.b, that the best Pareto front is obtained with four radio interfaces instead of five. From the above, we can then stipulate that the performance and robustness of a WMN infrastructure is better achieved when R=3 (less interferences) or R=4 (best tradeoff solutions that dominate most of the other Pareto fronts), and no additional gain is obtained when more than four radio interfaces are deployed.

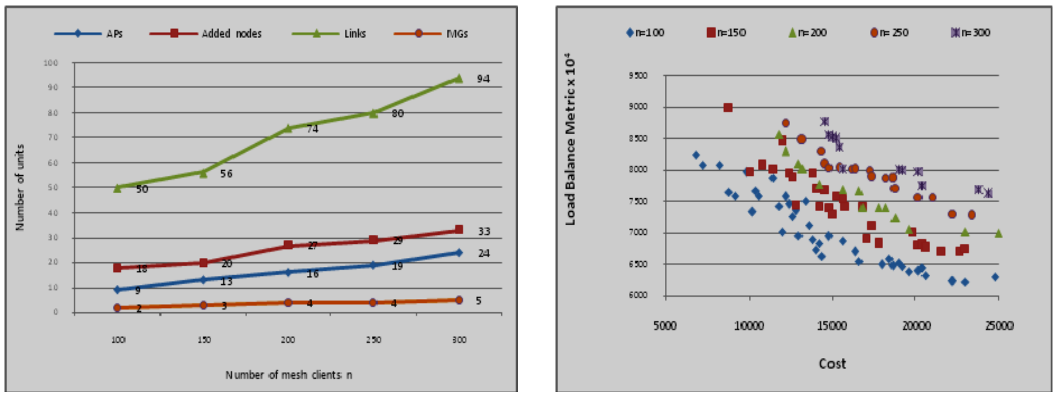
5.5.4 Impact of demand variation.

The last set of simulations carried out to evaluate our approach and to assess the scalability of the network (designed using our proposed model), consists of gradually increasing traffic demand d_i from 1 to 5 Mb/s. Figure 5.10.a shows that the number of network resources (APs, added nodes, MGs, and Links) increases linearly with the traffic demand the network has to support, which is as expected. However, the increase in the number of MGs seems following the same pattern as d_i variation (for one Mb/s of more traffic, only one MG is added in). This fact could be explained by the benefit of designing a biconnected network, where alternative paths are available to reroute traffic to MGs. Figure 5.10.b shows that the less d_i is, the more the load balancing is enhanced, and the less the deployment cost is, which is obvious.



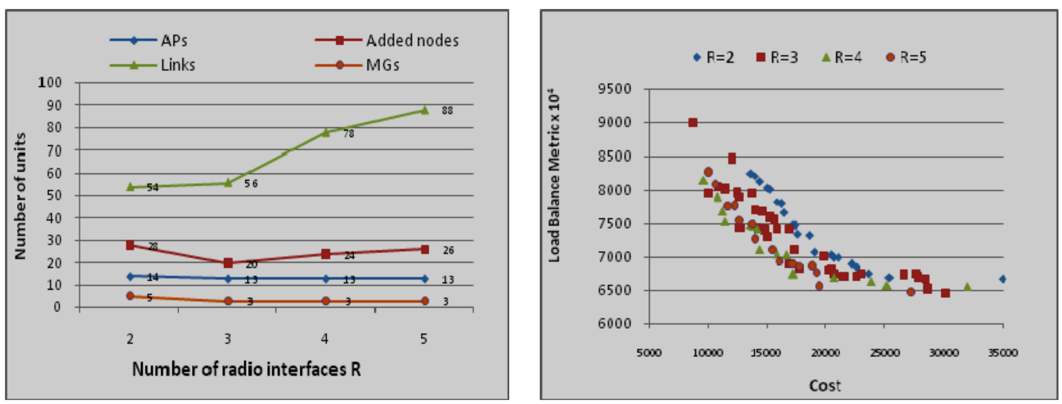
(a) (b)

Figure 5.7: **Impact of varying m**. (a) Resources utilization. (b) Pareto Optimal solutions.



