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# MODELS AND ALGORITHMS FOR THE DESIGN OF THIRD-GENERATION MOBILE NETWORKS

YUFEI WU
DÉPARTEMENT DE GÉNIE INFORMATIQUE
ÉCOLE POLYTECHNIQUE DE MONTRÉAL

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Cette thèse intitulée:

MODELS AND ALGORITHMS FOR THE DESIGN OF THIRD-GENERATION MOBILE NETWORKS

Présenté par : WU Yufei

En vue de l'obtention du diplôme de : Philosophiae Doctor

A été dûment acceptée par le jury d'examen constitué de :

M. CONAN Jean, Ph.D., président

M. PIERRE Samuel, Ph.D., membre et directeur de recherche

M. PESANT Gilles, Ph.D., membre

M. MOUFTAH Hussein, Ph.D., membre externe

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# RÉSUMÉ

Le déploiement de nouveaux réseaux mobiles de troisième génération (3G), l'extension des réseaux 3G existants et l'intégration des réseaux mobiles de 3G avec ceux de la deuxième génération (2G) et/ou d'autres réseaux exige l'analyse et l'optimisation de la planification des réseaux utilisant les technologies d'accès WCDMA/CDMA2000/TD-SCDMA. Les réseaux (3G) nécessitent une nouvelle approche de planification et d'optimisation. Une approche intuitive permettant de résoudre les problèmes des réseaux 3G mène souvent à des résultats non conformes à la réalité. Par conséquent, des méthodes efficaces de planification et d'optimisation doivent se baser sur des modèles plus complexes et sophistiqués.

Afin de pouvoir aborder le problème de planification des cellules pour des systèmes d'accès WCDMA, les informations suivantes sont souvent supposées connues: i) l'ensemble des sites candidats où les stations de base (BSs) peuvent être installées, ii) l'ensemble des configurations possibles pour chaque station de base (direction, inclinaison, hauteur), iii) l'estimation de la distribution du trafic par des modèles empiriques de prédiction et iv) la description de la propagation par des modèles approximatifs de canaux radio ou par des techniques de 'ray-tracing'. Afin de pouvoir prendre en compte des contraintes du rapport signal à interférence (RSI), deux modèles de contrôle de puissance sont à considérer: le modèle basé sur la puissance qui suppose que les puissances transmises sont ajustées afin de garantir une puissance reçu cible, et un modèle basé sur le RSI qui suppose que les puissances transmises sont ajustées afin de garantir une valeur RSI cible à tous les liens actifs.

Cette thèse présente aussi des modèles d'optimisation pour la planification des réseaux radio dans un environnement 3G en ascendant et descendant. En effet, ces modèles optimisent les paramètres des stations de base tels que leur localisation, la puissance maximale transmise et la hauteur de l'antenne. Ces paramètres peuvent être individuellement assignés à chaque station de base. Tous ces choix doivent satisfaire un ensemble de contraintes et optimiser un ensemble d'objectifs. Nous avons développé des

techniques d'optimisation heuristiques et stochastiques pour aborder un problème fortement combinatoire. Une analyse expérimentale étendue est présentée pour comparer les effets sur la capacité d'un réseau radio, la couverture, et les besoins d'investissement entre mécanismes de contrôle de puissance basés sur le RIS et ceux basés sur la puissance, entre environnement ascendant et descendant, et entre différentes configurations de coût des éléments réseau. Enfin, nous avons étudié la capacité et la couverture des scénarios multiservices avec des utilisateurs de voix et de données pour différents taux du trafic, différents niveaux $E_b/I_0$ requis, et différents gains de traitement.

Premièrement, nous avons appliqué trois algorithmes heuristiques pour résoudre la planification et l'optimisation de cellules descendantes de troisième génération (3G), à savoir : algorithme de recherche glouton local, algorithme de simulation conditionnelle, et la recherche taboue. La performance de ces trois différentes méthodes heuristiques est comparée sur un problème en utilisant les meilleurs paramètres des expériences précédentes. Les résultats de simulation indiquent que la recherche taboue est la méthode qui convient le mieux aux problèmes de planification et d'optimisation de cellules. Deuxièmement, nous avons introduit trois formulations du problème de planification de cellules descendantes: planification à coût minimal, planification à capacité maximale, et planification à profit maximal. La simulation de ces trois formulations a donné des résultats intéressants. Troisièmement, en utilisant la recherche taboue nous avons comparé les effets sur la capacité du réseau, la couverture, et les besoins d'investissement entre les mécanismes de contrôle de puissance basés sur le *RIS*. La grande différence dans les résultats de simulation est principalement due au fait que les puissances d'émission, dans les mécanismes de contrôle de puissance basés sur le *RIS*, sont choisies de façon à ce que la qualité du signal soit exactement égale à la cible *SIR*. L'interférence est considérablement inférieure à celle du modèle avec un mécanisme de contrôle de puissance basé sur la puissance, et ceci mène aux solutions ayant une excellente couverture avec un plus petit nombre de BSs choisi. Enfin, nous avons examiné les effets de différentes configurations de coût dans le problème de planification.

Cette thèse emploie également la recherche taboue pour résoudre le problème de planification de cellules ascendantes de troisième génération (3G) comme un problème d'optimisation discrète où la localisation de la station de base et la configuration sont les variables de base de décision. Notre objectif est double : d'une part suggérer un algorithme efficace de recherche taboue pour la planification et l'optimisation de cellules ascendantes de troisième génération (3G) et, d'autre part, utiliser l'optimisation pour découvrir les caractéristiques inhérentes de la localisation et la configuration des stations de base ascendantes de troisième génération 3G.

Premièrement, en se servant de la recherche taboue nous comparons les effets sur la capacité du réseau, la couverture, et les besoins d'investissement entre les mécanismes de contrôle de puissance basés sur le *RIS* et ceux basés sur la puissance. Deuxièmement, nous faisons une comparaison équitable entre les deux environnements ascendant et descendant en terme de couverture et de capacité pour un scénario de trafic de voix avec le mécanisme de contrôle de puissance basé sur le *RIS*. Pour les cas de test et du point de vue de couverture et du nombre de stations de base utilisées, la direction ascendante s'avère être la plus rigoureuse. La direction descendante conduit à des améliorations substantielles : un rapport de couverture de trafic plus élevé et un plus petit nombre de BSs utilisés. Enfin, nous examinons la capacité et la couverture pour des scénarios multiservice d'usagers de voix et de données avec différents taux de trafic, différents niveaux $E_b/I_o$ requis, et différents gains de traitement.

# ABSTRACT

Building greenfield third generation (3G) mobile networks, expansion of existing 3G mobile networks, and integration of 3G mobile networks with 2G and/or other networks, requires extensive analysis and optimization related to WCDMA/CDMA 2000/TD-SCDMA network planning. 3G mobile networks require a new planning and optimization approach. An intuitive approach to resolving 3G related problems often leads to results inconsistent with reality, thus the efficient planning and optimization methods must be based on increasingly complex and sophisticated models.

To address the cell planning problem for systems with WCDMA air interface, the following information are usually supposed to be known: i) a set of candidate sites where BSs can be installed, ii) a set of possible configurations of each base station (rotation, tilt, height), iii) the traffic distribution estimated by using empirical prediction models, and iv) the propagation description based on approximate radio channel models or ray tracing techniques. To take into account *SIR* constraints, two power control (PC) models are considered: a power-based PC model which assumes that emission powers are adjusted to guarantee a target received power and a *SIR*-based PC model that assumes that emission powers are adjusted to guarantee a *SIR* target value to all active links.

This thesis presents optimization models for radio network planning in 3G downlink. The models concern optimization of the base station parameters such as base station location, maximum transmit power and antenna height, all of which can be individually assigned to each base station. All these choices must satisfy a set of constraints and optimize a set of objectives. We develop heuristic and stochastic optimization techniques for tackling this highly combinatorial problem. In this downlink work, an extensive experimental analysis is presented to compare the effects on the radio network capacity, coverage, and investment requirements between *SIR*-based power control mechanism and power-based power control mechanism, between uplink and downlink environment, and between different network elements cost configurations.

Firstly, we apply three heuristic algorithms to solve the 3G downlink cell planning and optimization, namely, greedy local search algorithm, simulated annealing algorithm, and tabu search. The three different search heuristics are then compared with each other for their performance on the problem using the best parameters from the previous experiments. The simulation results indicate that tabu search is best-suited for this cell planning problem and optimization problem. Secondly, we introduce three formulations of the downlink cell planning problem: minimal cost planning, maximum capacity planning, and maximum profit planning. Interesting simulation results are obtained for three planning objective formulations. Thirdly, we compare the effects on the network capacity, coverage, and investment requirements between *SIR*-based power control mechanism and power-based power control mechanism by using tabu search. The significant difference in simulation results is mainly due to the fact that emission powers in *SIR*-based power control mechanism are selected in order to have a signal quality exactly equal to the target *SIR*. The interference is thus substantially lower than in a model with a power-based power control mechanism, and this leads to solutions having excellent coverage with a smaller number of BSs selected. Finally, we investigate the effects of different cost configurations in the planning problem.

This thesis also uses tabu search to solve the 3G uplink cell planning problem as a discrete optimization problem, where base station location and configuration are basic decision variables. Our goal is two fold: on the one hand to suggest an efficient tabu search algorithm for 3G uplink cell planning and optimization, on the other hand to discover inherent features of 3G uplink base station location and configuration with the help of optimization. Firstly, we compare the effects on the network capacity, coverage, and investment requirements between *SIR*-based power control mechanism and power-based power control mechanism by using tabu search. Secondly, we make a fair comparison of capacity and coverage between downlink and uplink for voice traffic scenario with *SIR*-based power control mechanism. For the test cases, uplink direction is found to be the most stringent one from the point of view of coverage as well as of the number of BSs used. The downlink direction yields substantial improvements: higher traffic coverage ratio and smaller number of BSs used. Finally, we investigate the capacity and coverage on multi-service scenarios with both voice and data users with different traffic rates, different $E_b/I_o$ requirements, and processing gains.

# CONDENSÉ EN FRANÇAIS

## CHAPITRE 1
## INTRODUCTION

Le déploiement de nouveaux réseaux mobiles de troisième génération (3G), l'expansion des réseaux 3G existants et leur intégration avec les réseaux 2G ainsi qu'avec d'autres types de réseaux, exigent une analyse poussée et une optimisation liée à la planification des réseaux WCDMA. Les réseaux mobiles 3G nécessitent une nouvelle approche de planification et d'optimisation. Une approche intuitive de résolution des problèmes reliés au WCDMA conduit souvent à des résultats non consistants avec la réalité. Ainsi, des méthodes de planification et d'optimisation efficaces doivent se baser sur des modèles sophistiqués et complexes. Cette thèse est consacrée à l'aspect de planification des systèmes de communications mobiles, qui peut être divisé conceptuellement en deux problèmes : la planification et l'optimisation des cellules et l'assignation des cellules.

### 1.1 Les motivations et les défis de recherche

D'un point de vue stratégique, la planification et l'optimisation des réseaux mobiles a évolué et révèle de nouveaux défis. En tant qu'élément des réseaux sans fils de prochaines générations, telles que les réseaux 3G, et à travers les évolutions technologiques et de normalisation, deux changements fondamentaux ont affecté le procédé de planification : 1) l'introduction des services de données et de multimédia dans un seul réseau centré sur la voix, et 2) la convergence des technologies pour accroître la compétition et les opportunités d'affaires. Aujourd'hui, le défi principal de la planification des réseaux est de considérer deux requis : 1) l'optimisation du réseau et l'investissement à long terme de l'opérateur, et 2) l'optimisation du délai d'arrivée au marché pour chaque nouveau produit.

D'un point de vue technologique, des défis généraux confrontant la planification des réseaux mobiles 3G sont basés sur le fait que beaucoup de problèmes sont interconnectés et qu'ils doivent être considérés simultanément : 1) la planification et l'optimisation ne signifient pas uniquement la satisfaction de l'état et les demandes actuelles, mais la solution choisie sera également conforme aux futures besoins dans le sens du chemin acceptable du développement; 2) l'estimation incertaine de la croissance du trafic. Il y a non seulement la question de la quantité totale de la croissance du trafic, mais aussi celle des futures services de distributions et des demandes; 3) En outre, il y a des contraintes réelles confrontant la planification réseau. Si l'opérateur a déjà un réseau, alors pour des raisons techniques et économiques, il doit utiliser une colocation de site. Dans les cas de nouveaux opérateurs, il y a beaucoup de limitations pratiques établies par le procédé d'acquisition; et 4) Tous les systèmes CDMA ont des interconnexions entre la capacité et la couverture et ainsi aussi la qualité. En conséquence, la planification et l'optimisation n'est pas seulement basée sur la propagation mais aussi sur l'interférence dans le réseau.

## 1.2 Les contributions et les originalités

Les principales contributions et originalités de cette thèse sont les suivantes :

- Cette thèse présente un modèle d'optimisation pour la planification du réseau radio dans un environnement descendant. Le modèle s'intéresse à l'optimisation des paramètres de la station de base tel que la localisation, la puissance maximale de transmission et la hauteur de l'antenne, qui peuvent être assignées individuellement à chaque station de base. Ce problème est NP-difficile. Par conséquent, on développe des heuristiques et des techniques d'optimisation stochastiques pour s'attaquer à ce problème combinatoire et complexe.
- Cette thèse propose également un modèle d'optimisation discret conçu pour supporter la décision, au cours d'un processus de planification de localiser et configurer les nouvelles stations de base dans un environnement 3G ascendant. Ce

modèle considère le signal/Interférence comme une mesure de qualité et capture sous différents niveaux de détails, les requis de la qualité du signal et les mécanismes de contrôle de puissance spécifique à l'interface air W-CDMA. On applique la recherche taboue pour résoudre le problème efficacement.

## CHAPITRE 2
## OPTIMISATION ET PLANIFICATION DES RESEAUX MOBILES

Ce chapitre fournit des données techniques pour l'optimisation et la planification des réseaux mobiles dans les environnements 3G. Nous présentons en détails les principales caractéristiques dans les réseaux radio 3G, et récapitulons également les principaux travaux qui ont préparé le terrain pour l'affectation, l'optimisation et la planification des cellules. Par la suite, nous passons en revue les approches et les méthodes d'optimisation employées dans cette thèse.

## CHAPITRE 3
## HIÉRARCHIE DE PLANIFICATION OPTIMALE DES LIAISONS DESCENDANTES DES CELLULES D'UN RÉSEAU MOBILE 3G

Nous formulons le problème de planification des liaisons descendantes des cellules dans les réseaux 3G comme un problème d'optimisation discret, où la puissance émise, la hauteur des antennes et l'emplacement des stations de base sont des variables décisionnelles de base. Un scénario de configuration de la liaison descendante intervient lorsque la station de base n'arrive plus à émettre de signal. Dans lequel cas, il est impossible d'accueillir de nouveaux usagers dans cette région sans modifier la configuration de cette station de base. Le volume du trafic associé à un scénario de configuration de la liaison descendante est généralement asymétrique avec une plus grande partie du trafic total sur la liaison descendante.

## 3.1 Formulation du problème

L'ensemble $S$ des sites disponibles d'emplacement des cellules, l'ensemble $I$ des nœuds de demande de trafic avec capacité requise $\mu$ ainsi que l'ensemble $L$ des configurations, sont tous considérés comme des paramètres d'entrée fixes. Nous présenterons trois formulations du problème de planification de cellules. Dans chacun des cas, nous utiliserons les variables suivantes :

- Les vecteurs multidimensionnels $\boldsymbol{y}$ et $\boldsymbol{w}$ pour représenter respectivement le nombre de stations de base choisies et leur configuration,
- La matrice $\mathbf{x}$ des capacités à affecter ,
- Le vecteur $\boldsymbol{p}$ des puissances d'affectation (représentant la participation de l'émetteur mobile).

À partir des variables de base ci-dessus, il sera possible de déduire la plupart des autres paramètres du sous-système radio.

### 3.1.1 Planification du coût minimal

*Optimisation du coût (COST)*: Lors du processus d'optimisation du coût, nous ne tenons pas compte de la capacité. L'objectif est de trouver une fonction qui minimise le coût total en espérant ainsi trouver une configuration de réseau faisable et moins coûteuse lors du processus d'optimisation.

### 3.1.2 Planification de la capacité maximale

*Optimisation de la capacité (CO)*: Dans cette partie d'optimisation, le paramètre de coût est complètement négligé. Le but est de trouver une fonction objective qui maximise les demandes de trafic satisfaites dans la zone en question (ou alors de réduire au minimum le nombre de nœuds prenant en charge le trafic et dont certaines de leurs contraintes sont non respectées (nœuds en panne)). D'une manière plus simple, nous appellerons ce scénario, *scénario d'optimisation pure de capacité.*

### 3.1.3 Planification du profit maximum

*Optimisation combinée du coût et de la capacité (COM)*: ici, le coût fait partie de la fonction objective. Le facteur de poids $\theta$ nous permet d'accorder la priorité soit à la minimisation du coût ou alors à la maximisation de la capacité. Pour trouver une valeur appropriée de $\theta$, un certain nombre de valeurs ont été utilisées lors de divers simulations avec la recherche taboue et des comparaisons ont été faites entre les différents résultats pour choisir la valeur appropriée.

## 3.2 Méthodes d'optimisation

Nous appliquerons trois heuristiques pour résoudre le problème de planification et d'optimisation de la liaison descendante des cellules dans les réseaux 3G soit : l'algorithme vorace, le recuit simulé et la recherche taboue. En utilisant les meilleurs paramètres trouvées lors des simulations précédentes, nous comparerons les trois heuristiques entre elles afin de voir laquelle est la plus efficace pour la résolution de notre problème.

Afin de pouvoir appliquer les heuristiques à notre problème de planification, nous avons définit :

- Une solution initiale faisable,
- Une région de l'espace des solutions contenant des solutions faisables,
- Les coûts des solutions ou des fonctions objectives.

Ceci permet de formuler les structures de données de l'algorithme faisant partie de l'heuristique de recherche locale. Nous avons également développé :

- Un modèle de représentation des solutions faisables,
- Des techniques de recherche pour les voisinages des solutions faisables,
- Des méthodes d'évaluation des gains sur le coût.

## 3.3 Simulations

Dans cette section, nous avons effectué des simulations de nos modèles d'optimisation et de planification des liaisons descendantes des cellules dans les réseaux 3G. Les évaluations de performance sont basées sur des spécifications des systèmes 3G avec la technologie WCDMA. Les stratégies d'optimisation utilisées dans ces expériences sont également applicables à d'autres systèmes (par exemple, TD-SCDMA, CDMA 2000).

### 3.3.1 contrôle de puissance : *SIR* versus puissance seulement

Nous pouvons dire que le contrôle de puissance basé sur la puissance du signal seulement n'est pas très efficace pour les liaisons descendantes par rapport au mécanisme de contrôle basé sur le rapport signal sur bruit (*SIR*); car il exige d'avoir beaucoup de stations de base (BS) avec une zone de couverture limitée contrairement à ceux que l'on choisirait avec un modèle de contrôle basé sur le *SIR*. L'expérience a prouvé que le modèle de contrôle basé sur le *SIR* peut permettre à chacun des BS de servir plus de demande de trafic. Cette différence significative est principalement due au fait que les puissances d'émission dans le modèle de contrôle basé sur le SIR sont choisies de manière à avoir une qualité de signal exactement égale à $SIR_{tar}$. L'interférence est ainsi sensiblement inférieure que dans un modèle avec un mécanisme de contrôle de puissance basé sur la puissance du signal seulement. Ce qui permet d'avoir souvent des solutions ayant une excellente couverture avec un nombre relativement faible de BS choisis.

### 3.3.2 Planification avec objectifs alternatifs

Dans le modèle de maximisation de la capacité, le coût du réseau n'est pas inclus dans le processus d'optimisation. Ce qui peut avoir comme conséquence des configurations de réseau avec un coût relativement élevé. Dans le modèle de minimisation du coût seulement, la capacité n'est pas incluse dans le processus d'optimisation. Ce qui peut avoir comme conséquence des configurations de réseau avec des capacités très basses et inacceptables. Notre but dans cette section est d'illustrer la différence entre la capacité et le coût en se servant de quelques exemples quantitatifs.

Pour ce faire, nous avons appliqué la recherche taboue pour résoudre le problème général de la planification, mais en utilisant alternativement les fonctions objectives, selon les trois scénarios mentionnés ci-dessus.

En comparant les différentes valeurs obtenues, nous remarquons que la puissance totale d'utilisation dans les trois cas est très similaire. Dans le processus d'optimisation de la capacité seulement, les résultats obtenus favorisent des réseaux avec un plus grand nombre de BSs. Contrairement aux réseaux résultants du processus d'optimisation du coût seulement, où l'on utilise moins de station de base (BS) avec une structure d'antenne plus élevée. En comparant les meilleures solutions réalisables de l'optimisation de la capacité (CO) à celles de l'optimisation par combinaison du coût et de la capacité (COM), nous constatons que, les puissances totales utilisées (c-à-d, 56.81 dBm pour le CO et 55.05 dBm pour le COM) et les hauteurs moyennes d'antennes obtenues (17.05 m pour le CO et 17.50 m pour le COM) dans les deux cas, sont approximativement les mêmes. Par contre, on constate que le nombre de BSs utilisés diminue de 12 (dans le cas CO) à 8 (dans le cas COM). Ce résultat indique que le réseau est "sur-approvisionné" dans le modèle CO, c'est-à-dire que l'optimisation n'essaie pas d'éliminer ni les BSs inutiles, ni l'excédant de puissance.

### 3.3.3 Planification du réseau 3G basée sur le coût

Dans cette partie, nous considérons deux types de coûts de configuration et nous utilisons la recherche taboue pour effectuer l'optimisation. Les configurations de réseau obtenues sont évaluées en fonction de la fréquence des antennes au niveau des BS ainsi que de l'ensemble $P$ des valeurs de puissance. Dans la première configuration, le coût des antennes en terme de puissance augmente considérablement pour des valeurs élevées et le coût des sites demeure relativement bas. Tel que prévu, le patron d'affectation des antennes des BSs résultant est composé d'un grand nombre d'antennes, en moyenne 15.83, avec une faible puissance.

Dans la deuxième configuration, nous répétons l'optimisation avec un coût de configuration modifié où la puissance des antennes des BSs est relativement moins coûteuse. L'optimisation produit une solution différente avec ces données d'entrée inversées. Le nombre moyen d'antennes est de 10.15. En raison du coût de la configuration et de sa relation avec la zone de couverture par BS, il est préférable de considérer seulement les antennes de taille moyenne. L'utilisation de grosses antennes exige d'avoir d'autres petites antennes pouvant couvrir les quelques zones qui resteront non couvertes par les grosses antennes. En raison du coût élevé des antennes à grosse puissance, leur nombre devrait être limité dans le réseau final.

# CHAPITRE 4

# PLANIFICATION DES CELLULES D'UN RÉSEAU MOBILE 3G ET OPTIMISATION DE LEUR LIAISON MONTANTE

Ici, nous formulons le problème de planification de la liaison montante des cellules des réseaux 3G comme un problème d'optimisation discret où la configuration et l'emplacement des stations de base sont considérés comme des variables décisionnelles de base. Un scénario de configuration de la liaison montante intervient lorsque la charge maximale de la liaison montante est atteinte avant que la station de base ne soit plus en mesure d'émettre un signal. Dans lequel cas, il est impossible d'accueillir de nouveaux usagers, dans la région couverte par cette station de base, sans dégrader la performance du réseau. Ce phénomène est plus susceptible de se produire dans des endroits où les capacités requises sont relativement basses et que le réseau a été planifié en considérant un volume de trafic bas sur la liaison montante des cellules; ce afin de maximiser la portée des cellules et ainsi réduire la nécessité d'ajouter d'autres sites. Le volume de trafic associé à un scénario de configuration de la liaison montante est généralement asymétrique.

## 4.1 Formulation du problème

Notre objectif est de formuler le problème de planification de la liaison montante au niveau des cellules comme un problème d'optimisation. L'ensemble $S$ des sites disponibles d'emplacement des cellules, l'ensemble $I$ des nœuds de demande de trafic avec les capacités requises, l'ensemble $L$ des types de configurations possibles sont tous considérés comme des paramètres d'entrée. À noter qu'ici, nous nous intéressons seulement qu'au scénario maximisant le profit. Les variables suivantes seront utilisées :

- Les vecteurs multidimensionnels $\boldsymbol{y}$ et $\boldsymbol{w}$ pour représenter respectivement le nombre de stations de base choisies et leur configuration,
- La matrice $\mathbf{x}$ des capacités à affecter,
- Le vecteur $\boldsymbol{p}$ des puissances d'affectation (représentant la participation de l'émetteur mobile).

Ainsi, à partir de ces variables de base, il sera possible de déduire la plupart des autres paramètres du sous-système radio.

La formulation du problème permet entre autres d'expliciter la différence qu'il y a entre le revenu potentiel de chaque site d'emplacement et ses coûts d'installation et de configuration. Cette différence est sujette à des contraintes de QoS en termes de rapport suffisant du signal sur le bruit (*SIR*). L'objectif du modèle est de maximiser le bénéfice total annuel (qui est égal au revenu total moins les coûts) généré par l'opérateur du réseau mobile.

## 4.2 Simulations

Des expériences ont été réalisées pour la planification et l'optimisation des liaisons montantes des cellules d'un réseau 3G. Les évaluations de performance ont été basées sur des spécifications des systèmes WCDMA des réseaux 3G. Cependant, les stratégies d'optimisation utilisées dans ces expériences sont également applicables à d'autres systèmes (par exemple, TD-SCDMA, CDMA 2000, WLAN).

### 4.2.1 Contrôle de puissance : *SIR* versus puissance

En comparant le nombre de BSs choisies avec le modèle de contrôle de puissance basé sur la puissance du signal seulement à ceux obtenues avec le modèle de contrôle basé sur le rapport signal sur bruit (*SIR*), nous remarquons que le dernier modèle permet d'avoir une économie d'environ 17% sur l'investissement effectué sur les stations de base (BS) et une amélioration de 9% sur la quantité du trafic couvert. Les résultats montrent aussi que sur les liaisons montantes, le mécanisme de contrôle de puissance basé sur le *SIR* est beaucoup plus efficace que celui basé sur la puissance du signal seulement.

En comparant les valeurs du rapport signal sur bruit au niveau de chaque station de base choisie et les puissances reçues pour chaque connexion, on peut constater que tous les rapports *SIR* atteints au niveau des BSs dans le modèle de contrôle de puissance basé sur le SIR sont naturellement de 5 dB, car 5 dB est la valeur seuil dans le processus d'optimisation servant à résoudre des programmes linéaires comme décrit dans cette thèse. Également, on constate que seules quelques stations de base ont un rapport signal sur bruit près du seuil requis de 5 dB et pour beaucoup de BS la qualité de service est de loin au-dessus du niveau exigé. Ainsi, les puissances émises sont plus grandes que celles requises dans le modèle de contrôle basé sur la puissance, par conséquent, les niveaux d'interférence sont plus élevés et les ressources radio, rares, ne sont pas utilisées aussi efficacement qu'elles pourraient l'être. La distribution du nombre de connexions actives affectées à chaque BS permet de fournir des informations intéressantes sur l'inefficacité du mécanisme de contrôle de puissance basé sur la puissance du signal seulement.

### 4.2.2 Comparaison entre les liaisons montantes et descentes pour le scénario de trafic de voix

Pour effectuer une comparaison équitable sur la capacité et la couverture entre la liaison montante et celle descendante, nous avons appliqué la recherche taboue à tous les cas tests pour la liaison montante et celle descendante avec le même nombre d'itérations lors de l'optimisation. Les résultats globaux montrent que, ceux obtenus dans les cas de contrôle de puissance basé sur le SIR avec un trafic équilibré (par exemple : appels de voix) sur la liaison montante, sont les plus rigoureux non seulement du point de vue de la couverture mais aussi du nombre de BSs utilisées. À notez que le modèle de la liaison descendante apporte lui aussi des améliorations substantielles : un rapport élevé entre la couverture et le trafic et un nombre faible de BSs utilisées.

### 4.2.3 Impacte des scénarios de service multiple 3G sur la capacité et la couverture

Une des démarcations importantes des réseaux 3G par rapport aux réseaux 2G est la capacité qu'ont les réseaux 3G à fournir des services diversifiés d'échanges de données à des débits différents en plus du trafic de voix déjà offert. Notre étude porte : sur la capacité et la couverture en se basant sur des scénarios de services multiples avec des usagers de voix et de données à des débits différents, sur les différentes conditions du rapport Eb/Io et enfin sur le traitement des gains. Des résultats sur les moyennes des rapports de couverture, le nombre d'usagers servis, le nombre de BSs requis ainsi que le nombre total des cellules ont été recueillis.

# CHAPITRE 5
# CONCLUSION

Plusieurs problèmes ouverts explorent d'avantage de recherches. Selon notre tentative d'utilisation de l'algorithme génétique pour résoudre le problème de planification et d'optimisation, nous constatons que l'algorithme génétique standard donne des performances qui ne sont pas plus mauvaises que celles de la recherche taboue ou encore le recuit simulé. Le seul problème est le temps de calcul. Nous croyons que l'algorithme génétique standard peut être sensiblement amélioré et rendu plus efficace. Le parallélisme de l'algorithme génétique peut aboutir à un grand perfectionnement. Puisque les fonctions objectives sont intensivement coûteuses en temps de calcul pour les problèmes de planification et d'optimisation, ce temps de calcul serait sensiblement réduit si les évaluations individuelles se font en parallèle.

Notre approche de planification et d'optimisation des cellules 3G considère le cas où la configuration du nœud en demande de trafic est fixée, c-à-d qu'elle ne change pas dans le temps. D'autre part, on peut prévoir des fluctuations dynamiques dans le temps et l'espace des demandes de trafic multiservices dans les réseaux mobiles 3G. Un réseau mobile qui s'adapte dynamiquement aux conditions variables sera d'un grand intérêt. Plusieurs améliorations sont possibles, ce qui exige d'avantage d'études de faisabilité et d'analyses de performance. Une possibilité est d'introduire l'adaptabilité en reconfigurant périodiquement les configurations des cellules du réseau selon les distributions statistiques des prévisions des demandes de trafic. Ceci requiert des méthodes d'optimisation très rapides.

Jusqu'ici, les modèles de planification et d'optimisation des cellules que nous avons proposés concernent principalement les problèmes de conception des nouveaux réseaux d'accès radio. Qu'arrive-t-il si la demande du trafic augmente? Que devrions-nous faire si les cellules existantes ne peuvent pas satisfaire les demandes croissantes du trafic? Ceci est ainsi appelé le problème de la planification de croissance. Le problème de la planification de croissance doit être étudié dans des travaux futurs. Comme les réseaux évoluent, on ajoute un grand nombre de stations de base avec des contrôleurs pour supporter la croissance du trafic et de la demande. Comment déployer cet équipement et comment optimiser certains critères est un problème complexe, ce qui réclame des méthodologies vigoureuses et utiles. La clé ici est de modéliser la demande et le comportement des usagers mobiles, qui déterminent la performance du réseau quand le trafic augmente et le réseau évolue.

Bien que dans cette thèse nous avons étudié plusieurs aspects de la planification et de l'optimisation des cellules, beaucoup reste à faire dans le domaine. Dans le but de la recherche dans plusieurs algorithmes, une suite de problèmes de tests comparatifs doit être construite en considérant différents scénarios de conception. Des développements ultérieurs peuvent être faits pour la planification et l'optimisation des cellules en prenant en compte plusieurs autres paramètres, tels que la pente haute et basse, le type et l'azimut de l'antenne, en plus de sa position, de sa hauteur et de sa puissance de transmission. Avec l'évolution des systèmes de communications mobiles, la méthodologie de modélisation et les algorithmes présentés dans cette thèse peuvent être appliqués aux réseaux sans fils WLAN et 4G.

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# ABBREVIATIONS AND ACRONYMS

| | |
|---|---|
| 2G | second generation mobile system |
| 3G | third generation mobile system |
| 4G | fourth generation mobile system |
| BS | base station |
| BSC | base station control |
| CAC | call admission control |
| CDMA | code division multiple access |
| CO | capacity optimization |
| COM | combined cost and capacity optimization |
| COST | cost optimization |
| ERP | effective radiated power |
| FDD | frequency domain duplexing |
| FDMA | frequency division multiple access |
| GA | genetic algorithm |
| GPRS | general packet radio service |
| GSM | global system for mobile |
| GTD | geometrical theory of diffraction |
| IEEE | Institute of Electrical and Electronics Engineers |
| IP | internet protocol |
| IS-95 | digital cellular standard IS-95 |
| IS-136 | digital cellular standard IS-136 |
| LNA | low-noise amplifier |
| LOS | line-of-sight |
| LP | linear programming |
| MIP | mixed integer programming |
| MSC | mobile switching center |

| | |
|---|---|
| NLOS | non-line-of-sight |
| NP | nondeterministic polynomial |
| OTD | orthogonal transmit diversity |
| PCS | personal communication system |
| PDC | personal digital communication |
| QoS | quality of service |
| RAN | radio access network |
| RF | radio frequency |
| RNC | radio network controller |
| Rx | receiver |
| RW | random walk |
| SA | simulated annealing algorithm |
| SGSN | service GPRS support node |
| SIR | signal-to-interference ratio |
| STS | space time spreading |
| TDD | time domain duplexing |
| TDMA | time division multiple access |
| TD-SCDMA | time division - synchronous code division multiple access |
| TP | test point |
| TS | tabu search algorithm |
| Tx | transmitter |
| UMTS | universal mobile telecommunications system |
| UTRAN | UMTS terrestrial radio access network |
| WCDMA | wideband code division multiple access |
| WLAN | wireless local area network |

# CHAPTER 1
# INTRODUCTION

Building greenfield third generation (3G) mobile networks, expansion of existing 3G mobile networks, and integration of 3G mobile networks with 2G and/or other networks, requires extensive analysis and optimization related to WCDMA network planning. 3G mobile networks require a new planning and optimization approach. An intuitive approach to resolving WCDMA related problems often leads to results inconsistent with reality, thus the efficient planning and optimization methods must be based on increasingly complex and sophisticated models. This thesis is devoted to the mobile access network planning aspect of 3G mobile communication systems, which can be conceptually divided into two issues: cell planning and optimization and cell assignment. In this introductory chapter, the following sections highlight the research challenges and motivations in this research field; the research scope and objectives are also introduced.

## 1.1 Basic concepts and definitions

Analog cellular networks are commonly referred to as first generation systems. The digital systems currently in use, such as GSM, PDC, IS-95 and IS-136 [46], are second generation systems (2G). These systems have enabled voice communications to go wireless in many of the leading markets, and customers are increasingly finding value also in other services such as text messaging and access to data networks, which is starting to grow rapidly.

Third generation mobile networks (3G), such as UMTS [30,41,55,97], CDMA2000 [127], and TD_SCDMA [75] will have to provide a wide variety of sophisticated applications, over the widest possible service area. From the viewpoint of the users, the success of these systems will depend on the quality of service (QoS) that they will provide, and especially, on whether it will be comparable to that provided by fixed networks. From the service providers' perspective, the aim will be to provide QoS in the most cost efficient manner. This, together with the continuing evolution of the 2G systems, will create new business opportunities not only for users, manufacturers and operators, but also for the providers of content and applications using these networks. Table 1.1 and Table 1.2 show the comparisons between generations of wireless networks.

**Table 1.1 Comparison of wireless cellular generations**

| Generation | 1G | 2G | 3G |
|---|---|---|---|
| Typical e.g. | NMT, AMPS | GSM, IS-95 | UMTS, IMT2000 |
| Design driver | Voice | Voice/Data | Data/Voice |
| Mod&MA | Analogue, FM | Digital, Various | Digital, Various |
| Architecture | Cellular, Hierarchical | Cellular, Hierarchical | Cellular, Hierarchical (Point cellular distrib.) |
| Voice capabilities | Moderate | Good | Wire-line quality |
| Multimedia capabilities | No | Moderate (best effort) | Good (Guaranteed QoS) |
| Data capabilities | CO with 2.4 kb/s | CO with 9.6 kb/s & evolution in CO up to 115.2 kb/s and PO up to 171.2 kb/s | PO. Outdoor & vehicle envir.: 144 kb/s. Outdoor & urban envir.: 384 kb/s. Indoor & dense urban envir.: 2 Mb/s. |

**Table 1.2 Features of 2G and 3G systems**

| System aspects | Existing 2G mobile systems | New 3G IMT-2000 systems |
|---|---|---|
| Use of digital technology | Already used for modulation, speech and channel coding as well as implementation and control of data channels | Increased use of digital technologies |
| Commonality between different operating environments | Each systems is primarily optimised for its specific operating environment | Optimisation of radio interfaces for multiple operating environments such as vehicular, pedestrian, intro-office, fixed wireless access and satellite, via a single flexible or scalable radio interface. |
| Frequency bands | Operate in frequency bands ranging from 800 MHz to 1.9 GHz, depending on the country | Use a common global frequency band |
| Data services | Limited to data rates below 115 kb/s (WAP-GRPS-SMS) | Transmission speeds up to 2 Mb/s |
| Roaming | Generally limited to specific regions, Handsets not compatible between different systems | Global frequency coordination and ITU standards will provide true global roaming and equipment compatibility |
| Technology | Spectrum efficiency, cost and flexibility limited by technology in use at time of system design | Spectrum efficiency, flexibility and overall costs all significantly improved. |
| Radio interfaces | TDMA, CDMA | W-CDMA TD-CDMA |
| Data speed | 9.6 kb/s with evolution up to 171.2 kb/s (2.5 G) | 144 kb/s – 2 Mb/s |

An important objective of the planning of next generation mobile networks is introducing them by minimally impacting the existing fixed communication infrastructures. In this respect, systems like UMTS have been conceived as consisting of the following three segments [18,56],1) the core network segment that provides the switching and transmission functions required; 2) the intelligent network segment that comprises the logic that enables the provision of services to mobile users; 3) the radio access network segment (RAN, UMTS Terrestrial RAN = UTRAN) that enables interworking between the mobile unit and the fixed network. In this thesis, we focus on the design and optimization of the RAN segment. Our reference network is UMTS. However, the models and algorithms proposed hereafter may be equally applicable to other 3G networks. Figure 1.1 shows the elements in a UTRAN.