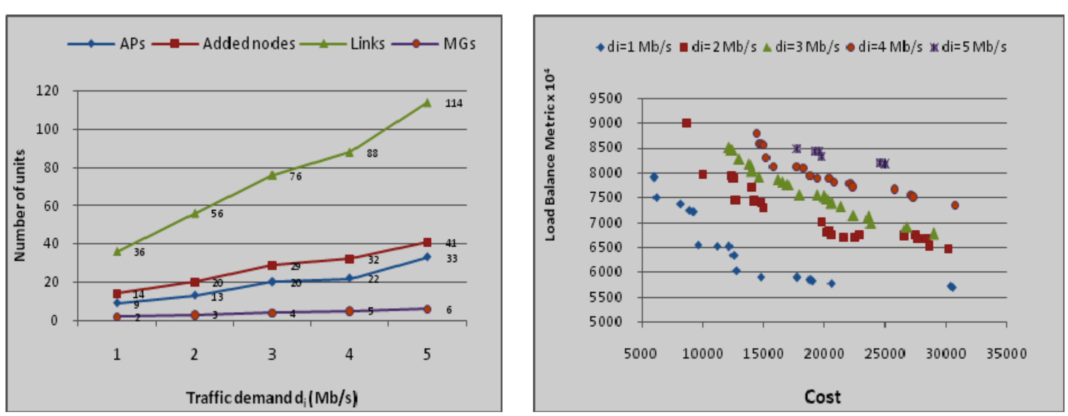
(a) (b)

Figure 5.8: **Impact of varying n**. (a) Resources utilization. (b) Pareto Optimal solutions.



(a) (b)

Figure 5.9: **Impact of varying R**: (a) Resources utilization. (b) Pareto Optimal solutions.



(a) (b)

Figure 5.10: **Impact of varying traffic demand**. (a) Resources utilization. (b) Pareto Optimal solutions.

5.6 Simulation via OMNET

In order to assess the impact of simple failure events (failure of one node at a time) on the performance of a robust network (designed as shown in Section 5.4), we use the discrete event simulator OMNET++ V.4.0 in conjunction with the INETMANET networking model [OM09]. We simulate a network composed of 31 APs, 6 MGs and 3 Relays (nodes in circle), a total of 40 mesh nodes deployed on 7x7 grid layout, as depicted in Figure 5.11. The network to be fed to the simulator is one solution amongst those generated by our solver (VMOPSO-R) in which APs and MRs are equipped with multiple IEEE802.11b radios, while MGs are equipped with multiple radios as well as an additional Ethernet device (to uplink to an external network). All nodes include a full IP network stack and APs include a TCP traffic generator (*ftp* application) in order to inject TCP traffic to the WMN in a one-to-one file transfer against a group of servers located outside of the WMN.

We set up three different scenarios. For each scenario, a network topology is simulated for the same fixed time T (T=600s). In scenario 1, we consider the initial network as shown in Figure 5.11, with no failed nodes (original topology), then with one node failure at a time; failure in node 5 followed by a failure in node 38. In Scenario 2, the same original topology is used, but the first node to fail is node 28 followed by node 38. In Scenario 3, we produce a failure in node 22 and then in node 38. (see Figure 5.11). The nodes to fail first (nodes 5, 28 and 22) are selected randomly to study the performance of the network after any set of failed nodes.

Each scenario, as defined above, is run 5 times on each failure situation (original topology, then with one failed node and finally with two failed nodes); thus, three set of experiments are carried out in the goal to compare their corresponding performance metrics.

We apply the Tukey's Honest Significance Test (Tukey HSD) [Mo05] with 5% of tolerable estimated error, to contrast each performance metric so that a clear picture about the difference among the three scenarios (Scenario 1, Scenario 2, and Scenario 3) could be obtained.

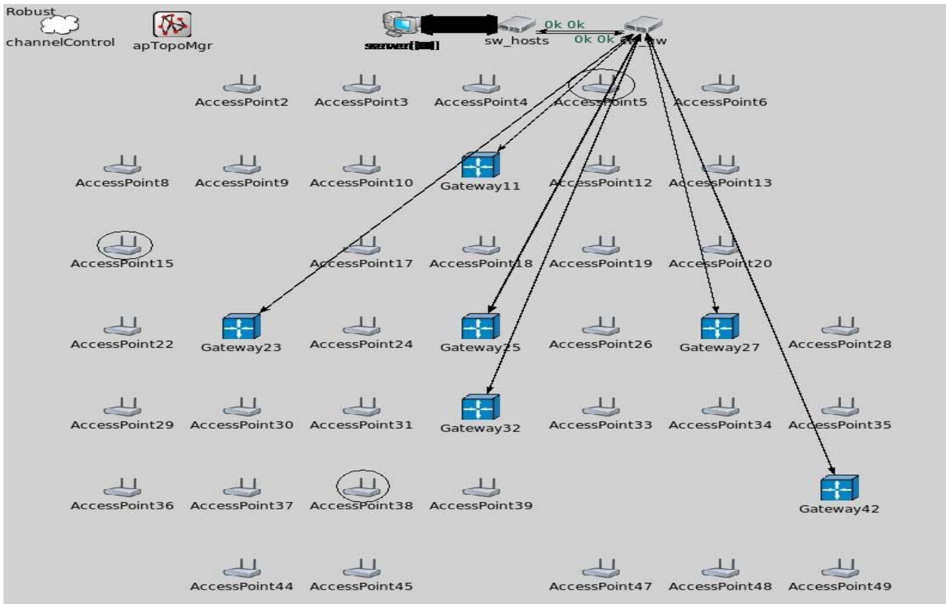


Figure 5.11: The original network to simulate

We evaluate each performance metric (bandwidth, interference, data losses and delay) by comparing its variability for the original topology, after failure of the first node and after failure of the second node, on each scenario. For each metric, we show only the most important graphs (the contrast graphs) that represent the real difference of means in order to show clearly whether the measurements are "equal" or "different".

The bandwidth is measured as the average amount of bits transferred by time unit through network data links; radios interference is measured in terms of packet collisions and retransmissions (lost ACK packets) over all the network ; packets delay is measured by the average round trip time (RTT) at TCP and ICMP (pings) levels between APs-MGs pairs; and finally, packet losses are measured by the total number of packets dropped by the radio interfaces (given up packets after 7 retransmissions without a single ACK received) and the input queue tails drops.

When analyzing average overall bandwidth (up and downstream) in each scenario, we observe that bandwidth decays accordingly when nodes start failing. However, scenario 3 shows no apparent difference among each failure situation. Further analysis on the three scenarios shows that the drop in bandwidth could oscillate from 49Kbps up-to 1.2Mbps. After each node failure, the traffic can still be routed to the gateways by rerouting the affected traffic across other nodes

(BCN algorithm). Consequently, those other nodes become more loaded (or possibly overloaded) than before, making traffic condition worst to each client being served through them.

A different behavior is found when analyzing each server bandwidth. Notice from Figure 5.12 that there is no statistical difference[4] [Mo05] among the bandwidth achieved by each server on the FTP transfer when the first and the second nodes have failed.