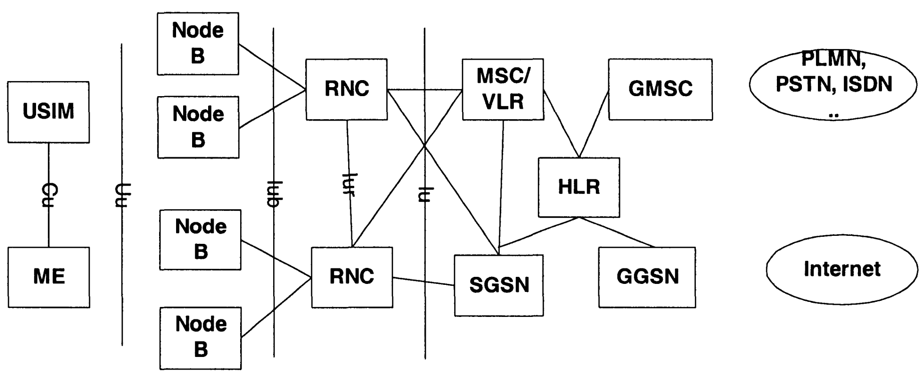



**Figure 1.1 UMTS network architecture**

UTRAN is built around two new nodes and three new interfaces (see Figure 1.1). The node B is effectively a UMTS "base station", while a Radio Network Controller (RNC) is comparable with a GSM Base Station Controller (BSC). Each RNC is connected to the Core Network (both packet and circuit domains) by the *Iu* interface; RNCs are connected together with the *Iur* interface. Each node B is connected to an RNC by the *Iub* interface. There are some fundamental limits on the numbers of cells and RNCs that can be supported, due to the way the cells and RNCs are identified. The node B converts the data flow between the *Iub* and *Uu* interfaces. It also participates in radio resource management. The RNC owns and controls the radio resources in its domain (the node Bs connected to it). RNC is the service access point for all services UTRAN provides for the core network.

## 1.2 Motivations and research challenges

From a strategic point of view, mobile network planning and optimization, traditionally driven by technology, has evolved and faces new challenges. In times of unchanging products and technology, mobile network planning and optimization was highly focused on radio coverage, frequency planning [83] and QoS. The inputs for the planning processes were demand and traffic forecasts, cost and current network standards and features – a mix of domestic and international standards. By still maintaining high (voice) QoS, the output of the process was a minimum cost network. As part of the next generation wireless networks, such as 3G, through technological and regulatory changes, two fundamental changes have affected the planning process [16,53,56]: 1) introduction of data and multimedia services into a single, voice-centric network, and 2) convergence of technologies to increase competition and business opportunities. Today, the main challenge to mobile network planning is to consider two "discordant" requirements [69,70]: 1) optimization of the network and a carrier's long-term investment, and 2) optimization of the time to market for each new product. Consequently, this responsibility has changed the objective for the network to be planned from that of "the minimum cost network" to "the network that maximizes the company's value". This requires the planning and optimization process to be closely linked to the company's strategy.

From a technological point of view, general challenges to face in 3G mobile network planning are based on the fact that a lot of issues are interconnected and should be considered simultaneously: 1) planning and optimization mean not only to meet current status and demands, but the selected solution shall also comply with the future requirements in the sense of acceptable development path. Furthermore, the network control mechanisms must support the operators' processes and indicate not only areas where coverage/capacity is a bottleneck, but identify areas where new services could be introduced within the existing infrastructure; 2) uncertain estimation of the traffic growth.

There is not only the question about the total amount of traffic growth, but also the question about the future service distribution and demands. Trend analysis can be utilized with the existing services, but introduction of a new service can result in a completely new service demand mix; 3) furthermore, there are real constraints network planning has to face. If the operator has already a network, then either due to economical or technical reasons site co-location will be used. In the case of greenfield operators, there are more and more practical limitations set by site acquisition process; and 4) all CDMA systems have an interconnection between capacity and coverage, and thus also quality. Consequently, the network planning and optimization itself is not only based on propagation estimation but also on the interference situation in the network. Ideally, site selection consideration is based on the network analysis with planned load and traffic/service portfolio.

### 1.3 Research objectives

In this thesis, our focus is to provide models and planning methods for the design of 3G mobile access networks, which consist of a radio network and a transmission network in order to satisfy traffic demands over a predefined area with a sufficient signal quality, with the minimized network hardware cost or the maximized revenue income. Due to the high complexity of the problem, we divide the planning and optimization of a mobile access network into two subproblems – the radio network part (also called cell planning and optimization) consisting of the cells sites and the mobiles, and the transmission network part (not considered in this thesis) connecting the cell sites to the switching centers or RNCs. The presented models and methods address both the technical requirements and the economic factors. Specifically, our research objectives are listed as follows:

- propose optimization models for radio cell planning and optimization in 3G downlink environment;
- develop heuristic and stochastic optimization techniques for 3G downlink cell planning and optimization problems;

- propose discrete optimization models aimed at supporting the decision in the process of cell planning and optimization in the 3G uplink environment;
- develop heuristic and stochastic optimization techniques for 3G downlink cell planning and optimization problems.

## 1.4 Planning processes and optimization methodologies

Knowing the characteristics of a mobile network and the general environment constraints in which it operates, gives us a good idea of what the network planning process and its objectives ought to be. According to [56,69,70], network planning is the continual iterative process of 1) monitoring the current network characteristics, 2) understanding environmental constraints/considerations, 3) forecasting future needs and technology, 4) evaluating technical opportunity, 5) creating most appropriate, consistent, and coordinated plans to a long, medium, and short term basis, and 6) modifying plans based on results of actual implementation, in order to provide ongoing cost-effective and timely telecommunication services to the users. This thesis considers 3G mobile network planning, including dimensioning, detailed capacity and coverage planning, and network optimization. The 3G radio network planning process is shown in Figure 1.2. In the dimensioning phase, an approximate number of BS sites, BSs and their configurations and other network elements is estimated, based on the operator's requirements for coverage, capacity and QoS. Capacity and coverage are closely related in 3G networks, and therefore both must be considered simultaneously in the dimensioning of such networks.

Some fundamental theoretical differences between 2G systems (assumed TDMA based) and 3G CDMA systems imply a different network planning approach [40]. The detailed planning is itself an optimization process. In the case of 2G systems, the detailed planning concentrates strongly on the coverage optimization. The 3G system planning is more interference and capacity analysis than just coverage area estimation. During the radio network planning, BS site configurations need to be optimized, antenna selections and antenna directions and even site locations need to be tuned as much as possible in order to meet the QoS, the capacity and service requirements with minimum cost.

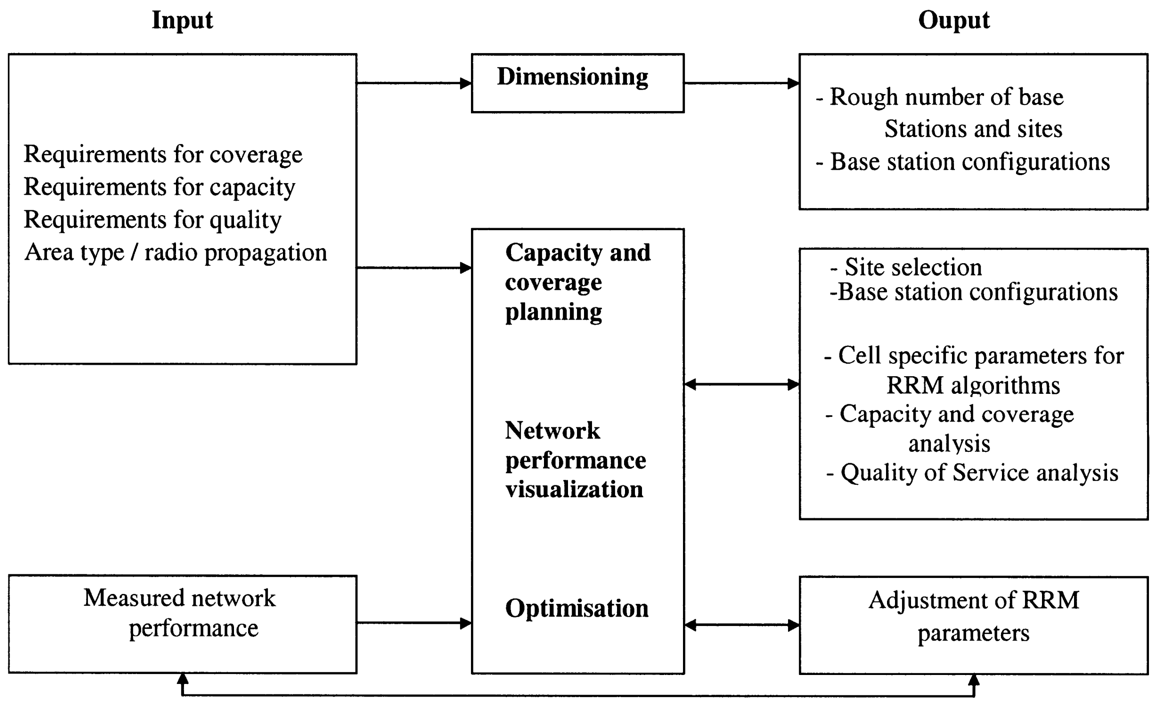



**Figure 1.2 WCDMA radio network planning process**

The traditional approach in mobile network planning, which is shown in Figure 1.3, is an iterative process which starts by setting coverage objectives. Then, by using geographic and demographic data as well as propagation analysis, an initial network planning is obtained. The initial plan is optimized by iterative change of network variables as shown in Figure 1.3. However, the number of tunable parameters in a 3G network is significantly higher than that of a 2G TDMA network. Therefore, classical iterative approach may result in an inefficient network planning and optimization. In the approach proposed by [14], the authors intend to take into account all the key parameters of a 3G network, and attempt to jointly optimize the network settings. This approach is shown in Figure 1.4.

At about the same time as the advent of the first generation wireless systems, some robust and efficient search techniques for optimization were invented – genetic algorithms, simulated annealing, and tabu search. These metaheuristic search techniques have proved to be very effective in providing good solutions to NP-hard combinatorial optimization problems in polynomial time [2,43,85]. The application of these techniques to a large number of fields such as industrial production, management, financial services, game theory, telecommunications, graph theory, biological modeling, and VLSI has been increasing steadily.

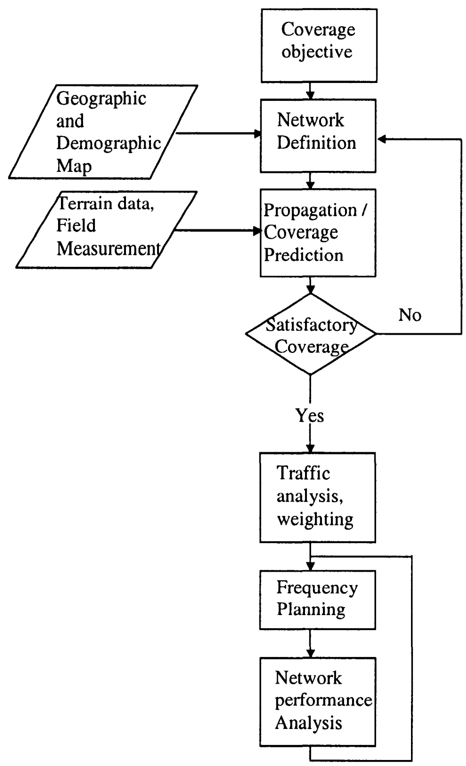



**Figure 1.3 Classic planning techniques**

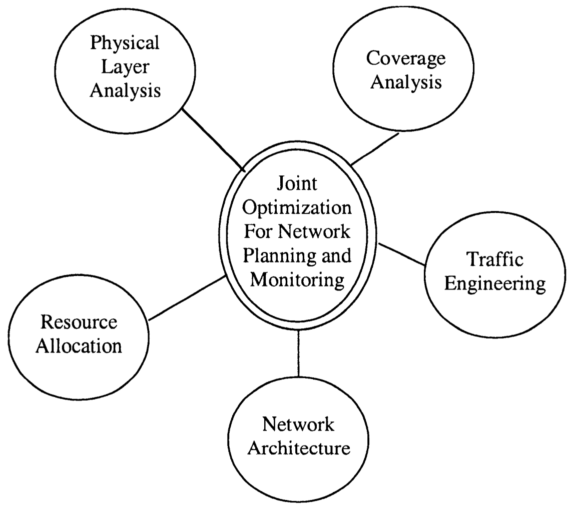



**Figure 1.4 Joint optimization approach**

The application of these search algorithms to the field of mobile communication is still in its early stage. In this thesis, these algorithms will be used in the planning and optimization of 3G mobile access networks. Furthermore, these metaheuristics could be used together with greedy algorithms and other methods to generate more efficient hybrid search algorithms.

## 1.5 Contributions and originalities

We typically formulate the planning problems as optimization ones. Major contributions and originalities of the thesis are the following:

- This thesis presents an optimization model for radio network planning in 3G downlink environment. The model concerns optimization of the base station parameters such as base station location, maximum transmit power and antenna height, all of which can be individually assigned to each base station. All these choices must satisfy a set of constraints and optimize a set of objectives. This problem is NP-hard and consequently cannot be practically solved by exact methods for real size networks. Thus, we develop heuristic and stochastic optimization techniques for tackling this complex and highly combinatorial problem. To evaluate the effectiveness of the methods, an extensive experimental analysis is presented. Compared to all related previous works, the main novel contributions of our model are five-fold: firstly, instead of minimizing the cost, we consider the three different planning objectives and find the net revenue income as the objective can better tradeoff capacity and cost, which reflects the requirements of most mobile operators. Secondly, the decision variables and traffic capacity are embedded in the objective function and are optimized in a single integrated step. This can result in the tradeoff between the cost reduction and the capacity improvement, compared with approaches where they are considered separately. Thirdly, the model represents three-tier hierarchical cell structure that contains macrocell, microcell and picocell, because at each selected base station location, the network can use different equipment types to generate coverage areas corresponding to different cell sizes. Fourthly, the QoS constraints are set as hard constraints, while other works treat them as soft constraints. More importantly, the QoS constraints accurately represent the real radio environment by taking into account the effect due to each active connection. Finally, because the optimal 3G radio network configuration is mainly a function of the geographical traffic demand features of the target service area, we incorporate different traffic classes, such as voice and data, into our model and consider the impacts of different types of traffic on choosing an optimal radio network configuration.

- This thesis also proposes discrete optimization model aimed at supporting the decision in the process of planning where to locate new base stations in the 3G uplink environment. This model considers the signal-to-interference as quality measure and capture at different levels of details the signal quality requirements and the specific power control mechanism of the WCDMA air interface. This problem is NP-hard, we apply the tabu search to solve the problem efficiently. Compared to all related previous works, the main novel contributions of our model are as follows: in addition to the contributions mentioned in the downlink model, we make a detailed comparison between downlink and uplink for voice traffic scenario with *SIR*-based power control mechanism. With the balanced voice traffic scenario, the uplink is found to be the most stringent one from the point of view of coverage as well as of the number of BSs deployed. The downlink direction yields substantial improvements: higher traffic coverage ratio and smaller number of BSs. More interestingly, we investigate the capacity and coverage on multi-service scenarios with both voice and data users with different rates, different $E_b/I_o$ requirements, and processing gains. This work accurately captures the traffic effects down to a very finer level on the capacity, coverage, and cost of the radio access network.

## 1.6 Outline of the thesis

This thesis is organized in five chapters. Chapter 2 provides the fundamentals and basic techniques of radio network planning and optimization. In Chapter 3, we present the mathematical model for locating and configurating BSs in a 3G radio network for the downlink direction. In order to solve it in reasonable amount of time, three heuristic algorithms are introduced and compared with, which are simulated annealing, tabu search, and greedy algorithm. We extend the scope of the design and optimization problem in radio network to the uplink direction in 3G environment in Chapter 4. We complete the dissertation in Chapter 5, with a discussion of the proposed models and algorithms and a brief outlook for possible future research topic.

# CHAPTER 2
# MOBILE NETWORK PLANNING AND OPTIMIZATION

The wireless telecommunications industry has undergone explosive growth in the last decade. Spectrum has become severely congested. To operate in today complex wireless world, users require more sophisticated services. Good network design and optimization is no longer a nicety, but rather a necessity. It is a prerequisite for workable, cost-effective wireless systems. The evolution to 3G networks faces a number of new challenges, many of them related to the planning and optimization of true multi-service radio networks. This chapter provides background materials and techniques for mobile network planning and optimization in 3G environments. We present the detailed review of the key characteristics in 3G radio networks, and also summarize major works that pave the way of cell planning and optimization and cell assignment. Afterwards, we review briefly some of the optimization methods and approaches which are used in this thesis.

## 2.1 Cell planning and optimization fundamentals

The following briefly covers some of the key concepts of mobile network planning and optimizations. Its objective is to provide an overview of certain concepts which are used in our proposed models and numerical implementations.

### 2.1.1 Cell types

A cell [74] is the area served by a base station transmitter, which is the basic geographical unit of a cellular system. In practice, engineers draw hexagonal-shaped cells on a layout to simplify the planning and design of a cellular system because it approaches a circular shape that is the ideal coverage area of a base station. In the real world, however, each cell varies depending on the radio environment. Due to constraints imposed by the natural and man-made terrain, the real shape of cells is very irregular.

Based on the size of cells, they can be classified as one of the following three types as shown in Table 2.1. Macrocells [21] provide overall coverage, especially to fast-moving mobiles. The base station antenna is mounted above the surrounding buildings, providing a cell radius from around 1 to 30 km. Microcells are used in areas with high subscriber density such as urban and suburban areas. Base station antennas are placed at an elevation of street lamps, so the shape of microcells is defined by the street layout. The cell length is up to 1 km. Picocells [21] are designed for very high mobile user density or high data rate applications, typically in indoor environments. Base station antennas are below the rooftop or at the elevation of bookshelves so the coverage is dictated by the presence of furniture and people. The radius of picocells is between 10 and 200 m.

**Table 2.1 Summary of the three cell types**

| Cell type | Cell radius | Transmit power | Antenna height | Use |
|---|---|---|---|---|
| macrocell | 1 ~ 30 km | 1 ~ 10 W | > 30 m, top of tall buildings | large area coverage, support high speed mobiles |
| microcell | 0.2 ~ 1 km | 0.01 ~ 1 W | < 10 m, street lamp elevation | high subscriber density areas |
| picocell | < 200 m | < 100 mW | celling / top of bookshelves | mainly for indoor |

### 2.1.1.1 Hierarchical cell structure

For an optimal mobile network performance, it is proposed that mobile network is planned with a hierarchical cell structure [112,113], which consists of macro, micro and pico cells. In general, the more stringent the QoS and capacity requirements, the smaller the cell needs to be. Basically, a cell has the same capacity regardless of the area it covers. As the area covered gets smaller, there will be few mobiles within the area and hence the cell will be able to provide the capacity required. A possible use of the hierarchical cell structure is shown in Figure 2.1. In this structure, microcells are often the only way to improve the capacity in urban areas. However they do result in handover problems. First, more handovers are required because the cells are smaller. Second, handover decisions now need to be made much faster. The typical solution to this is to leave macro cells in place to use these for handover. Macro cells guarantee a continuous coverage for fast moving mobiles, while small cells are necessary to achieve good spectrum efficiency and high capacity for hot spot areas. When the mobile detects that the signal strength is falling, it defaults back to the large cell while it takes the necessary time to find another small cell with sufficient signal strength. Such macro cells also means that the microcells do not need to cover the whole city, which can be extremely difficult to achieve, with the macro cell providing coverage in any gaps.