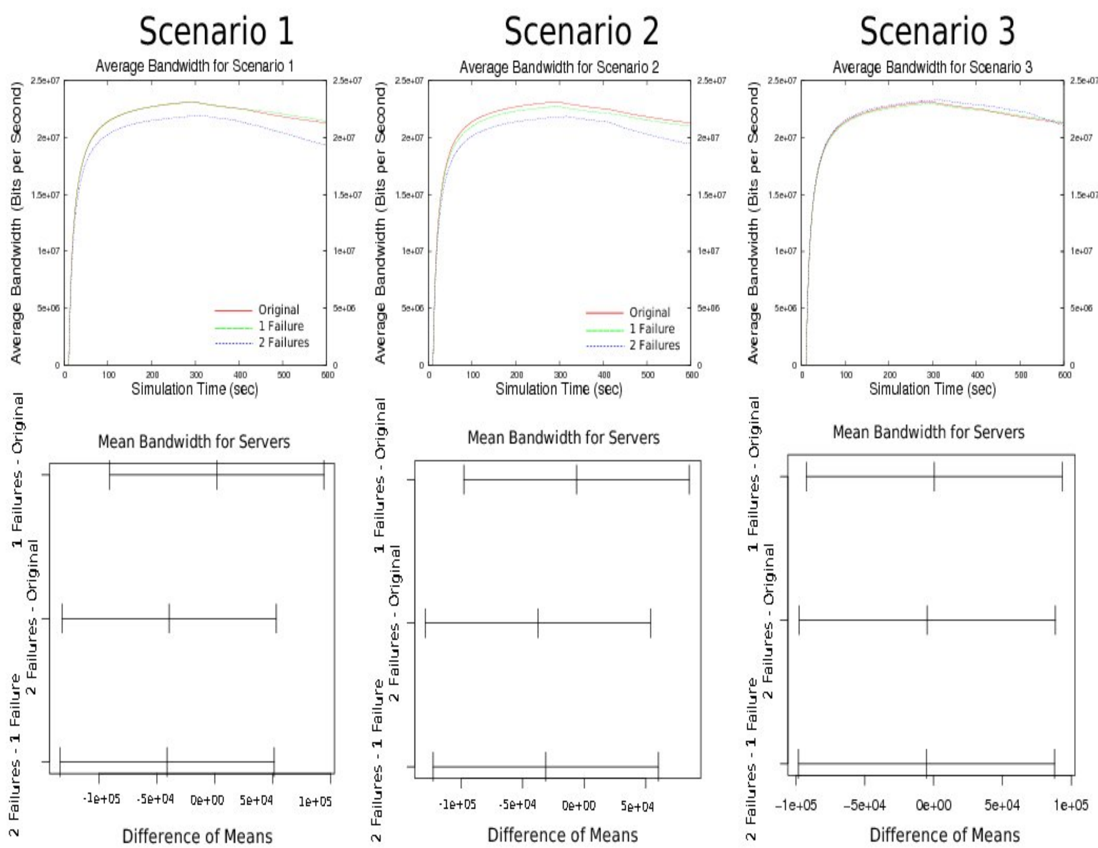


Figure 5.12: Tukey HSD and Bandwidth measure for the three scenarios

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4 When contrasting two failure cases means, µ1 - µ2, three cases can occurs: the difference is always positive, that means population 1 has a bigger mean that population 2. The difference is negative, and when the difference is 0, populations could be the same. Thus, exploring each interval on the difference of means charts, when both limits are positive, the difference is always positive; when both limits are negative, the difference is always negative; and when the limits have different signs , zero is included in the interval, the difference could be zero.

Regarding interference level in each scenario, first, we observe, across scenarios, a little increase in the number of collisions in APs and MGs when the number of failed nodes increases (Figure 5.13). Regarding retransmissions, APs show no difference on the effort made when transmitting a single packet. But, in Gateways, this effort is reduced while the failed nodes number increases. The effort is measured by the number of attempts made by the wireless interface (IEEE802.11) to transmit a packet before it receives an ACK from the receiver. This is as expected, since when nodes start failing, the bandwidth is reduced, then less packets are being transmitted on each channel; consequently, the probability to deliver correctly a packet in the first attempt is higher. Concluding, we observe that there is not a statistical difference in terms of interference when nodes start failing; the only effect observed (a logical one), is that efforts in transmitting a packet decrease.