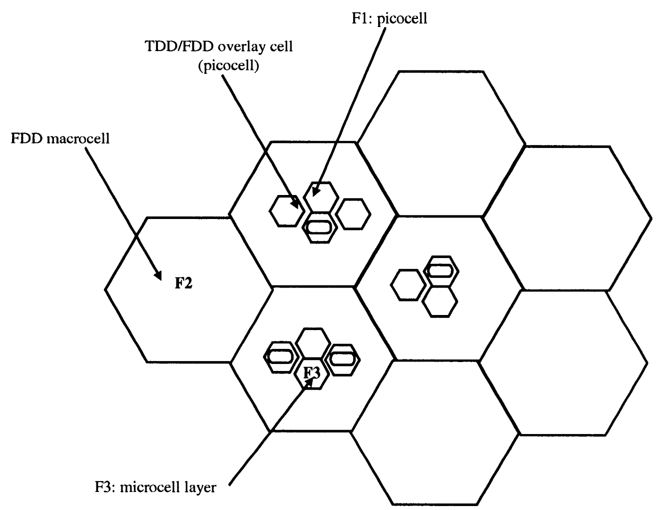



**Figure 2.1 3G hierarchical cell scenario**

In order to avoid interference, the macro cells need to use a different frequency from the microcells. The macro cells keep only a few frequencies to deal with handover and providing coverage in areas not covered by microcells. This is particularly true in CDMA networks, because mobile units configured for the larger cell will be operating with much higher powers than those configured for the smaller cells. If both cells operated on the same frequency, then the capacity of the smaller cell would be near zero [65,117]. Hence, different frequencies must be used. Because of the wide bandwidth and hence high capacity of a CDMA system, this may be inefficient. This disadvantage does not occur in TDMA since the cells would be assigned different frequencies in any case.

### 2.1.2 Radio propagation

A profound knowledge of the radio wave propagation or the radio channel characteristics is a prerequisite to achieving an optimum system design. In this section, an overview is presented on several propagation models that are widely used in practice.

#### 2.1.2.1 Path loss

Path loss or propagation loss $L$ is the parameter commonly used to characterize the local average signal in mobile channels. It is defined as the relationship between the transmitted power $P_t$ of the transmitter $T_x$ antenna and the received power $P_r$ by the receiver $R_x$ antenna. In most cases, it is expressed in dB, so

$$L = 10\log\frac{P_t}{P_r} = P_t(dB) - P_r(dB) \tag{2.1}$$

The propagation loss in equation (2.1) encompasses all the impairments that the signal is expected to suffer as it travels from the transmitter to the receiver. Much research has been performed to try to rationalize the signal strength that is received [94,104]. To simplify the problem and to help predict the received signal, mobile radio planners consider that the path loss experienced when transmitting a signal through the channel is composed of three distinct phenomena: distance-related attenuation, slow fading, and fast fading [71,88,101]. Distance-related attenuation simply expresses the fact that as the distance from the base station increases, the signal strength decreases. Slow fading is a mobile radio phenomena caused by the mobile passing behind a building. During the period the mobile is behind the building, the signal received will be reduced. Driving along a road, the mobile will pass behind a sequence of buildings, causing the signal to reduce in strength, or fade, on a relatively slow basis. Fast fading is another mobile radio phenomena caused by the signal arriving at the receiver via multipath propagation. There are many prediction models that are used to predict path loss [27,28,29,38,67].

#### 2.1.2.2 Macrocell propagation models

In macrocells, it is important to predict the average received signal strength at a given location. Usually radio transmission takes place over irregular terrain. The terrain profile of a particular area, as well as the presence of trees, buildings, and other obstacles, must be taken into account for estimating the path loss. The data needed to describe such environments would be very large and the computational effort involved would be excessive. As a result, empirical models are widely used for propagation prediction in macrocells because these models have the advantage of implicitly taking into account all propagation factors, both known and unknown, through actual field measurements.

Among numerous macro propagation models, the Okumura-Hata model [54] is considered to be one of the most significant. It is fully empirical model developed on the basis of an extensive series of measurements in urban environments. In [54], Hata presented a standard formula, which has been extended to cover the frequency range above 1.5 GHz by the propagation model, named COST 231 [29]. The extended model for medium to small cities is as follow :

$$L_{dB} = F + B\log R - E + G \tag{2.2}$$

where :

$$B = 44.9 - 6.55\log h_b$$

$$E = (1.1\log f_c - 0.7)h_m - (1.56\log f_c - 0.8)$$

$$F = 46.3 + 33.9\log f_c - 13.82\log h_b$$

$$G = \begin{cases} 0 \text{ dB medium - sized cities and suburban areas} \\ 3 \text{ dB metropolitan areas} \end{cases}$$

$$1500 \text{ MHz} \le f_c \le 2000 \text{ MHz}$$

$R = r \times 10^{-3}$ great circle distance between base station and mobile [km]

$r$: great circle distance between base station and mobile [m]

$h_b$ : base station antenna height above local terrain height [m]

$h_m$ : mobile station antenna height above local terrain height [m].

### 2.1.2.3 Microcell propagation models

Experimental observations reveal that in microcells the path loss as a function of the distance between the transmitter and receiver is well described by a power law with the exponent close to two up to a distance called "breakpoint". Beyond this breakpoint, a power decay with a considerably larger exponent (≈ 4~5) is observed [98,125]. In this case the path loss is modeled as

$$L_{micro} = \begin{cases} L_1 + 10\gamma_1 \log(d), & d \le d_b \\ L_1 + 10\gamma_1 \log(d) + 10\gamma_2 \log(d/d_b), & d > d_b. \end{cases} \tag{2.3}$$

This is known as the dual-slop model. $L_1$ is the reference path loss at $d$ = 1 m, $d_b$ is the breakpoint distance given by:

$$d_b = \frac{4.h_{BS}.h_{mobile}}{\lambda}$$

where $h_{BS}$ and $h_{mobile}$ are BS and mobile antenna heights, respectively. $\lambda$ is the wavelength. Typically, values of the exponents are found by measurements to be around $\gamma_1$ = 2 and $\gamma_2$ = 4, with breakpoint distances of 200~500 m. In order to plan the sites of microcells effectively, it is important to ensure that co-channel cells have coverage areas which do not overlap within the breakpoint distance.

For microcells, the BS antennas can be above, below, or at the same level as the surrounding buildings. Usually, two situations are distinguished according to the relative locations of the transmitter and receiver: line-of-sight (LOS) [17,98] in case of no obstacles in the propagation path, otherwise non-light-of-sight (NLOS) [125]. Multiple-ray models have been used in urban microcells, under LOS situations, when the $T_x$ and $R_x$ antennas are well below rooftop levels [21,98]. Uni-Lund model is valid for a $T_x$ antenna below rooftop level [21]. The model considers two situations: LOS and NLOS.

### 2.1.2.4 Indoor propagation models

It has been observed that propagation within buildings is strongly influenced by specific features such as the layout of the building, construction materials, and the building types. An empirical method that considers the attenuation through the individual walls and floors is given by [22,101]:

$$L_{indoor} = L_0 + L_c + \sum_{i=1}^{W} n_{wi} L_{wi} + (n_f)^e L_f \tag{2.4}$$

where

$L_0$ : free space loss between the transmitter and receiver

$L_c$ : constant loss

W: number of wall types

$n_{wi}$ : number of penetrated walls of type $i$

$L_{wi}$ : penetration loss through a wall of type $i$

$n_f$ : number of penetrated floors

$L_f$ : loss between adjacent floors

$e = (n_f + 2)/(n_f + 1) - k$ , where $k$ is a constant.

$L_c$ and $k$ must be determined empirically. Some recommended values at 1800 MHz area are [21,22]: $L_{w1}$ = 3.4 dB for light walls, $L_{w2}$ = 6.9 dB for heavy walls, $L_f$ = 18.3 dB and $k$ = 0.46.

Indoor radio propagation is dominated by the same mechanisms as outdoor. Ray-tracing and the geometrical theory of diffraction (GTD) have been applied for indoor propagation prediction. These deterministic methods can be used for site specific prediction, provided that sufficient details of the building geometry and materials are available. However, there are limitations in using such methods for practical picocell planning and optimization, due to the difficulty of obtaining and using sufficiently accurate physical data. In addition, the influence of furniture and the movement of people can have a significant (and time-varying) effect on signal coverage. Therefore, the combination of deterministic modeling with statistical measurements is expected to be more practical for the prediction of indoor radio propagation.

### 2.1.3 Radio link performance

Before deploying a cell, a cluster of cells, or a system, RF engineers need to know whether or not the WCDMA planning of the cell, cluster, or system will support the basic radio links. In other words, are all the radio parameters adequate to maintain a high-quality radio link between the base station and the mobile? In this section, we explain the basic concepts behind radio links, performance measurements, construction of link budgets for uplink and downlink environments.

#### 2.1.3.1 Link budget

Link budget planning is part of the network planning process, which helps to dimension the required coverage, capacity and quality of service requirement in the network [65,94,101]. UMTS WCDMA macro cell coverage is uplink limited, because mobiles power level is limited to voice terminal (125mW). Downlink direction limits the available capacity of the cell, as BS transmission power (typically 20-40W) has to be divided to all users. In a network environment both coverage and capacity are interlinked by interference. So by improving one side of the equation would decrease the other side. System is loosely balanced by design. The object of the link budget design is to calculate maximum cell size under given criteria [65,99]:

- Type of service (data type and speed);
- Type of environment (terrain, building penetration);
- Behavior and type of mobile (speed, max power level);
- System configuration (BS antennas, BS power, cable losses, handover gain);
- Required coverage probability;
- Financial and economical factors;

and to match all of those to the required system coverage, capacity and quality needs with each area and service.

In an urban area, capacity will be the limiting factor, so inner city cells will be dimensioned by required Erlangs/km² for voice and data. Even using 25dB as in building penetration loss into the building core area, link budget would typically allow about 300m cell range, which is a way too much for a capacity purposes. In a rural area uplink power budget will determine the maximum cell range, when typically cells are less congested. A typical cell range in rural areas will be several kilometers depending on a terrain [86,94].

#### 2.1.3.2 Forward link performance analysis

Before implementing a cell, a cluster of cells or a system, RF engineers need to know whether or not the CDMA design of the cell, cluster, or system will support the basic radio links. In other words, are all the radio parameters adequate to maintain a high-quality radio link between the base station and the mobile? There are two important parameters to consider in CDMA forward link design: the $E_b / I_o$ of the pilot channel, the $E_b / I_o$ of the forward traffic channel [73,99,105].

**Pilot channel**

$E_b / I_o$ is the energy per chip per interference density measured on the pilot channel; it is effectively the signal strength of the pilot channel. The mobile continuously measures $E_b / I_o$ and compares it against the different thresholds, such as the pilot detection threshold T_ADD and the pilot drop threshold T_DROP [65]. The results of these comparisons are reported back to the base station so that the base station can make a determination of whether or not the mobile should be handed off from one base station to the next. Thus, the $E_b / I_o$ plays a prominent role in determining whether or not a mobile is within the coverage area of a base station. Furthermore, the pilot signal is transmitted by a base station at a relatively higher power than those of other forward-link logical channels. A call cannot be set up without the mobile's successful reception of the pilot channel because, along with other functions, the pilot channel serves as a coherent carrier phase reference for demodulation of other logical channels on the forward link. Therefore, the $E_b / I_o$ effectively determines the forward coverage area of a cell or sector, and one has to ensure that the forward link strength $E_b / I_o$ is sufficient. The $E_b / I_o$ can be given by [99]:

$$E_b / I_o = \frac{a_0 P_0(\theta_0) L_0(\theta_0, d_0) G}{I_h + I_n + I_0 + I_m + I_t + N} \tag{2.5}$$

$P_0(\theta_0)$ = home base station (sector 0) overhead ERP including pilot, paging, and sync powers in the direction q0 to the probe mobile;

$a_0$ = fraction of home base station overhead ERP allocated to pilot power;

$L_0(\theta_0, d_0)$ = path loss from home base station in the direction q0 to the probe mobile a distance $d_0$ away;

$G$ = receive antenna gain of probe mobile;

$I_h$ = power received at the probe mobile from overhead power emitted by home base station;

$I_n$ = power received at the probe mobile from other interference of non-CDMA origins. This term is included to accommodate all other possible interference sources that could be jamming the system in the CDMA band;

$I_0$ = the sum of overhead powers from other base stations;

$I_m$ = the total traffic channel power (from the home base station) received at the probe mobile (which is measuring the $E_b / I_o$);

$I_t$ = the total traffic channel power (received at the probe mobile) from all other base stations;

$N$ = thermal noise power.

**Traffic channel**

On the link level, we are concerned with the $E_b / I_o$ of the forward-link traffic channel. As shown in Chapter 3, the link $E_b / I_o$ translates directly into bit error rate, which has implications on forward-link voice quality. Making sure that the link supports an adequate $E_b / I_o$ ensures the quality of the link [56,65,99]:

$$E_b / I_o = \frac{T_0(\theta_0)L_0(\theta_0, d_0)G}{I_h + I_n + I_0 + I_{m'} + I_t + N}(\frac{W}{R}) \tag{2.6}$$

$T_0(\theta_0)$ = home base station (sector 0) traffic channel ERP in the direction $\theta_0$ to the probe mobile;

$L_0(\theta_0, d_0)$ = path loss from home base station in the direction $\theta_0$ to the probe mobile a distance $d_0$ away;

W/R = processing gain;

$I_{m'}$ = the effective total traffic channel interference (from the home base station) intercepted by the probe mobile.

### 2.1.3.3 Reverse link performance analysis

Since there is no pilot channel on the reverse link, we are only interested in the $E_b / I_o$ of the reverse traffic channel. The link $E_b / I_o$ translates directly into BER, which has implications on reverse-link voice quality. Making sure that the link supports an adequate $E_b / I_o$ ensures the quality of the link [65,99]:

$$E_b / I_o = \frac{T' L_0'(\theta_0, d_0)G_0(\theta_0)}{I_m' + I_t' + I_n' + N}(\frac{W}{R}) \tag{2.7}$$

$T'$ = reverse traffic channel ERP of the probe mobile; the transmit pattern is assumed to be omnidirectional;

$L_0'(\theta_0, d_0)$ = reverse path loss from the probe mobile in the direction $\theta_0$ to the home base station a distance $d_0$ away;

$G_0(\theta_0)$ = receive antenna gain of home base station in the direction $\theta_0$ to the probe mobile;

$I_m'$ = the total interference introduced by the reverse traffic channel transmissions of all the mobiles;

$I_t^{'}$ = the total interference introduced by the reverse traffic channel transmissions of all other mobiles that are not served by the home base station;

$I_n^{'}$ = power received at the home base station from other interference of non-CDMA origins. This term is included to accommodate all other possible interference sources that could be jamming the system in the CDMA band.

### 2.1.4 Traffic

The planning of the 3G mobile networks faces three new major challenges. First, there is the tremendous increase in the demand for mobile communication services. Second, the new technologies of the 3G generation networks require demand-based planning method. And third, due to deregulation acts, the competition between the mobile service operators is increased [111]. Therefore, the traffic behavior and distribution in the network service area is critical in order to design and manage a 3G system [89,119].

#### 2.1.4.1 Traffic estimation

The traffic is estimated by using the geographical and demographical characteristics of the service area. This traffic demand model relates factors like land usage, population density, vehicular traffic, and income per capita with the calling behavior of customers. The model should apply statistical assumptions on the relationship of traffic and clutter type with the estimation of the demand. In the used geographical traffic model, the traffic density $E_{geo}^{(t)}(x,y)$ is the aggregation of the traffic originating from these various factors [110]:

$$E_{geo}^{(t)}(x,y) = \sum_{\text{allfactors } i} \eta_i \delta_i^{(t)}(x,y)$$

where $\eta_i$ is the traffic generated by factor $i$ in an arbitrary area element of unit size, measured in Erlang per area, and $\delta_i^{(t)}(x,y)$ is the assertion operator:

$$\delta_i^{(t)}(x,y)=\begin{cases}0 & \text{factor } i \text{ is not valid at (x, y)}\\ 1 & \text{factor } i \text{ is valid at (x, y)}\end{cases}$$

The core technique of the traffic characterization is the representation of the spatial distribution of the demand for traffic by discrete points, called demand nodes [110,111]. Demand nodes are widely used in economics for solving facility location problems. A demand node represents the center of an area that contains a quantum of demand from traffic viewpoint, accounted in a fixed number of call requests per time unit. The notion of demand nodes introduces a discretization of the demand in both space and demand. In consequence, the demand nodes are dense in areas of high traffic intensity and sparse in areas of low traffic intensity [109].

#### 2.1.4.2 Traffic classification

In general, applications and services can be divided into different groups, depending on how they are considered. In 3G systems, four traffic classes have been identified in Table 2.2 [56].

**Table 2.2 Classification of traffic**

| **Traffic class** | **Conversational class Real Time** | **Streaming class Real Time** | **Interactive class Best Effort** | **Background class Best Effort** |
|---|---|---|---|---|
| **Fundamental characteristics** | - Preserve time relation (variation) between information entities of the stream<br>-Conversational pattern (stringent and low delay ) | - Preserve time relation (variation) between information entities of the stream | - Request response pattern<br>-Preserve payload content | -Destination is not expecting the data within a certain time<br>-Preserve payload content |
| **Example of the application** | voice | streaming video | web browsing | telemetry, emails |

### 2.1.5 Capacity

Uplink and downlink are not operated in an identical condition, and their performance characteristics are vastly different. Both directions are ultimately limited by interference, but there are large dissimilarities, since the forward link access is of one-to-many type and the reverse link is of many-to-one type. According to [31], either of two links can determine the whole system capacity. It is generally difficult to draw a firm conclusion, which of the links limits the system capacity and coverage, and what are the limiting factors. The limited links is determined, for instance, by other-cell interference, multipath fading, effectiveness of power control, spatial distribution of users, as well as generation, synchronization, modulation and coding of the spread-spectrum signal [119,120].

In [31,44,118,119], the overall capacity of narrowband CDMA systems, where the main service has traditionally been the voice communications, is often argued to be uplink limited. WCDMA and 3G mobile communications with multimedia services may well change this stance. An uplink limited system capacity in a WCDMA network is more likely to occur in a rural environment, where far-away mobile units can not transmit with the required power. Dense urban areas are more likely to have the downlink limited capacity, since the base station could run out of transmit power, because the total BS power is shared between all the users [56,65].

Uplink and downlink capacity relationship has been concluded to be highly dependent on the network configuration such as base station locations [31,89]. The coverage of a WCDMA network is assumed uplink limited in high load case [56,115]. In UMTS networks, the traffic and load can be asymmetric between uplink and downlink. Some applications such as web-browsing or electronic newspaper download cause the capacity utilization to be strongly biased toward downlink. It is concluded in [89] that a small amount of web-browsing traffic turned the downlink direction as the capacity limiting factor of a WCDMA network. In addition, it is suggested in [31] that a WCDMA network capacity is generally downlink limited. There will also exist link-balanced multimedia applications (e.g., video telephony) that require a similar bandwidth for both links. If the balanced services, such as voice and video telephony, dominate the total traffic load, the cell capacity is more likely to be determined by the reverse link.