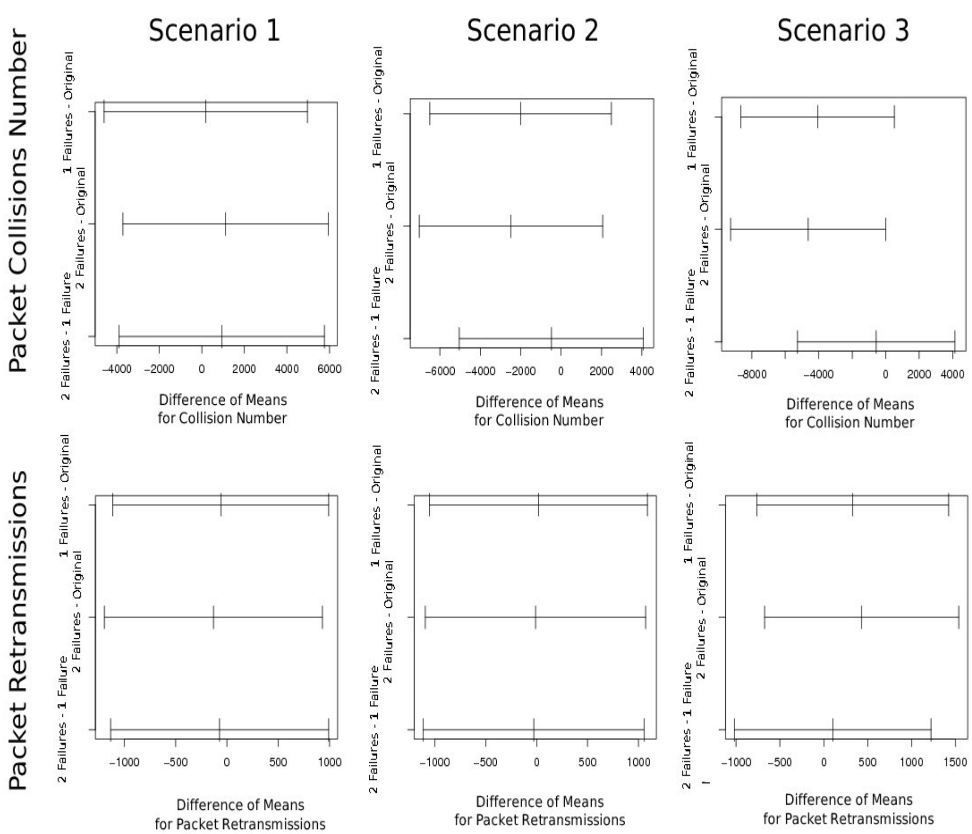
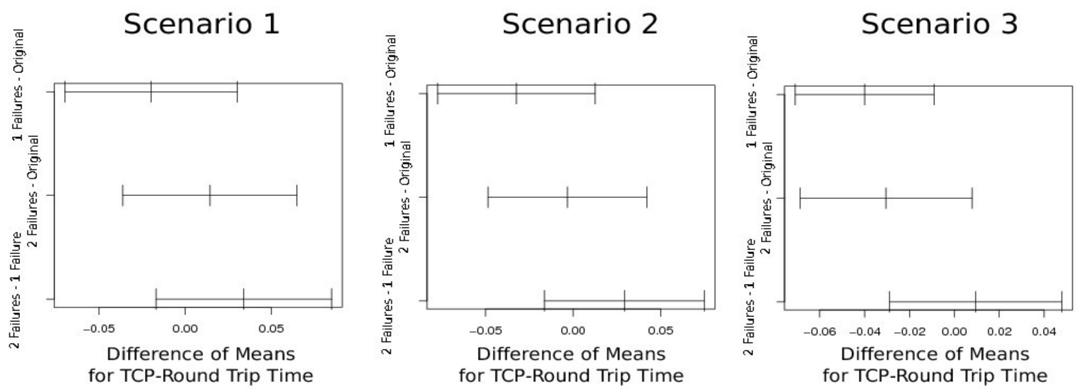
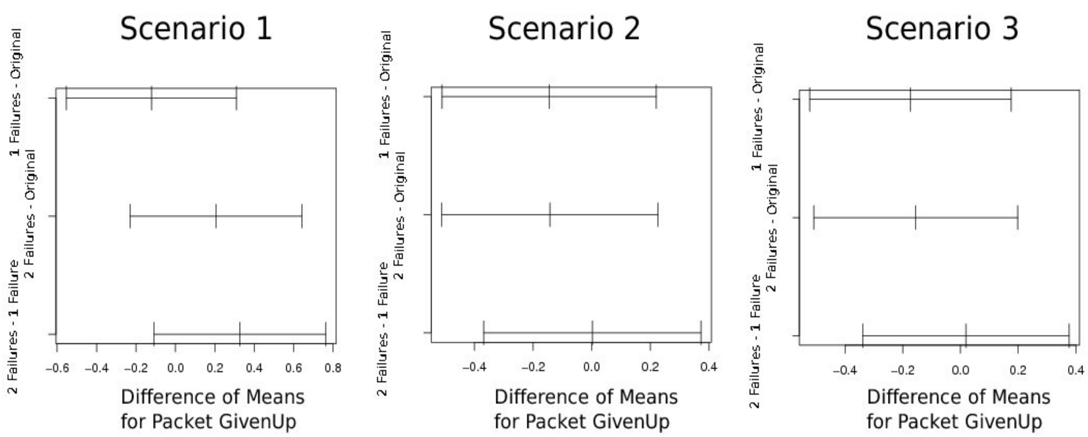


Figure 5.13: Statistical comparison of interference.



a) Packet losses: number of given-up packets.



b) Packet delays: TCP Round Time Trip (RTT)

Figure 5.14: Differences in mean for packet losses and delay.

Finally, we measure packet losses and packet delay and compare them across scenarios. For packets losses, we measure the number of packets lost due to excessive retransmissions (numGivenUp). When observing the packet losses due to an exhausted radio device when transmitting a packet (after 7 retries, the packet is discarded), notice, from Figure 5.14.a, that there are no significant differences among scenarios; however, a tendency to increase the packet losses is identified when nodes start to fail (each time the contrast is more in the positive side).

Since the number of failed nodes is low (2 nodes as maximum), packet losses may become statistically bigger when more failed nodes are introduced to the network topology.

For packet delay, we measure the round trip time (RTT) between each AP and its external server (MG). Figure 5.14.b shows that slight statistical differences of packet delays (TCP and Pings) are observed when nodes start to fail. In a similar way as stated before, this difference may be bigger when more failed nodes are considered.

In summary, the only effect that could be observed, when nodes start failing, is the reduction of the overall average bandwidth in all scenarios. This can be explained by the fact that the same traffic must be re-routed through a smaller number of nodes. However, when analyzing the average bandwidth from the point of view of each server, the overall bandwidth is not affected for WMN with one and two failed nodes. Then we can state that no matter the set of failed nodes (3 sets in our simulations), the whole WMN will have similar "performance" with an exception where the overall bandwidth may be affected.

5.7 Conclusions

In this work, we address one of the fundamental problems for designing a WMN: how to construct a robust network while designing the WMN infrastructure under QoS and financial constraints? We devise a new approach based on ear decomposition to construct a robust infrastructure with a minimum number of nodes. Through a case study, where we formulate the WMN design as a simultaneous optimization of deployment cost and load balancing objectives, we show the impact and benefits of our devised approach in designing cost-effective and robust WMN infrastructures. In the light of the results obtained in Sections 5.5 and 5.6, a spectrum of alternative trade-offs solutions is provided to the network planner allowing a flexible decision making. It has been shown that the key parameter R is crucial in determining the cost effectiveness of the produced infrastructure. Even if the resulting infrastructure is robust, selecting a large value of R (R>4) may deteriorate the performance of the network and may increase the total number of mesh nodes forcing the network planner to pay more (expensive topologies) for unworthy networks. Varying the number of MCs (n) and Traffic demand (d_i), have proved the effectiveness and scalability of our approach in designing robust and cost-effective WMN infrastructures. Next we will investigate the impact of limiting the number of communication hops while designing robust WMNs.

Chapitre 6

CONCLUSIONS

Dans cette thèse, nous avons proposé de nouveaux modèles et algorithmes pour la conception des réseaux maillés sans fil (WMNs). Principalement, nous nous sommes intéressés aux trois problèmes majeurs : le problème de conception de WMNs sous les contraintes financières, de performance et de couverture géographique, le problème d'extensibilité du réseau et enfin le problème de fiabilité/robustesse.

Le problème de conception de WMN à multiple radios et à multiples canaux consiste à sélectionner les locations et les types de nœuds et à choisir également le nombre de radios par nœud et le type de canal par radio. Il faut optimiser une ou plusieurs fonctions objectifs à cette phase de sélection tout en garantissant une couverture complète aux usagers du réseau et une connectivité sans fil avec fluidité du trafic.

L'extensibilité du réseau est une caractéristique importante à considérer lors de sa conception. Elle indique sa capacité à continuer à fonctionner suite à la croissance de la demande et son potentiel à être élargi après sa conception si l'ajout de nouveaux composants devient nécessaire.

La robustesse joue un rôle très important dans les réseaux de transport ou de communication à cause de l'ampleur des impacts des pannes sur le coût et sur la continuité du service. Le moyen le plus sûr de la garantir est de prévoir, au moment de la conception, des nœuds supplémentaires à travers lesquels le trafic affecté sera détourné en cas de pannes. Dans ce qui suit, nous résumons les contributions majeures de cette thèse et nous concluons avec quelques directions de recherches futures.

6.1 Résumé des contributions

Dans le chapitre 2, une plateforme de classification des études de recherches liées à l'amélioration de la performance des WMNs a été proposée. Nous avons vu que malgré le nombre important de contributions dans le domaine de conception de ce type de réseaux, la majorité des études est restée limitée à la conception de protocoles ou d'architectures. Il est à noter que très peu de travaux dans la littérature visent la conception de réseaux du point de vue d'une planification de leur déploiement. Dans ce cas d'étude, nous avons considéré les facteurs qui contribuent à la dégradation de la performance du réseau, tels que le type de trafic, la puissance de transmission, le taux d'interférence et de congestion présentes dans le réseau, la longueur moyenne des voies de communication ainsi que la relation entre ces facteurs et la capacité du réseau, avant de choisir les locations et les caractéristiques des composants du réseau. Bien que la performance du réseau soit aussi importante pour les opérateurs des réseaux que pour les clients, il est à noter que les travaux sur la planification du déploiement de WMNs se concentrent sur l'optimisation du coût de déploiement comme unique objectif à optimiser.