### 2.1.5.1 Forward link capacity

Upper limits on forward-link capacity are fundamentally determined by restrictions on sector-radiated power and by mobile receiver *SIR* requirements. The forward-link signal comprises message traffic for mobiles, sector-specific signal (pilot) used for sector surrounding mobile stations, as well as the inherent randomness in their locations, generates an averaging effect that facilitate prediction. The relatively low level of co-channel interference allows the use of a β corresponding to surrounding fully loaded cells without being overly conservative [119]. Furthermore, for large *N*, all interference can be reduced by a factor $a$ that reflects the mean voice activity across all active channels on the reverse link. The capacity of forward link capacity can be defined as *N* [99]:

$$N = \frac{G}{ad}\frac{1}{(1+\beta)} + 1 - \frac{1}{a(1+\beta)}\frac{FN_{th}W}{S} \tag{2.8}$$

where

$a$ = voice activity factor;

β = interference factor;

W = system bandwidth;

$N_{th}$ = power special density of thermal noise;

$F$ = base station noise figure;

$S$ = received signal strength;

$G$ = processing gain;

$d$ = required minimum signal-to-interference ratio.

### 2.1.5.2 Forward link capacity improvement methods

Since wireless service providers typically cannot lower the signal-to-interference ratio $E_b / I_o$ requirement that comes with the chip set, they have to resort to changing the characteristics of their systems to increase RF capacity. On the forward link, wireless service providers can employ different methods to minimize the loading factor [126].

Note that loading factor is defined at each mobile. These methods can be classified along two dimensions: spatial and power.

The spatial dimension consists of those methods that attempt to manipulate the transmit antenna pattern of a base station and thus spatially isolate its forward coverage area. Using this method, a base station reduces unwanted transmissions to other mobiles in other adjacent cells [99]. Other spatial methods include six-sectors, microcells, and various smart antenna schemes. On the other hand, the power dimension consists of those methods that attempt to minimize the transmission power of the base station. From the perspective of a mobile, it is receiving interference power from neighboring sectors. The goal of the various capacity-enhancing methods in this category is then to minimize the transmission power the adjacent sectors. The methods in this category include various transmit diversity schemes such as transmit polarization diversity, orthogonal transmit diversity (OTD), and space time spreading (STS) [65,126].

#### 2.1.5.3 Reverse link capacity

The capacity of the cell is defined by the number of connections that can simultaneously exist with an acceptable level of mutual interference. According to [56], the WCDMA's uplink soft capacity is limited by the amount of interference, caused by mobile units, that can be tolerated in a given cell to overcome path loss, shadowing and fast-fading. Interference originates mainly from the same cell users, but much interference arrives at the given base station also from the users controlled by the base stations of other cells. In addition, there is always system noise, for example, the environmental (thermal) and manmade background noise. Identical users and perfect power control are assumed, the uplink capacity can be formulated as follows [65,108]:

$$N = F.\left(\frac{G_p}{E_b/I_o} + 1\right) \tag{2.9}$$

where:

$F = \frac{I_{own}}{I_{own} + I_{other}}$ ;

$E_b = (P_s.G_p)/W$ ;

$I_o = (I_{own'} + I_{other} + N)/W$ ;

$I_{own'} = (N - 1).P_s$ ;

$I_{own} = N.P_s$ ;

$N$: number of users;

$P_s$ :received signal power ;

$I_o$: noise density ;

$I_{own}$: other user interference in own cell ;

$I_{own}$: total own cell interference ;

$I_{other}$: other cell inteference ;

$N_o$: background noise ;

$G_p$: processing gain ;

$W$: total bandwidth of a carrier.

A bit-energy-to-noise-density level of $E_b/I_o$ of a user depends on the bit rate, bearer service, multipath profile, mobile speed, receiver algorithms and base station antenna structure.

#### 2.1.5.4 Reverse link capacity improvement methods

On the reverse link, capacity-enhancing methods can also be similarly classified along two dimensions: spatial and power [126]. The spatial dimension consists of those methods that attempt to spatially isolate the reverse coverage of a sector. Going from an omni-directional coverage area to a sectorized coverage area has the effect of reducing the amount of interference power received at the home sector from those mobiles in other adjacent sectors. Other spatial methods include six-sectors and microcells. Of course, various smart antenna schemes represent an extreme case of the spatial method.

The power dimension consists of those methods that attempt to reduce the transmission power of the mobile. Because the transmission pattern of a mobile is typically omni-directional, a mobile in a neighboring cell does not focus its transmission toward its own base station. Some popular methods in this category include various receive diversity schemes [72,74] and the use of low-noise amplifiers (LNAs) [94,104].

### 2.1.6 Sectorization

In a sectorized cell, instead of using an antenna that radiates signal equally in all directions (known as an omni-directional antenna, or omni), antennas that only radiate narrow beams of 120 degrees (in a three-sided arrangement) or 60 degrees (in a six-sided arrangement) are used. The three sided case, for example, has the effect of splitting the cell into three equal-sized pie-shaped slices. Sectorization brings a number of advantages in a WCDMA network [100].

In a WCDMA network, the same frequency can be used in each sector, increasing the capacity of the network by the number of sectors deployed. In a TDMA network, when a cell is sectorized, the cell radius remains the same. Hence, the transmitted power remains the same [23]. Hence, the distance required to the next cell using the same frequency also remains the same. However, there are now more cells within this sterilization radius, and hence more frequencies need to be found to avoid interference. So although the sector is smaller than the cell, and hence has to support less traffic, it also has fewer frequencies with which to do this (because the total frequency assignment has been divided by a larger cluster size). So there is little change in the overall capacity. This is not the case with WCDMA where using the same frequency in adjacent sectors only slightly increases the interference to neighboring cells and slightly reduces their capacity [84].

The reason [23] for sectorization in a TDMA network is that the sectorization allows for a greater path loss than a nonsectored approach because the gain of the sectored antennas provides the mobile with a stronger signal. This has the effect of increasing the range. Further, in city areas, sectorization prevents some multipath reflections that might occur if an omni-directional antenna was used, since signals are now sent in a narrower beam reducing the chance of reflections. In suburban and rural areas, sectorization is used less. This is because in these areas it may be that only one frequency is required to provide sufficient capacity. If sectorization was adopted, a different frequency would need to be deployed in each sector that would waste equipment, resulting in a significant cost increase.

TDMA could achieve a real gain if, instead of making a cell into a number of smaller cells by sectorizing it, it was divided into smaller circular cells, that is, the base stations were distributed around the cell and transmitted on a lower power level. This approach results in similar equipment costs but much higher site rental and backhaul costs, therefore, it tends to be avoided expect where absolutely necessary.

### 2.1.7 Power control

Capacity can be maximized by minimizing the total level of system interference, that is, by controlling all CDMA signals so they are at the lowest level necessary to meet *SIR* (signal-to-interference) ratio requirements. Power control ensures that each signal meets minimum requirements for communication while avoiding undue levels of interference with other signals [94,104].

A closed-loop algorithm on the forward link and open- and closed-loop algorithms on the reverse link accomplish control. The measurement of parameters known to influence the desired output forms the basis of the open-loop mechanisms whereas the direct measurement of the output itself forms the basis of the closed-loop mechanisms [84,87].

Reverse-link control ensures the minimum necessary *SIR* at the BS for each mobile station. In the open-loop path, the mobile station makes power adjustments based on its estimate of path-loss from BS to mobile station. The mobile station's measurement of received total power forms the basis for this estimate. These adjustments compensate for path-loss variations that are correlated between the forward and reverse links. In the closed-loop path, the BS compensates for uncorrelated path-loss variations (e.g. multipath fading) and additional sources of interference by estimating the received *SIR* from the mobile station and transmitting appropriate power adjustment commands. The final value of mobile station transmit power is jointly determined by these two control paths [128].

Forward-link control ensures the minimum necessary *SIR* at each mobile station. In this closed-loop mechanism, the mobile station requests forward-link power adjustments based on its received frame error rate [52,94].

### 2.1.8 Call admission strategies

Call Admission Control (CAC) regulates the establishment and modification of radio access bearers to prevent the system from becoming overloaded [60]. CAC is used to achieve high traffic capacity and to maintain the stability of radio access network. CAC in uplink and downlink is different. Uplink and downlink can be practically decoupled, since admission control decision in radio resource management is made practically independently in uplink and downlink. Moreover, as already pointed out, uplink and downlink are run on different basis, as the access in the former type of link is many-to-one instead of one-to-many in the latter type of link. Admission control in UMTS is inherently different from the systems whose resources are finite and specified. The number of channels per sector is fixed, for instance, in FDMA and TDMA systems such as GSM. Thus, the capacity limit in those systems is a hard limit, and the CAC only has to take care of the allocation of available channels for the users. A WCDMA network has no hard limit on the maximum capacity, which makes admission control a complex soft capacity management problem.

Several admission control strategies have been proposed in the literature. One design choice is to restrict the admission by fixing the amount of resources, for instance, the maximum number of connections [57] or the maximum total bit rate of the cell. A *SIR* based policy is introduced in [1,76], where the admission decision is made on individual basis comparing mobile user's *SIR* value measured at a BS to this base station receiver's *SIR*-threshold value.

The total interference based strategy was first proposed in [60]. There, the CAC blocks calls at a base station, when the measured total power at that base station exceeds the predetermined threshold. The total interference limiting admission controls essentially retains the soft-capacity feature of UMTS. Interference-based admission control treats different types of services in a uniform manner, and it is adaptive to load changes between the cells. However, on the minus side, it may be difficult to judge precisely what values the threshold parameters, such as the maximum allowed total received power have.

### 2.1.9 Related works in cell planning and optimization

In this section, we summarize major works that paved the way of cell planning and optimization. The problem of optimum siting of base station transmitters in a microcell or PCS system has been addressed using the simulated annealing optimization technique [12]. The results show that plausibly optimum transmitter sites can be successfully selected automatically regardless of how inadvertent the starting positions of the transmitters are. In [61], the authors develop a fuzzy expert system to incorporate the expert experience for cell dimensioning, i.e., adjusting the parameters of cells. Second, they propose a new approach for automatic BS placement. It employs a genetic algorithm and takes advantage of a versatile and adaptive objective function to find the optimal cell sites. The hierarchical approach can effectively reduce the computational complexity. Moreover, the authors present a technique of cell splitting for automatic capacity growth. For example, in [12,102,103], the models are for both microcells and picocells in coverage limited environments. In general these approaches use an objective function directly related to path loss which is optimized to determine base station locations. In [25], authors propose a model which considers interference limited environments and use an objective function which directly relates to QoS. In [85], the goal of the cell planning and optimization models is to cover the maximum number of subscribers in an effective and efficient manner. The authors [63] present a profit maximization model for base station location, frequency assignment, and customer allocation in hierarchical cellular networks based on the FDMA or TDMA technology. The authors in [35] develops a cost minimizing cell planning and optimization model that simultaneously determines three important variables – base station location, power level and frequency group assignments for the antennas at each selected base station. It can represent different antenna configurations and frequency groups commonly used in practice. In [79], the integer models, reflecting different needs and targets, are developed. Basically every individual model aims at serving most of the traffic while simultaneously keeping the amount of interference and multi-coverage small.

In 2G systems, two fundamentally different technologies are adopted. They are TDMA-based, such as GSM and narrowband CDMA-based, e.g. IS-54. The BS location in a 2G cellular CDMA system has been considered in [5,106]. Given the data of call-traffic distributed over the service area and potential sites of BSs, the objective of the problem is to locate BSs so as to minimize the associated cost for establishing BSs while keeping the probability of blocking under control. An efficient algorithm has been developed for solving the design problem by extensively testing it using randomly generated problems. Computational results showed that the proposed algorithm consistently performed so well both in solution quality and in speed as to be practicable. In [4,5,6], authors show how to maximize the number of simultaneous users in a network by varying the pilot-signal powers and the BS locations in CDMA. They calculated the implied costs of network capacity with respect to pilot-signal powers and BS locations. Implied costs capture the effect of increases in the pilot-signal power of one BS or the relocation of one BS on the capacity of the entire network. The results confirm that for a uniform user distribution, a uniform network layout with equal-sized cells is optimal. For a non-uniform traffic distribution, the cells need to be relocated inside the hot spot. The results show that increasing the pilot power of a congested cell is better than decreasing it. Even though the intra-cell interference increases, a greater reduction in inter-cell interference is achieved which yields an increase in overall capacity. Unlike TDMA, CDMA is an interference limited system. Hence it has a soft capacity limit governed by, among other things, the power radiated by users and base stations. The power control is a major technical complexity that CDMA systems have to handle. Thus, a different cell planning and optimization model would need to be developed for CDMA based cellular system. [109] formulates a CDMA cellular cell planning and optimization as a discrete multiobjective model. The model is defined in terms of BS locations, their powers, and their antenna heights. These design variables are used to quantify call quality and demand coverage to be maximized, and cost to be minimized. In [106], the authors consider a CDMA system in which blocking is enforced when the relative interference exceeds a certain threshold level. Its objective of the problem is to locate base stations so as to minimize the associated cost for establishing base stations while keeping the probability of blocking under control.

In [79], a demand node concept is adopted as a simplified traffic load model. A variety of benefit criteria, reflecting different needs and targets, is developed for the BS positioning problem. Basically, all criteria aim at serving most of the traffic while simultaneously keeping the amount of interference and multi-coverage small. All objective functions are formulated as integer linear problems, and are solved for relevant examples of realistic problem size. In cases where an integer LP solution could not be found, simulated annealing was successfully applied as an approximate method. A three step efficient approach has been proposed in [114]: a pre-processing phase based on a filtering principle, an optimization phase using tabu search, and a post optimization phase based on fine tuning. The pre-processing phase is parameterized allowing users to generate a variety of reduced sets of BSs, of interest for devising an ultimate solution. The tabu search algorithm is based on a binary representation of the search space, integer techniques such as frequency-based tabu list management, and penalty-based diversification. Various techniques are available for post optimization, either to improve the objectives or to enhance constraint satisfaction. By applying this approach to two large and realistic test data sets, it proves to be flexible, robust and effective. In [42], the authors examine the complexity of finding an optimal way to build base stations in order to supply a specified demand of traffic in a CDMA network. The meaning of "optimal" here takes a number of effects into account, such as gain from supplied users, construction costs and ongoing costs for base stations, and higher customer satisfaction if the intra-cell interference is low. The authors prove that restricted versions of the problem, which are still good enough for practical purposes, have a polynomial-time approximation scheme but no fully polynomial-time approximation scheme.

A first attempt to a 3G UMTS BS location and configuration is reported in [9]. Because in UMTS networks, BS location can not only based on signal predictions, but it must also consider the traffic distribution, the power control mechanism as well as the power limits and the signal quality constraints. In [9], authors discuss integer programming models and discrete algorithms aimed at supporting the decisions in the process of planning where to locate the new BSs. They also consider the *SIR* as quality measure and two power control mechanisms which keep the received signal power or the estimated *SIR* at a give target value. The focus is on uplink direction which turns out to be the most stringent one in the presence of full-duplex balanced connection such as voice calls. The authors present randomized greedy and stingy procedures as well as a randomized method combining the types of steps used in the two above procedures. In [10], the authors continue the work in [9], the experimental results show that the enhanced power-based power control mechanism model yields interesting solutions but those obtained with the *SIR*-based power control method use in a more efficient way the scarce radio resources and the computed *SIR* values are closer to the actual values in real systems. In [62,127], authors present an integer programming model for BS location and service assignments in WCDMA networks, which takes as input a set of candidate two locations with corresponding costs, a number of customer locations with corresponding demand for traffic, and the revenue potential for each unit of capacity allocated to each demand node. The authors also propose an interesting algorithm which uses a propriety branching scheme, an optimization gap tolerance of at least 1%, and two sets of global valid inequalities that tighten the upper bounds obtained from the linear programming relaxation.

## 2.2 Search algorithms

Our problems have practical and theoretical importance, which are of combinatorial nature. Combinatorial problems are intriguing because they are easy to state but many of them are very difficult to solve they are NP-hard. Local search and extensions thereof based on metaheuristics, which have been developed at the interface between artificial intelligence and operations research, are among the best available techniques for obtaining high-quality solutions to large instances of NP-hard problems in a reasonable time. This section briefly describes several important local search metaheuristics, including tabu search, simulated annealing, and some aspects of constraint programming methodology.

### 2.2.1 Combinatorial optimization

An optimization procedure seeks to find the optimal solution $x^* = min\{ f(x) | x \in S \}$, where $f$ is the objective function with domain $S$ - the set of possible solutions to the given problem. A combinatorial optimization problem is defined as an optimization problem where $S$ has discrete members. When the problem complexity is low, either an exhaustive search of the space, or deterministic algorithms (such as linear and nonlinear programming, dynamic programming, branch-and-bound algorithms, and polyhedral cutting plane approaches may be used to obtain the solution). For more difficult problems, heuristic and stochastic search techniques must be employed to find the optimal point in a large solution space.

### 2.2.2 Neighborhood search

A subset of $S$, designated $N(x)$, may be associated with each point $x \in S$. $N(x)$ is referred to as the neighborhood of $x$. At each step, most search techniques for optimization proceed from the current point $x$ by considering a point or a set of points in $N(x)$. Such neighborhood-based search algorithms are then differentiated from each other by the way in which the considered points are accepted (via some selection criterion based on objective function evaluations) [2,64]. The common ingredients of a neighborhood based search technique are shown in Figure 2.3. Local search techniques such as steepest descent algorithms move from point to neighboring point, accepting each successive point as a solution only if it has a lower cost than the current solution. This causes entrapment in the point with the lowest objective function value in the neighborhood – a local optimum. Global search techniques provide an escape from such traps by providing the ability to selectively accept successive points even if they have a higher cost than the current solution.

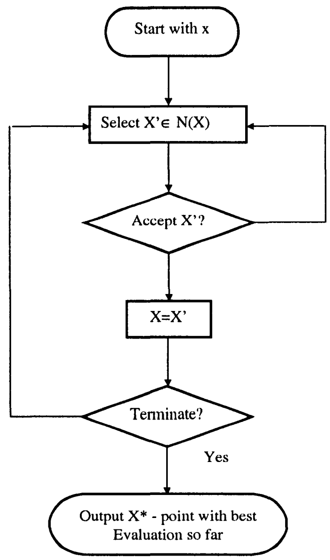



**Figure 2.3 General neighborhood based search algorithm for optimization**

Choosing a neighborhood affects the properties of a local search. The smaller a neighborhood, the more likely will find itself in a local optimum, with no neighbor providing a means of escape. On the other hand, a larger neighborhood gives a lesser chance of becoming trapped in a local optimum, but computation at each iteration is greater [96].

There are two approaches to examining the neighborhood. One is first improvement which examines the neighborhood and moves the first neighbor with a lesser objective function value. The other is steepest descent which examines the entire neighborhood and then take the move that gives the best improvement in the objective function value. Steepest descent tends to find short paths between solutions, evaluates the neighborhood more uniformly, and it is inherently deterministic while first improvement is not. Steepest descent has no real mechanism to move out of a local minima. Some techniques to avoid becoming trapped include increasing the neighborhood size and using random sampling, but these are not always satisfactory [51,96].

The following describes the four algorithms used in this thesis: random walk (RW), genetic algorithm (GA), simulated annealing (SA), and tabu search (TS). These algorithms are very simple and easy to implement, and are very general and robust in their simplest form – assuming nothing about the structure of space being searched. To improve their efficiency when applied to specific problems, they may be modified suitably (via better neighborhood definitions) or even hybridized with heuristic techniques.

### 2.2.3 Random walk

Random walk is perhaps the simplest of the neighborhood-based search techniques. At each step, a point $x' \in N(x)$ is generated from the current point $x$. If $x'$ has an objective function evaluation not greater than the current point ($f(x') \leqslant f(x)$), it is accepted and the search proceeds by setting $x = x'$. If $f(x') > f(x)$, however, the point $x'$ is accepted with a probability $p$ – which is the probability of accepting uphill moves. This is shown in Figure 2.4. Varying the parameters $p$ from 0 to 1, we get a whole family of random walk algorithms that range from greedy search ($p = 0$) to purely random search ($p = 1$). In several problems of interest one may expect that since greedy search will result in the search converging to a local minimum, a small non-zero uphill probability can help in escaping such minima. When the uphill probability is too high, however, the search becomes more random and there may be a performance drop due to this. For some problems, a greedy search that is repeated from different starting points (sometimes known as multiple-start local search) may be utilized to increase the possibility of locating near-optimal solutions.

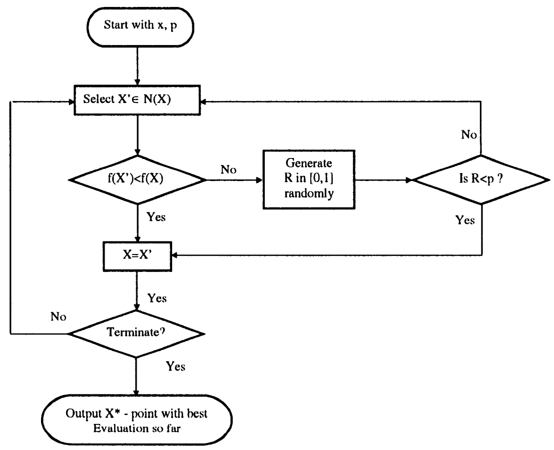



**Figure 2.4 Random walk**

### 2.2.4 Tabu search

Tabu search (TS) is a popular meta-heuristic as shown in Figure 2.6. The idea of tabu search, in its simplest form, is to first make the lowest cost move at each stage in the search, and, second, to accept cost degrading moves. This means that in a local minimum, tabu search will move out, since it can accept cost degrading moves. However, unless prevented, it could immediately fall back to the local minimum it left by making the opposite if such an opposite move exists and such a move is now the best one can be made (which is common) [49,96].

To counteract this cycling effect, tabu search employs various mechanisms, the typical one being the tabu list $T$ [48], a finite list of forbidden moves. At any given iteration, if the current solution is $x$, its neighborhood $N(x)$ is searched aggressively to yield the point $x'$ which is the best neighbor such that it is not on the tabu list. Note that it is not required that $f(x') \leqslant f(x)$, only that $f(x') = min(f(x^+)|x^+ \in N(x) \setminus T)$. Very often though, to reduce complexity, instead of searching all the points in $N(x)$, a subset of these points called the *candidate list* is considered at each step. The size of the candidate list may even be varied as the search proceeds. As each new solution $x'$ is generated, it is added to the tabu list and the oldest member of the tabu list is removed.

Thus, the tabu list prevent cycling by disallowing repetition of moves within a finite number of steps (determined by the size of the list). This, along with the acceptance of higher cost moves, prevents entrapment in local minimum. It may also be desirable to include in the tabu list attributes of moves rather than the points themselves. Each entry in the list may thus stand for a whole set of points sharing the attributes. In this case, it is possible to allow certain solutions to be acceptable even if they are in the tabu list by using what are called *aspiration criteria.* If a neighborhood is exhausted, or if the generated solutions are not acceptable, it is possible to incorporate into the search the ability to jump to a different part of the search space (this is referred to as *diversification*). One may also include the ability to focus the search on solutions which share certain desirable characteristics (*intensification*) by performing some sort of pattern recognition on the points that have shown low function evaluations in the past.

The choice of moves that generate the neighborhood of a point is problem-specific. Different implementations can be generated by varying the definition and structure of the tabu list, the aspiration criteria, the size of the candidate list, intensification and diversification procedures, etc. To speed up the search, faster ways to determine the best neighbor are required [47].

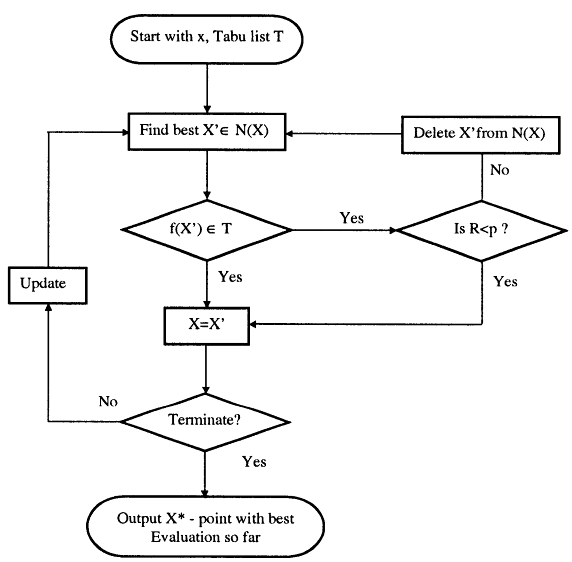



**Figure 2.6 Tabu search**

### 2.2.5 Simulated annealing

Simulated annealing operates by allowing cost degrading moves based on a probabilistic rule. Given that the current solution $x$ has objective function value $f(x)$, and the proposed solution $x'$ has cost $f(x) + d$ ($d$ can be positive or negative), simulated annealing accepts the new solution with probability 1, if $d \leqslant 0$ {non degrading move}, and with probability *exp(d/θ),* if $d > 0$ {degrading move} [3]. The procedure is illustrated in Figure 2.5.

Notice first that non-degrading moves are always accepted. Second, degrading moves are accepted with a probability which increases with a decrease in objective function value difference *d*, and a decrease in a parameter $\theta$. Ignoring $\theta$ for the moment, we see that if a particular move degrades the objective function by a large amount, it is less likely to be accepted than one which degrades the objective function by a small amount [66].

The parameter $\theta$ is known as the temperature and it controls the way the search operates. The effect of $\theta$ is that for large $\theta$, cost degrading moves have a high chance of acceptance. For low $\theta$, the opposite situation holds, with only moves that slightly degrade the objective function having any real chance of acceptance. The idea is to select a good cooling schedule, which begins the search with $\theta$ high, and gradually lower $\theta$ as search progresses. This results in the search being able to roam freely near the beginning [116]; by contrast, later on, when the temperature $\theta$ is low, the search looks more like greedy search, making only non-degrading moves. We should note that there are basically two types of schedule, having analogies to homogeneous and inhomogeneous Markov chains respectively. In the homogeneous case, annealing is carried out at a fixed temperature until equilibrium is reached (this involves a further problem in that one has to decide when this has occurred.) Once this state is judged to have been reached, the temperature is reduced, and the procedure repeated. The number of attempted moves at each temperature may be quite large, although the temperature steps can be relatively large also. In the inhomogeneous case, the temperature is reduced (but by a very small amount) after every move. This is less complicated than the homogeneous case, and is the one more commonly used in practice [116].

It is worth noting that, in simulated annealing, the moves to be examined must be drawn from the neighborhood in a random fashion. Otherwise, the moves specified first in the neighborhood will have a larger chance of acceptance than those that occur further on in the neighborhood which is contrary to the ethos of simulated annealing [24,68].

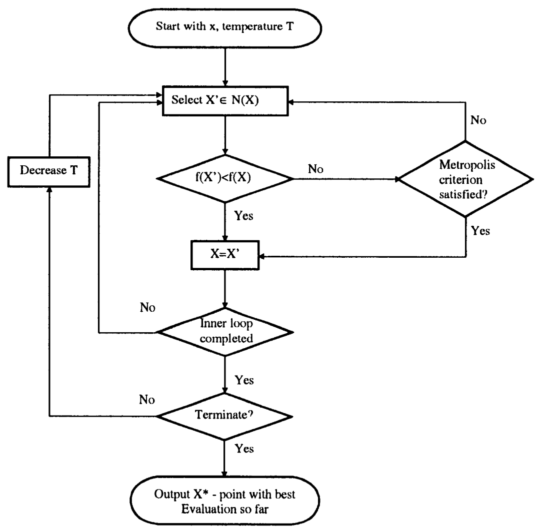



**Figure 2.5 Simulated annealing**

### 2.2.6 Genetic algorithm

These algorithms derive their inspiration from the natural process of biological evolution. Solutions are encoded into strings or chromosomes. The algorithm operates on a population of these chromosomes, which evolve to the required solution through operations of fitness-based selection, reproduction with crossover and mutation that are fundamentally similar to their natural analogs. Figure 2.7 shows a diagram for the simple genetic algorithm [50].

Briefly, the process is as follows: an initial population $P$ of $N$ chromosomes is chosen. At each generation, a new population $P'$ is generated by repeating the following procedure: first, two parents are picked from $P$ in such a way that the probability of selection is proportional to their fitness. Then, new offspring are generated from these parents by crossover with some probability of $P_c$. Finally, with a probability $P_m$, these recombined chromosomes are then randomly mutated. The population thus generated replaces the current population. The procedure is repeated until some termination criterion is satisfied. Termination criteria may be defined such that the algorithm stops when an acceptable solution is found in the population or after a predefined number of function evaluations or generations have been processed [13].

Very often, for specific applications, the crossover and mutation operators may be redefined or extended, and a local search may be incorporated at the end of each generation to speed up convergence. The encoding of the solution space into chromosomes, the size of the population, and the mutation and crossover probabilities all vary widely depending on the implementation.

The traditional mutation and crossover operators do in some sense define a neighborhood for each chromosome in a population, but it is possible to relate genetic algorithms to the other neighborhood search schemes in a more direct way if we do not consider crossover [82]. This is done by specifying that the mutation operator for the chromosome corresponding to solution space point $x$ is such that it yields a chromosome corresponding to point $x'$ with the property that $x' \in N(x)$. This is the approach considered in the thesis. It is noted here that the significant difference between GA and the other search techniques described here is that it allows for a more parallelized search of the solution space since a population of points is considered at each step instead of just a single point [2].

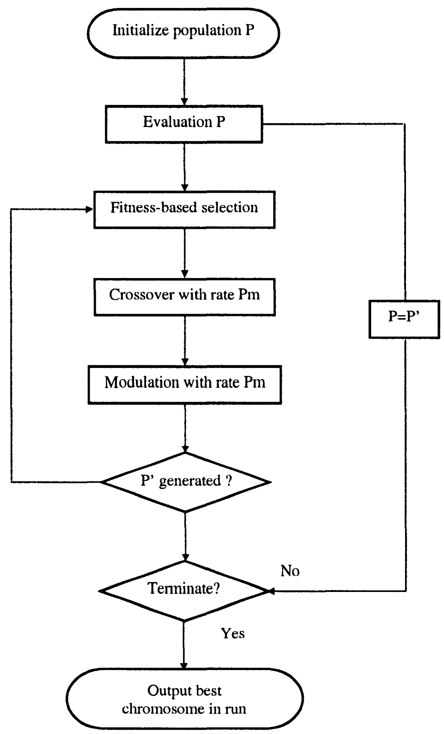



**Figure 2.7 Genetic algorithm**

### 2.2.7 Integer programming

When formulating linear programming problems, we often found that, strictly, certain variables should have been regarded as taking integer values but, for the sake of convenience, we let them take fractional values reasoning that the variables were likely to be so large that any fractional part could be neglected. Whilst this is acceptable in some situations, in many cases it is not, and in such cases we must find a numeric solution in which the variables take integer values [77].

Problems in which this is the case are called integer programs (IP's) and the subject of solving such programs is called integer programming (also referred to by the initials *IP*). IP's occur frequently because many decisions are essentially discrete (such as yes/no, go/no-go) in that one (or more) options must be chosen from a finite set of alternatives [85]. Note here that problems in which some variables can take only integer values and some variables can take fractional values are called mixed-integer programs (MIP's).

For solving linear programming problems, we have general purpose (independent of the LP being solved) and computationally effective (able to solve large LP's) algorithms (simplex or interior point) [15]. For solving IP's, similar general purpose and computationally effective algorithms exist.

Solution methods for IP's can be categorized as:

- general purpose (will solve any IP) but potentially computationally ineffective (will only solve relatively small problems) ;
- special purpose (designed for one particular type of IP problem) but potentially computationally more effective.

Solution methods for IP's can also be categorized as optimal and heuristic. An optimal algorithm is one which (mathematically) guarantees to find the optimal solution. It may be that we are not interested in the optimal solution:

- because the size of problem that we want to solve is beyond the computational limit of known optimal algorithms within the computer time we have available ;
- we could solve optimally but feel that this is not worth the effort (time, money, etc) we would expend in finding the optimal solution.

In such cases, we can use a heuristic algorithm - that is an algorithm that should hopefully find a feasible solution which, in objective function terms, is close to the optimal solution. In fact, it is often the case that a well-designed heuristic algorithm can give good quality (near-optimal) results [2,19,34,36,37,39].

# CHAPTER 3
# 3G DOWNLINK CELL PLANNING AND OPTIMIZATION

Every cellular network requires cell planning and optimization in order to provide adequate coverage, capacity, and quality of service (QoS). A cell is the area served by a base station transmitter, which is the basic geographical unit of a cellular system. It is the smallest building block of a cellular network. In practice, engineers draw hexagonal-shaped cells on a layout to simplify the planning and design of a cellular system because it approaches a circular shape that is the ideal coverage area of a base station transmitter. In the real world, however, each cell varies depending on the radio environment. Due to constraints imposed by the natural and man-made terrain, the real shape of cells is very irregular. They can be classified as macrocells, microcells, and picocells.

Cell planning and optimization is a very complex task, as many aspects must be taken into account, including the topology, morphology, traffic distribution, existing infrastructure. Things become more complicated when several constraints are taken into account, such as the system capacity, service quality, frequency bandwidth. Cell planning and optimization generally consists of two parts: base station locationing and base station dimensioning. Base station location problem is mainly concerned with the site locations for the base stations and the number and type of base stations for each site. Base station dimensioning amount to selecting the optimal set of configuration parameters for each base station, such as height, maximum transmit power, and tilt angle. Therefore, cell planning and optimization can be defined as an optimization process which tries to find out an optimal set of base station sites from a large set of potential base station sites and finds out the optimum set of parameter values for each base station, subject to certain constraints, so that the optimal (or good enough) system performance is achieved and / or the cost is minimized. Clearly, the cell planning and optimization process is NP-hard.

In this chapter, we focus on planning efficient 3G downlink radio networks providing multi-services over a predefined service area. We formulate the 3G cell providing multi-services over a predefined service area. We formulate the 3G cell downlink planning problem as a discrete optimization problem, where the emitted power, antenna heights and base station locations are basic decision variables. A downlink scenario occurs when the BS runs out of transmit power. Additional users cannot be added without modifying the site configuration [56]. Downlink scenarios are likely to occur in suburban or urban environments where the network has been planned to handle a relatively high uplink cell load. The traffic associated with a downlink scenario is generally asymmetric with a greater amount of traffic on the downlink. Downlink scenarios are also likely to occur when the network has been configured with low BS transmit power capacity, which may have been done in some circumstances to reduce the requirement for power amplifier modules [91].

The main aspects [121,123,124,127] of our model and approach concern five points: firstly, instead of minimizing the cost, we consider the net revenue income as the objective, to better reflects the requirements of potential mobile operators. Secondly, the decision variables and traffic capacity are embedded in the objective function and are optimized in a single integrated step. This can result in the tradeoff between the cost reduction and the capacity improvement, compared with approaches where they are considered separately. Thirdly, the model represents a three-tier hierarchical cell structure that contains macrocell, microcell and picocell, because at each selected base station location, the network can use different equipment types to generate coverage areas corresponding to different cell sizes. Fourthly, the QoS constraints are set as hard constraints, while other works treat them as soft constraints [9,19,62]. Finally, because the optimal 3G radio network configuration is mainly a function of the geographical traffic demand features of the target service area, we incorporate different traffic classes, such as voice and a variety of data, into our model and consider the impacts of different types of traffic on choosing an optimal radio network configuration.

For solving such a difficult optimization problem we apply heuristic and stochastic optimization techniques. The detailed implementation of the methods is given in the next sections. Our goal is twofold: on the one hand to suggest effective algorithms for 3G downlink cell planning and optimization, on the other hand to discover inherent features of 3G downlink base station location and configuration with the help of optimization. The Sections 3.2 and 3.3 deal with the first issue. The second one is treated in Section 3.4.

## 3.1 System model

In this section, we present the system model for the third generation mobile hierarchical cell planning and optimization problem. The model proposed in this investigation is applicable for cell planning and optimization for 3G downlink environment. Our system model is built on the following basic elements: working area and traffic, propagation and link budget, base station configurations, and power control methods, etc. The following subsections provide details.

### 3.1.1 Working area and traffic

A working area is a geographical region where the mobile network is to be deployed. The working area is described by $\rho$. Any point from $\rho$ is referred by its coordinates $(x, y)$. Two discrete sets of points are identified on $\rho$.

- A set of sites which are candidates for the positioning of base stations, denoted by $S = \{1, \ldots, m\}$, where a BS can be installed and that an installation and maintenance cost $c_j$ is associated with each candidate site $j$, $j \in S$. Each site is defined by its coordinates $(x, y)$, and eventually by its height above sea level $z$.
- A set of traffic test points (TPs) $I = \{1, \ldots, n\}$. Each TP $i \in I$ can be considered as a centroid where a given amount of traffic $d_i$ is requested and where a certain level of service (measured in terms of $SIR$) must be guaranteed [110]. The required number of simultaneously active connections for TP $i$, denoted by $u_i$, turns out to be a function of the traffic, i.e., $u_i = \phi(d_i)$. The mobile terminals are located on TPs, where the network must overcome a signal quality threshold $SIR_{min}$, to ensure a given quality of service (QoS). The value of the threshold depends on the service

type. To check the signal quality level at each TP, the field strength has to be computed at each point.

### 3.1.2 Radio path

A number of parameters are specified to characterize the transmission, the radio path, and the reception. These parameters are explained next. For every pair ($i \in I,\ j \in S$) of mobile $i$ and base station $j$, there is path loss between the receiver and the transmitter. Due to, e.g., mast head amplifiers, this does not need to be symmetric for the uplink and downlink.

The path loss can be computed with data from the propagation model together with the characteristics of the antennas. It depends on:

- The path loss for the reference height and the height gain for the physical location of the transmitter and receiver.
- The properties of an installation such as the antenna gains for transmission and reception, antenna pattern, direction and tilt, cable and combiner loss and user of amplifiers. Especially the angle of radiation is important here.
- The properties of the mobile, like antenna gain and pattern, and cable and connector losses.
- The service specific body loss for the mobile's side of the transmission link.