Dans le chapitre 3, nous avons montré que le problème de planification des WMNs est un problème d'optimisation de nature multi-objective. Nous avons présenté un modèle générique de planification de WMNs où les deux objectifs de coût de déploiement et de débit total du réseau sont optimisés simultanément. Trois modèles sont dérivés de ce modèle générique. Ils diffèrent essentiellement par l'approche adoptée pour maximiser la fonction objectif débit. Afin de résoudre les trois modèles bi-objectifs pour des réseaux de taille réelle, un algorithme basé sur la méta-heuristique MOPSO est proposé. Une étude comparative entre ces modèles d'optimisation, basée sur des simulations empiriques, a été réalisée. L'analyse dans cette étude propose au décideur de choisir le modèle où la charge sur les liens du réseau est bien équilibrée pour obtenir un rapport qualité-prix satisfaisant; par contre, si le réseau est susceptible de connaître des augmentations importantes de la demande des clients, alors il serait préférable de choisir le modèle qui suggère de minimiser les interférences en équilibrant le nombre d'utilisations des canaux. Les résultats de simulations sur OMNET ont néanmoins montré que le modèle qui maximise le débit en équilibrant la charge du trafic sur les liens du réseau donne de meilleurs résultats que les deux autres modèles.

Dans le chapitre 4, nous avons introduit la notion de contraintes de sauts « *hop constraints* » afin de trouver les positions stratégiques des passerelles. Nous avons proposé un algorithme de placement de passerelles (*CGPA*) basé sur une approche de groupage de nœuds sans introduire les structures arborescentes. Le nombre de sauts a été adopté comme borne supérieure sur la distance entre la passerelle et tous les nœuds du groupe desservi par celle-ci. Nous avons aussi proposé un modèle de conception de WMN qui a servi de cas d'étude pour l'application du *CGPA*. Le modèle proposé optimise simultanément trois fonctions objectifs : le coût d'installation, les interférences et la congestion au niveau des passerelles. Les résultats de simulation ont montré que l'algorithme de placement des passerelles *CGPA* garantit l'extensibilité du réseau et permet aussi de limiter le délai des communications. Il est à noter qu'en plus des avantages que présente le *CGPA*, nous avons constaté que les solutions générées par le modèle couplé avec le *CGPA* offrent des solutions avec un rapport qualité-prix très satisfaisant.

Finalement, dans le chapitre 5, nous avons développé un algorithme (*BCN*) pour construire une topologie robuste. Cet algorithme est basé sur une approche de décomposition en oreilles (*ear decomposition*). Le but de cet algorithme est de placer les nœuds du réseau lors de la phase de conception de l'infrastructure de sorte qu'un nombre suffisant de nœuds soit installé pour assurer la robustesse et la QdS aux clients sous des contraintes financières. Dans cette partie d'étude, nous avons montré que la robustesse du réseau, son coût d'installation et sa performance sont des facteurs étroitement liés les uns aux autres. À cette fin, nous avons proposé un modèle bi-objectif faisant appel au *BCN* pour construire des réseaux fiables qui tolèrent les pannes simples (une panne à la fois). Dans ce modèle, le coût total d'installation et l'équilibrage de la charge sur les liens du réseau sont les deux objectifs à optimiser simultanément. Les résultats de simulations ont montré que le choix du nombre d'interfaces radio par nœud joue un rôle déterminant dans la conception de réseaux fiables et performants. Par exemple, choisir un grand nombre de radios R (R>4) augmente évidemment la robustesse du réseau car chaque nœud aura un degré égal à R. Néanmoins, cela peut entraîner une détérioration de la performance du réseau et un plus grand déploiement de nœuds. Ce qui amène l'opérateur à payer plus cher pour des infrastructures moins performantes.