Noise includes thermal noise and other noise sources, such as received noise and interference from distant antennas. We will use $\eta_0$ to represent downlink mobile noise. In this chapter, we assume omnidirectional BSs or directive BSs with a uniform horizontal diagram. We use COST 231 propagation model [27] to calculate the propagation gain $g_{ij}$, $0 < g_{ij} \leq 1$, for the radio link between TP $i$, $1 < i \leq n$ and a candidate location $j$, $1 < j \leq m$. The propagation information is thus summarized by the gain matrix $G = [g_{ij}]_{1 < i \leq n,\ 1 < j \leq m}$.

### 3.1.3 Base station

Many types of base station antennas exist with differing characteristics. These characteristics include radiation patterns, transmitter gains and losses, receiver gains and losses, and receiver sensitivity, etc. Some characteristics are fixed, while others are decision variables to be assigned during the optimization process. In this chapter, we will focus on decision variables. We assume that three types of antenna are available that could be deployed at a candidate site. These are an omnidirectional antenna, a small directional antenna, and a large directional antenna. The associated gains and losses of these antennas are shown in Table 3.1 [56].

**Table 3.1 Antenna gains and losses**

| Antenna | Gain (dB) | Loss (dB) |
|---|---|---|
| omni | 11.15 | 7 |
| small | 17.15 | 7 |
| large | 15.65 | 7 |

To configure an antenna, values for power, azimuth (horizontal direction of antenna relative to North) and tilt (vertical angle of the antenna, relative to the horizontal) need to be allocated by the cell planner (whether manually or automatically by an optimization system). The range for each of these values is generally as follows [69,94]:

- Power: 26 to 55 dBm,
- Height: 5 to 30m,
- Azimuth: $0^o$ to $359^o$ (for directional antenna only),
- Tilt: $0^o$ to $-15^o$ (for directional antenna only).

A base station can be described in the downlink environment by a sextuplet BS = (location, antenna, tilt, azimuth, power height). It corresponds thus to the choice of a site, maximum transmit power of antenna, and the parameter values of the antenna. For example, the BS = (356, LD, 0, 30, 38, 30) corresponds to the placement of three large directive antennas on the site numbered 356. This base station has a tilt of $0^o$, an azimuth of $30^o$, and maximum transmit power of 38 dBm. Other components are also involved in the definition of a BS, such as BS sectorization, BS receiver sensitivity, and the same applies to the mobiles. Since these values are constant for a given situation, they will not be further discussed in the chapter.

### 3.1.4 Mobile

As the BS, the mobile is defined by the following data:

- Antenna transmitter power,
- Antenna transmitter gain,
- Antenna transmitter loss,
- Receiver sensitivity,
- Receiver gain,
- Receiver loss.

### 3.1.5 Power control

In this chapter, we try two power control mechanisms in our downlink. One is the power-based power control mechanism, the other the *SIR*-based power control mechanism. The power-based power control means that the power emitted from any BS $j$ for a connection to any given TP $i$ is adjusted so as to guarantee a received power at TP $i$ equal to a target value $P_{tar}$. In a downlink direction, the signal quality constraint for each connection amounts to [99,121]:

$$\frac{P_{tar}}{\lambda I_{in} + I_{out} + \eta_0} \geq SIR_{\min} \tag{3.1}$$

where $SIR_{\min}$ is the minimum *SIR* before de-spreading and $\lambda$ is the orthogonality factor due to multipath propagation. $I_{in}$ is the total interference due to the signals transmitted by the same BS. $I_{out}$ is the interference received by the TP $i$ due to the signals from the other BSs. $\eta_o$ is the thermal noise power. We assume equality in (3.2) is guaranteed for a perfect power control. Ideally, WCDMA signals for two distinct downlink connections in one cell are orthogonal, that is, they are mutually not perceived as interfering. Multi-path propagation and diffraction weaken this property. The orthogonality factor states how much of a signal may be considered orthogonal, a factor of $\lambda$ = zero means total orthogonality. The remainder has to be treated as interference at the receiving mobile.

For each connection with the *SIR*-based power control, the emission power is adjusted so as to guarantee a signal quality level at a mobile that is equal to the minimum value $SIR_{\min}$. As we know, the *SIR* for a radio link depends on three factors. If $R$ is the data rate of the carried service, $W$ is the 3G UMTS specific chip rate of 3.84 MHz, and $E_b/I_o$ is the required ratio between signal bit energy and interference spectral density (including noise spectral density), then

$$SIR = \frac{S}{I} = \frac{E_b}{I_o} \cdot \frac{R}{W} \tag{3.2}$$

The $E_b/I_o$ depends on the service and on the speed of the mobile, among others [99]. So far the $E_b/I_o$ values have typically been obtained from radio link simulations, but more and more real measurements become available. $W/R$ is equal to the *spreading factor* (*SF*) (also called *processing gain*), which is the ratio between the spread signal rate and the user transmit rate. The de-spreading process performed at the receiving end can completely or partially suppress the interference of orthogonal signals and reduce that of other signals by the factor *SF*.

## 3.2 Downlink cell planning as an optimization problem

In this section, we define the decision variables, design constraints and objective function for profit-maximized 3G downlink cell planning and optimization, and formulate the decision process as a discrete integer optimization problem.

### 3.2.1 Decision variables

It is natural to model the available BS sites as a discrete set of geographical locations. In this case, there are some limitations on the antenna height depending on the tower height and the occupancy of the tower by other services. The antenna height of a BS can affect the area and shape of the cell coverage. In downlink environment, the emitted power of the BS antennas is also confined to a range of permitted values. In 3G, there is basically no need to do frequency planning. Other BS antenna configuration parameters are also considered. The antenna downtilt can reduce the interference to the neighboring cells and enhance the coverage for the weak spots within the cell. The directional antennas in a sectored cell can reduce co-channel interference and enhance system capacity.

For the purpose of illustration of the problem complexity, let us make an example as follows. Assume that the height and maximum transmit power of a BS antenna are illustrated in the following sets which are considered to be input parameters to 3G cell design:

$$\Im = \{(x_j, y_j)\} \quad j \in [1,m] \tag{3.3}$$

$$\Re^j = \{P_t^j\} \quad t \in [1,P^j], j \in [1,m] \tag{3.4}$$

$$\aleph^j = \{H_t^j\} \quad t \in [1,H^j], j \in [1,m] \tag{3.5}$$

Set $\Im$ in (3.3) represents available BS sites. Assume each site can host at most one BS. The power set (3.4) and antenna set (3.5) are defined individually for each BS antenna. The symbols $m$, $P^j$ and $H^j$ denote the size of the respective sets.

To formulate the problem, we introduce the following decision variables with respect to site ($x_j$, $y_j$):

| | |
|---|---|
| $y_j = \{0,1\}$ | BS activity indicator, defined such that $y_j = 1$ if site $j$ is occupied by a BS, $y_j = 0$ otherwise. |
| $p_j = \lfloor 1, P^j \rfloor$ | Index of the emitted power of antenna at site ($x_j$, $y_j$). It indexes the feasible power set, $\Re^j$. This figure is meaningful only if $y_j = 1$. |
| $h_j = \lfloor 1, H^j \rfloor$ | Index of the antenna height at site ($x_j$, $y_j$). It indexes the feasible BS antenna height set, $\aleph^j$. This figure is meaningful only if $y_j = 1$. |

Therefore, the vectors $\boldsymbol{y}$, $\boldsymbol{p}$, and $\boldsymbol{h}$ determine the radio access network (cell system configuration).

Assuming $N$ new BSs and the same power and antenna height sets at each location, i.e., $P^j = P$ and $H^j = H$ for $j \in [1,m]$ with size $P$ and $H$ respectively, the set of possible configurations ($\Omega$) of the planning problem has the size of

$$\Omega = (P.H)^N . \frac{m!}{(m-N)!.N!} \tag{3.6}$$

provided that not more than one BS can be placed at a single site. If we also let $N$ be a decision variable, the size of the total state space becomes

$$\Omega = (P.H + 1)^m - 1 \tag{3.7}$$

The primary objective of our downlink cell planning and optimization is to configure a radio access network such that the capacity requirements of all traffic demand TPs in the working area and the signal quality at each TP are satisfied as much as possible. A traffic demand node TP can be served by a BS only if the signal quality from the BS at the TP point meets a system-specific requirement. Therefore, the number of BSs and their configurations in a solution depend not only on the total required capacity demand of all TPs but also on the signal quality constraint at the TPs. If we do not consider the configuration of other BS parameters (except height, maximization transmit power, and antenna horizontal direction), we can introduce an integer variable $x_{ij}$ to represent a capacity assignment at BS site $j$ for service of TP $i$.

Let us define the two basic classes of decision variables:

$$x_{ij} = \begin{cases} 1 & \text{if TP } i \text{ assigned to a BS } j \\ 0 & \text{otherwise} \end{cases} \tag{3.8}$$

$$y_j = \begin{cases} 1 & \text{if a BS installed at site } j \\ 0 & \text{otherwise} \end{cases} \tag{3.9}$$

for $i \in I$ and $j \in S$. Suppose we consider directive BSs with three identical 120 degree sectors and with an omnidirectional antenna diagram along the horizontal axis. Let the index set $I_j^{\sigma} \subseteq I$ denote the set of all TPs $I$ that fall within the sector $\sigma$ of the BS installed in site $j$. obviously, for each $j$, $I_j^1 \cup I_j^2 \cup I_j^3 = I$ and the index sets $I_j^{\sigma}$ with $\sigma = 1, 2, 3$ are disjoint.

We now turn to the general setting in which a BS antenna can be in one out of $q$ different configurations, denoted by set $L = \{1,\ldots, q\}$[127]. A configuration represents a sextuplet BS = (location, type, height, tilt, azimuth, power). This accounts, for instance, for a variable tilt selected out of a set of possible angles with respect to the vertical axis, and for a variable height selected from a finite set of values with respect to the ground level. Since propagation gains depend on the BS antenna configuration, we denote by $g_{ij}^{w}$ the propagation gain from TP $i$ to potential site $j$ if the BS antenna is in configuration $w$. For the general setting, extended decision variables are needed for each configuration:

$$x_{ijw} = \begin{cases} 1 & \text{if TP } i \text{ assigned to a BS } j \text{ with configuration } w \\ 0 & \text{otherwise} \end{cases} \tag{3.10}$$

$$y_{jw} = \begin{cases} 1 & \text{if a BS with configuration } w \text{ installed at site } j \\ 0 & \text{otherwise} \end{cases} \tag{3.11}$$

for $i \in I$, $j \in S$ and $w \in L$. Once these basic decision variables have been determined, other dependent variables, such as loading factors and *SIR* for each mobile terminal, etc., can be easily derived from.

### 3.2.2 Design constraints

Constraints (3.12) below make sure that each TP $i$ is assigned to at most one BS. Note that by restricting the assignment variables $x_{ijk}$ to take binary values, it is required that in every feasible solution all active connections must be assigned to a single BS. In order to simplify the problem, we do not consider the mobility factors, such as soft handoff.

$$\sum_{j \in S} \sum_{w \in L} x_{ijw} \leq 1 \tag{3.12}$$

If the left hand side of constraints (3.12) was forced to be equal to one, that is, each TP must connect to a BS, the results would too demanding for network resources. In some cases, a feasible solution would not be found. Therefore, constraints (3.12) are relaxed and intentionally allow some TPs not to be assigned.

Another set of constraints are common for both power-based power control model and *SIR*-based power control model. This set of constraints is called minimum service requirements. In the United States, the Federal Communications Commission (FCC) regulates the telecommunications industry. Rather than stipulating the proportion of the population in each coverage area that has to have access to service, the FCC has regulated the rate at which a service provider develops a market [58]. The stipulations are as follows:

- From the date the license is granted, each service provider has five years to develop a network infrastructure to service the allocated market. For a service provider with a license for 30 MHz of bandwidth, the network has to be able to reach geographical areas that combined have at least 1/3 of the population in the market. For a service provider with a license for 15 MHz of bandwidth, the corresponding requirements is at least ¼ of the population in the market.
- At the end of this five-year period, any geographical area within a market that is not covered with sufficient signal strength to offer service in this area will be revert back to the FCC for allocation to other service providers.
- Within 10 years from the date the license is granted, one 30 MHz licensee must cover geographical areas that combined have at least 2/3 of the population in the market.

The minimum service restrictions are handled by the following set of constraints:

$$\sum_{j\in S}\sum_{w\in L}\sum_{i\in I}\mu_i x_{ijw} \geq \beta.\sum_{i\in I}\mu_i \tag{3.13}$$

The constraints (3.13) ensure that service is available in the working area that have at least a proportion $\beta$ of all traffic demand nodes.

In our model, the cost of a BS involves the cost of site installation and cost of the configuration:

$$C_j(y_{jw}) = C_j^S + C_j^L \tag{3.14}$$

The overall cost of a radio access network in the predefined working area, $C(\mathbf{y})$, is the sum of the non-configuration cost of each BS antenna $C_j^S$, and its associated configuration cost $C_j^L$, i.e., $C(\mathbf{y}) = \sum_{w\in L}\sum_{j\in S} y_{jw}.C_j(y_{jw})$. Cost is an extremely important factor for choosing an adequate network configuration. Denote $C_{max}$ an externally given ceiling cost, or a budgetary limit in total monetary investment. In most cases, it is practical to consider the budget constraints as follows:

$$\sum_{w\in L}\sum_{j\in S} y_{jw}.C_j(y_{jw}) \leq C_{max} \tag{3.15}$$

### 3.2.2.1 Constraints with power-based power control model

Constraints (3.16) correspond to the most stringent constraints among the coherence

$$x_{ijw} \leq \min\left\{1, \frac{g_{ij}^{w} P_{\max}}{P_{tar}}\right\} y_{jw} \tag{3.16}$$

constraint $x_{ijw} \leq y_{jw}$, which ensures that TP $i$ is only assigned to site $j$ if a BS with configuration $w$ is installed in $j$, and the power limit on a single connection from BS $j$ to TP $i$:

$$\frac{P_{tar}}{g_{ij}^{w}} x_{ijw} \leq P_{\max} y_{jw} \tag{3.17}$$

where $P_{max}$ is the maximum emission power for the connection from site $j$ to TP $i$ and $P_{tar}/g_{ij}^{w}$ corresponds to the emission power required by BS $j$ to guarantee the target received power $P_{tar}$ at TP $i$. For each pair of site $j \in S$ and TP $i \in I$, constraints (3.17), which are active only if TP $i$ is assigned to BS $j$ (i.e., $x_{ijw} = 1$), correspond to the signal quality requirement. Finally, constraints (3.18) impose an upper limit $P_{tot}$ on the total emission power of every BS.

$$\sum_{i \in I} \frac{P_{tar}}{g_{ij}^{w}} x_{ijw} \leq P_{tot} y_{jw} \tag{3.18}$$

Please note that the subscripts $i \in I$, $j \in S$ and $w \in L$ are applicable to all the constraints in this chapter, unless otherwise stated.

In addition to the constraints (3.17) and (3.18), the quality of service constraints should be emphasized. Since in a power-based power control mechanism $P_{tar}/g_{ij}^{w}$ is the power that needs to be emitted from a BS with configuration $w$ in site $j$ to guarantee a received power of $P_{tar}$ at TP $i$. For each connection between a BS installed in $j$ and a TP $i$ falling in a sector of this BS, the $SIR$ constraints can be expressed as follows [7]:

$$\frac{P_{tar} x_{ijw}}{\alpha \left( \sum\limits_{\substack{k \in I_j^{\sigma_{ijw}} \\ x_{kjw}=1}} u_k \frac{g_{ij}^{w} P_{tar}}{g_{kj}^{w}} x_{kjw} - P_{tar} \right) + \sum\limits_{v \in L} \sum\limits_{\substack{l \in S \\ l \neq j}} \sum\limits_{\substack{k \in I_l^{\sigma_{ilv}} \\ x_{kl}=1}} u_k \frac{g_{il}^{v} P_{tar}}{g_{kl}^{v}} x_{klv}} = SIR_{\min} x_{ijw} \tag{3.19}$$

where for any site $l \in S$, $w \in L$, the index set $I_l^{\sigma_{ilw}}$ denotes the set of all TPs in $I$ that fall within the sector $\sigma_{ilw}$ of the BS with configuration $w$ and location $l$, which contains TP $i$.

For any single connection between a BS located at site $j$ and a TP $i$ falling in one of its sectors (denoted by $\sigma_{ijw}$), the numerator of the left-hand-side term in constraints (3.19) corresponds to the power of the relevant signal received at TP $i$ while the denominator amounts to the total interference due to all other active connections in the working area. Indeed, the first summation term expresses the total power received at TP $i$ that is directed from BS $j$ to every TP $k$ in $I_j^{\sigma_{kjw}}$, i.e., all TPs assigned to BS $j$ with configuration $w$ and falling within the same sector as TP $i$, from which the received power $P_{tar}$ of the relevant signal is subtracted. The second summation term expresses the interfering power received at TP $i$ that is directed from all BSs $l$, with $l \neq j$, to other TPs falling within the sectors $\sigma_{ilv}$ of each BS $l$ that do also contain TP $i$.

### 3.2.2.2 Constraints with *SIR*-based power control model

For each connection, the emission power is adjusted so as to guarantee a signal quality level that is equal to or greater than a target value $SIR_{tar}$. This is a more sophisticated power control mechanism. Since the received power at each mobile terminal $p_i$, $i \in I$, must be considered as an explicit decision variable. If TP $i$ is assigned to a site $j$, $p_i$ is not taken to be equal to $P_{tar}$, but to be enough to have $SIR = SIR_{tar}$. In the presence of a *SIR*-based power control mechanism, the emission power values $p_i$ can be freely selected provided they do not exceed the maximum transmit power $P_{max}$ that a BS is allowed to assigned to a mobile terminal. Constraints (3.20) state that a TP $i \in I$ can be assigned to a BS $j \in S$ only if a BS with a configuration $w \in L$ has been installed in $j$:

$$x_{ijw} \leq y_{jw} \tag{3.20}$$

Since the received power must be nonnegative and there exist an upper bound on the maximum power $P_{max}$ that a BS can assign to each connection, we have:

$$0 \leq p_i \leq \sum_{j \in S} \sum_{w \in L} P_{\max} g_{ij}^{w} x_{ijw} \tag{3.21}$$

Moreover, the limit on the total power that each BS $j$ can emit is accounted for by the following inequality:

$$\sum_{i\in I}\frac{p_i}{g_{ij}^{w}}x_{ijw} \le P_{tot}\,y_{jw} \tag{3.22}$$

Given the *SIR*-based power control mechanism, for each pair of TP $i$ and site $j$, we consider the following *SIR* constraints:

$$\frac{p_i x_{ijw}}{\alpha\left(\sum\limits_{\substack{k\in I_j^{\sigma_{ijw}}\\ x_{kj}=1}} u_k \frac{g_{ij}^{w} p_k}{g_{kj}^{w}} x_{kjw} - p_i\right) + \sum\limits_{v\in L}\sum\limits_{\substack{l\in S\\ l\neq j}}\sum\limits_{\substack{k\in I_l^{\sigma_{ilv}}\\ x_{kl}=1}} u_k \frac{g_{il}^{v} p_k}{g_{kl}^{v}} x_{klv} + \eta_0} = SIR_{tar} x_{ijw} \tag{3.23}$$

which makes sure that the *SIR* of any active connection between BS $j$ and TP $i$ (i.e., $x_{ijw}$ = 1) is equal to or greater than $SIR_{tar}$. Note that constraints (3.23) are trivially satisfied whenever $x_{ijw} = 0$. The thermal noise $\eta_0$ should play a role in simulation convergence and cannot be omitted as in the model with power-based power control mechanism.