Pour résoudre les modèles proposés dans les chapitres 3, 4 et 5, nous avons développé un algorithme évolutionnaire (VMOPSO-R) dérivé de l'algorithme d'optimisation multi-objectif par essaim particulaire (*Multi-objective Particle Swarm Optimization - MOPSO*) et des algorithmes génétiques (*Genetic Algorithms – GAs*). Cet algorithme peut facilement être adapté aux problèmes réels d'optimisation qui se caractérisent par un ensemble de contraintes à satisfaire, par plusieurs objectifs, souvent contradictoires, à optimiser ainsi que par un immense espace de recherche à explorer. Nos solutions ont été approximativement comparées avec celles de problèmes similaires.

Malheureusement, comme la seule contribution qui traite le problème de conception de WMN tel que nous l'avons considéré est basée sur une approche d'optimisation mono-objectif, la comparaison entre les solutions était pénalisée par la non-compatibilité des résultats obtenus (solutions multidimensionnelles par opposition à une solution unique unidimensionnelle). Néanmoins, cette comparaison a permis de vérifier si l'algorithme génère des solutions plus ou moins raisonnables.

6.2 Directions des recherches futures

Bien que les solutions proposées dans cette thèse puissent être utilisées dans des situations précises, beaucoup de travail reste à faire pour rendre nos solutions plus générales et prêtes à être utilisées dans la pratique. Les contributions proposées dans cette thèse supposent que les positions des nœuds du réseau sont réparties sur une grille carrée. Bien que beaucoup de travaux aient montré les avantages de cette répartition par rapport à la performance du réseau, il est à noter que dans la réalité, il est très difficile de trouver de telles locations vu la nature des surfaces géographiques qui sont généralement remplies d'obstacles. Nous suggérons donc d'entreprendre une étude comparative pour déterminer la performance d'un réseau déployé sur une grille et celle du même réseau déployé sur la même grille, mais ayant subi des perturbations afin de tenir compte de la nature de la surface.

Un autre point important à considérer dans toute conception de réseau sans fil est d'offrir aux nœuds du réseau la capacité d'adapter le rang de transmission afin de réduire le nombre de collisions et de minimiser l'impact de l'interférence. Dans les modèles proposés dans cette thèse, tous les routeurs ont le même rayon de transmission, cependant cela n'est qu'une hypothèse pour alléger un peu la complexité des problèmes traités et la quantité élevée des variables de décision. La variation du rayon de transmission peut facilement être incluse dans les modèles définis dans les chapitres 3, 4, et 5 avec des variables de décision additionnelles.

Dans le chapitre 4, nous avons proposé un algorithme pour un placement optimal des passerelles qui est basé sur une approche de groupage des nœuds du réseau. Les résultats empiriques ainsi que les simulations ont montré que l'algorithme place effectivement les passerelles de façon à augmenter la performance du réseau, à minimiser le délai des communications et à respecter le coût total de déploiement. La question qui se pose ici est de savoir si, dans la réalité, les places générées par l'algorithme peuvent réellement être assignées aux passerelles, compte tenu qu'une connexion câblée doit préalablement exister dans chaque location potentielle. Nous croyons que dans les travaux futurs il faut prévoir une liste de positions où les passerelles peuvent réellement être fixées. Cette liste servirait donc de donnée d'entrée à l'algorithme proposé avec, évidemment, quelques modifications.

Dans le chapitre 5, nous nous sommes limités au contexte d'une panne simple. Le cas de la panne simple reste le cas le plus fréquent, mais il serait intéressant d'étudier le cas de pannes multiples qui ne fait que renforcer la tolérance aux pannes en général. Le développement de ce point s'ajoutera à nos futures avenues de recherches.

Finalement, et d'après Wolpert et Macready [WM97], dire qu'une méthode de recherche ou d'optimisation est meilleure qu'une autre n'est *pas fondé*, sauf si on *trouve* une classe de problèmes où la méthode est meilleure qu'une autre. Cela revient à dire que puisque les problèmes évoqués dans cette thèse n'ont pas été traités de la même façon dans la littérature, il est quasiment impossible de dire si l'algorithme VMOPSO fournit des solutions proches de l'optimum. Nous proposons de résoudre les mêmes problèmes par des heuristiques bien connues (ou méta-heuristiques), telles que SPEA2 (*Strenght Pareto Evolutionnary Algorithm 2*) [ZL02] ou NSGAII (*Non-dominated Sorting Genetic Algorithm II*), [DP02] et de comparer leur capacité à résoudre le problème de conception de WMNs avec celle de VMOPSO. Nous réservons ce sujet de recherche pour des études futures.

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