In the *SIR*-based model, if a current set of active BSs, denoted by the vector $\boldsymbol{y}$ and an assignment vector $\boldsymbol{x}$ of the TPs to these active BSs are known, the corresponding value of the power $p_i$ received by each TP $i$ from the BS it is assigned to can be determined by solving the corresponding simultaneous linear equations from the equalities in (3.23). For the purpose of clearer illustration, we do not consider the configuration variable $w \in L$ in the following formulation. Consider the *SIR* constraints (3.23) (omit $w$ variable) and define for each TP $i$ the following coefficients:

$$b_{ik} = \begin{cases} \alpha(\mu_k - 1) & \text{if } k = i, \\ \alpha(\mu_k \dfrac{g_{ij}}{g_{kj}} x_{kj}) & \text{if } k \neq i \text{ and both TPs are assigned to} \\ & \text{the same sector } \sigma_{ij} \text{ of BS } j, \\ \mu_k \dfrac{g_{il}}{g_{kl}} x_{kl} & \text{if } k \neq i \text{ and TP } k \text{ is assigned to a sector } (\sigma_{kl}) \\ & \text{of BS } l, l \neq j, \text{ which also contains TP } i, \\ 0 & \text{otherwise} \end{cases} \tag{3.24}$$

Then the *SIR* constraints (3.23) become a system of linear equations:

$$\frac{p_i}{\sum_{k\in I_j^\sigma} b_{ik}p_k + \eta_0} = SIR_{tar} \tag{3.25}$$

which can be rewritten as:

$$p_i = SIR_{tar}\left(\sum_{k\in I} b_{ik}p_k + \eta_0\right) \tag{3.26}$$

Discarding the *SIR* constraints (3.23) corresponding to pairs of BS $j$ and TP $i$ with $x_{ij} = 0$, we obtain a linear system with one equation for each TP $i \in I$ that is assigned to a given BS, i.e., such that $\sum_{j\in S} x_{ij} = 1$ for the given assignment pattern $\boldsymbol{x}$. Thus, for each TP $i$ assigned to a BS, the received power $p_i$ can be determined by solving a linear system of $n$ simultaneous equations with $n$ variables. By letting $\mathbf{B}$ denote the $n \times n$ matrix composed of coefficients $b_{ik}$ and $\boldsymbol{p}$ the $n$-dimensional power's vector, the equations can be written as:

$$\boldsymbol{p} = SIR_{tar}(\mathbf{B}.\boldsymbol{p} + \eta_0\mathbf{1}) \tag{3.27}$$

where $\mathbf{1}$ is the n-dimensional vector with all 1 components. Note that the candidate values of the received powers $p_i$ provided by the solution:

$$\boldsymbol{p} = \eta_0\left(\frac{1}{SIR_{tar}}\mathbf{1} - \mathbf{B}\right)^{-1}\mathbf{1} \tag{3.28}$$

must be verified. If each one of these $p_i$ values satisfies the corresponding constraints (3.21), the solution composed by $\boldsymbol{y}, \boldsymbol{x}, \boldsymbol{p}$ is feasible. Otherwise, some TPs must be put into outage (by setting $x_{ij} = 0$ for some $i$ and all $j$ in S) in order to obtain a feasible solution. Since TPs that are far away from their BSs require higher emitted powers which in turn tend to generate higher interference, we try to delete first TPs that are farther away from the BSs they are assigned to.

### 3.2.3 Problem formulation

Our aim is to formulate the 3G cell downlink planning problem as an optimization problem. The available cell sites ($S$), the traffic demand nodes ($I$) with capacity requirements ($\mu$), configuration set ($L$) are fixed input parameters. We will introduce three formulations of the cell planning problem. In all cases, the following variables are the basic decision variables:

- The number of selected base stations and their configuration, denoted by multi-dimensional vector $\boldsymbol{y}$ and $\boldsymbol{w}$,
- The capacity assignment matrix, $\boldsymbol{x}$,
- The power assignment vector (mobile transmitter participation), $\boldsymbol{p}$.

Based on these basic decision variables, most of radio access network parameters can be derived from.

#### 3.2.3.1 Minimal cost planning

A practical objective deals with the price of the solution in terms of installation and provision costs. In this formulation, the goal of the planning is to achieve as low cost as possible. Instead of optimizing the technical performance, such as coverage outage, which would potentially lead to a network with unnecessary high resource usage, we choose the objective for minimizing the network cost. The planning objective is defined as follows:

$$\text{minimize} \qquad \sum_{w \in L} \sum_{j \in S} y_{jw} . C_j (y_{jw}) \tag{3.29}$$

subject to (power-based power control model)
(3.10), (3.11), (3.12), (3.13), (3.15), (3.16), (3.18), (3.19).

Or (*SIR*-based power control model)
(3.10), (3.11), (3.12), (3.13), (3.15), (3.20), (3.21), (3.22).
(3.23).

### 3.2.3.2 Maximum capacity planning

A more real-life formulation of the cell planning problem is to aim for maximizing the satisfied capacity demands. The optimization problem can be written as:

$$\text{maximize} \qquad \sum_{w\in L}\sum_{j\in S}\sum_{i\in I}\mu_i x_{ijw} \tag{3.30}$$

subject to (power-based power control model)

(3.10), (3.11), (3.12), (3.13), (3.15), (3.16), (3.18), (3.19).

Or (*SIR*-based power control model)

(3.10), (3.11), (3.12), (3.13), (3.15), (3.20), (3.21), (3.22).

(3.23).

The objective function is the sum of the served capacity demands. The constraints for this optimization scenario are the same as in the previous formulation.

### 3.2.3.3 Maximum profit planning

This model explicitly considers the trade-off between the revenue potential of each BS site with its cost of installation and configuration. This trade-off is subject to *QoS* constraints in terms of sufficient *SIR* ratios ((3.19), or (3.23)). The objective of the model is to maximize the total annual profit generated by the cellular network operator, which is equal to the total annual revenue minus the annual costs. Mathematically we have:

$$\text{maximize} \qquad \theta\sum_{w\in L}\sum_{j\in S}\sum_{i\in I}\varepsilon\mu_i x_{ijw} - \sum_{w\in L}\sum_{j\in S} y_{jw}.C_j(y_{jw}) \tag{3.31}$$

subject to (power-based power control model)

(3.10), (3.11), (3.12), (3.13), (3.15), (3.16), (3.18), (3.19).

Or (*SIR*-based power control model)

(3.10), (3.11), (3.12), (3.13), (3.15), (3.20), (3.21), (3.22).

(3.23).

$\varepsilon$ denotes the annual revenue ($) generated by each channel utilized in the working area. $\theta$ is a weighting factor. Relation (3.31) represents the maximum profit optimization when $\theta$ = 1.

### 3.3 Optimization methods

We will apply three heuristic algorithms to solve the 3G downlink cell planning and optimization problem, namely, greedy local search algorithm, simulated annealing, and tabu search. The three different search heuristics are then compared with each other for their performance on the problem using the best parameters from the previous experiments.

In order to apply three heuristic algorithms to the planning problem, we must define:

- An initial feasible solution,
- Neighborhoods for feasible solutions, and
- Costs of solutions or objective functions.

Initial solutions appear in two flavors: random, and the result of a greedy algorithm. each has its companions. In our implementation, the randomly generated initial solutions are used. The definition of neighborhood used in the search methods can affect performance. The key to a good neighborhood definition is primarily ease of manipulation. A good formulation makes all of the manipulation and computation flow quickly and easily. A clumsy neighborhood adds to the algorithm's complexity.

This brings up the computational methods and data structures, which are part of the local search heuristics. We must also develop:

- Representations for feasible solutions,
- Search techniques for neighborhoods, and

- Evaluation methods for gains in cost.

Most feasible solution representations are straightforward. Occasionally clever representations can be found which are easier to manipulate than obvious one. Thus designing solution representations is an art form.

Searching neighborhoods can be very time consuming if the neighborhood is large and if evaluating the objective function for solutions in the neighborhood is lengthy. There are two common search strategies. One is a greedy search called *first improvement* because the first solution found that is better than the original is immediately adopted. The other involves searching the entire neighborhood for the best solution and is called *steepest descent*. It is not clear that the extra time involved in searching an entire neighborhood is that useful. The following subsections describe the implementation details of the solution representation, neighborhood definition, and search technique for neighborhood.

### 3.3.1 Solution representation

Decision variables are the BS locations, their powers, their antenna heights, etc.. Given the BS locations, powers, heights, etc., a radio access network configuration is defined as a set of vectors $[(x_1, y_1, p_1, h_1, \ldots), \ldots, (x_m, y_m, p_m, h_m, \ldots)]$, which can be represented abstractly by the previously introduced network configuration vector $\boldsymbol{y}$. In practice, configuration parameters can take values from a certain range. For example, the power of each BS takes values from a certain range, i.e., $p_j \in [p_{min}, p_{max}], j \in S$. similarly, the antenna height of each BS takes values from a certain range, i.e., $h_j \in [h_{min}, h_{max}], j \in S$. although powers and antenna heights and other configuration parameters can take theoretically any values within their respective ranges, the available sizes of BSs in the market take certain discrete values only. The resolution of the discretization within the respective ranges is assumed to sufficiently represent practical solutions. After a network configuration $\boldsymbol{y}$ is decided, every traffic demand nodes TP $i \in I$ is assigned to a serving BS using a demand allocation algorithm, described later in this section, that is, to determine the vector $\boldsymbol{x}$.

Each point in the search space would represent which subset of the potential locations were actually chosen, and their respective configurations, plus the capacity assignment pattern (denoted by vector $\boldsymbol{x}$). As shown later, $\boldsymbol{x}$ is automatically determined once the configuration vector $\boldsymbol{y}$ is chosen. This is, we create two solution vectors. The first, $\boldsymbol{y}$, holds only the network configuration information, and is used to perform a heuristic search over which BSs are open (built) and which are closed (not built), as well as their respective configuration parameters. The second vector $\boldsymbol{x}$, maintains the assignment of a traffic demand node TP to a BS and represents a part of solution to the problem. It is only used to store solutions as they are found and not used actively in the heuristic search process. As mentioned previously, heuristic search decides which BS and its configuration parameters will be open or closed, but the assignment of traffic to BSs is performed by the capacity assignment algorithm, executed after each move.

### 3.3.2 Neighborhood definition

Each feasible search space point, denoted by $J(\boldsymbol{x}, \boldsymbol{y})$, is a particular set of locations, powers, heights, and other configurations for each BS, and a particular assignment pattern of demand nodes to each selected BS satisfying the various constraints. To generate a new neighbor, two sets of neighborhood generating operators are required, one that moves the locations and configurations of BSs and another that changes the demand node assignment for each BS. The first set of operators is defined as follows:

- *on-off:* a BS site is chosen randomly. If there is a BS at the site, it is removed. If there is no BS at the site yet, a new BS is placed at the site.
- *local move:* one of the decision variables (power, height, or other configuration parameters) of a randomly chosen BS is appointed randomly, and the new neighbor is generated by taking its value one size above or one size below its current value.

### 3.3.3 Capacity assignment algorithm

The second set of operators is the capacity assignment algorithm as shown below. Given the locations of BSs, their powers, heights and other configurations, demand nodes $I$ should be assigned first to the available BS that has the largest signal attenuation factor before establishing connections to other node Bs (*we can prove it mathematically*). The algorithm works like this:

- *Step 1.* Start with a given radio access network configuration $\boldsymbol{y}$.
- *Step 2.* For each $i \in I$, calculate minimum power $P_{tar} / g_{ij}^{w}$ (for *SIR*-based power control, we use $g_{ij}^{w}$ as criteria) according to propagation matrix $G = [\, g_{ij}^{w} \,]$; assign demand node $i$ to its closest BS $j$, requiring the minimal transmit power; calculate $\boldsymbol{x}$. In this step, constraints (3.16) are automatically satisfied.
- *Step 3.* If $\boldsymbol{x}$ from step 2 and $\boldsymbol{y}$ satisfy constraints (3.18), go to step 4; otherwise repeat the process: randomly select and disconnect a demand node $i$ belonging to the overcrowded BS $j$, which will reduce its transmit power accordingly, until constraints (3.18) are satisfied.
- *Step 4.* If $\boldsymbol{x}$ from step 3 and $\boldsymbol{y}$ satisfy constraints (3.19), go to step 5; randomly select and disconnect a demand node $i$ belonging to the overcrowded BS $j$, which will reduce its transmit power accordingly, until constraints (3.19) are satisfied.
- *Step 5.* Output final capacity assignment vector $\boldsymbol{x}$.

### 3.3.4 Initial solution generation

An initial network configuration is generated by intuitively (randomly) placing BSs at potential locations with a uniform distribution, in such a way that the number of initial locations is approximately half the total number of possible locations in our implementation, and assigning their powers, antenna heights, and other configuration parameters within the respective feasible ranges. Then every traffic demand node TP $i$ is assigned to a closest serving BS using the demand assignment algorithm, described earlier in this section.

The next step is the optimization process. The heuristic algorithm receives as input the initial network configuration, finds better configurations by improving the measure of performance in successive iterations and returns a final good quality network configuration and traffic assignment pattern.

### 3.3.5 Simulated annealing

A detailed description of SA can be found in [53]. In precise (though general) terms, the algorithm will include the following steps:

- *Step 0.* Set up the algorithm parameters, including initial ($t_o$) and stopping ($t_f$) temperatures, cooling schedule.
- *Step 1.* An initial solution $J^o(\mathbf{x}, \mathbf{y})$ is chosen randomly in such a way that the number of BSs is equal to half the total potential locations, and that the power, the height and other configuration parameters of a selected BS are chosen from an element of the corresponding feasible set. Then, the capacity assignment algorithm is applied to generate the demand node assignment pattern. Calculate the network cost, $f(J^o)$ from relation (3.29), (3.30), or (3.31).
- *Step 2.* Initialize iteration counter variable, $l \leftarrow 0$.
- *Step 3.* Repeat
  - ✓ Step 3.1. $l \leftarrow l + 1$.
  - ✓ Step 3.2. Choose at random a new candidate configuration $J^{l+}$, which is generated based on the current configuration $J^l$, according to the neighborhood operators. Usually, two consecutive states are different from each other in a small detail.
  - ✓ Step 3.3. Choose at random $\theta \in [0, 1]$.
  - ✓ Step 3.4 If $\theta \leqslant \min\{1, \exp([f(J^{l+}) - f(J^l)]/t_j\}$, then $J^{l+1} \leftarrow J^{l+}$; else, $J^{l+1} \leftarrow J^l$.
  - ✓ Step 3.5 Choose $t_{l+1} \leqslant t_l$.
- *Step 4.* Until $t_{l+1} \leqslant t_f$.
- *Step 5.* Stop.

### 3.3.6 Tabu search

In tabu search, besides the neighborhood definition, cost function, set of moves as described previously, other important implementation aspects have to be determined: aspiration conditions and candidate list. According to aspiration conditions, a subset of the taboo moves in the tabu list may be overridden,. The new best solutions will be selected among those that are neighboring and either not taboo, or taboo and aspirant. The specific solution selected is the one that is best in the implementation of the objective function. Solutions are placed in the taboo set to escape from local optima and prevent cycling. The aspiration criteria are applied to maintain some promising solutions. In our implementation, in order to reduce complexity, instead of searching all the points in the neighborhood, a subset of these points called the candidate list is considered at each step. The size of the candidate list may even be varied as the search proceeds. The tabu search implementation for the cell planning and optimization problem may be described as follows:

- *Step 0.* $l \leftarrow 0$. The counter of the algorithm iterations, $l$, is initialized. An initial solution $J^o(\boldsymbol{x}, \boldsymbol{y})$ is chosen randomly in such a way that the number of BSs is equal to half the total potential locations, and that the power, the height and other configuration parameters of a selected BS are chosen randomly from an element of the corresponding feasible set. Then, the capacity assignment algorithm is applied to generate the demand node assignment pattern. Calculate the network cost, $f(J^o)$ from relation (3.29), (3.30) or (3.31). The set of taboo and aspirant moves is initialized, i.e., $T(l) = \varnothing$, and $A(l) = \varnothing$. A candidate list $M(l)$ is initialized.
- *Step 1.* If the stop criterion is satisfied, the procedure ends and a transition to *Step 9* is performed.
- *Step 2.* The set of move operators $M$ is applied to solution $J^l$, and hence, a new set of candidate solution list $M(l)$ is produced. Each move produces a new neighbor of the current search space point.
- *Step 3.* The $M(l)$ set is examined to satisfy the constraints (3.17), (3.18), and (3.19)

(assume power-based power control model) forms the new set of solutions $N(l)$ that are neighbouring to solution $J^l$.

- *Step 4.* The set of solution, $C(l)$, that are candidate for obtaining the best solution status, and therefore, for replacing solution $J^l$ in the next algorithm iteration, is formed through the relation $C(l) = N(l) - T(l)$. Moreover, solution $J^l$ is appended in the $C(l)$ set.
- *Step 5.* The $A(l)$ set is formed. More specifically, the objective function value that is scored by the solutions in the $T(l)$ set is computed. Those solutions that improve the objective function by more than a given level are removed from the $T(l)$ set and placed in the $A(l)$ set.
- *Step 6.* The set of solutions $C(l)$ is enhanced through the relation $C(l) = C(l) \cup A(l)$.
- *Step 7.* The solution of the $C(l)$ set that is the best in improving the objective function becomes the best solution that will be used in the next algorithm iteration.
- *Step 8.* $l \leftarrow l + 1$. The next algorithm iteration is prepared. Therefore, the set of taboo moves that will be used in the next algorithm iteration is updated through the relation $T(l + 1) = T(l) \cup M(l)$. Moreover, solutions that have stayed in the taboo set for more than a given number of algorithm iterations are removed form the $T(l + 1)$ set. Finally, $A(l + 1) = \varnothing$ and $C(l) = \varnothing$. A transition to *Step* 1 is performed.
- *Step 9.* End.

## 3.4 Numerical simulations

Numerical experiments are made for 3G downlink cell planning and optimization. The system performance evaluations are based on 3G WCDMA system specification. The optimization strategies used in these experiments are also applicable to other systems (e.g., TD-SCDMA, CDMA 2000). We will present in detail a realistic planning scenario in this section.

### 3.4.1 Input data

For the fictitious realistic-sized planning scenario, the geographical area of 2 km × 2 km is discretized, thus being divided into 200 × 200 grid points. Each grid point represents the abstract center of a rectangular area of 10 m × 10 m. The grid size should be smaller than the size of cells and the finer the grid the more accurate the results. Traffic demand node TPs and potential BS locations are located in those grid points. As described in section 3.1, each traffic demand node $\mu_i$, $i \in I$ is characterized by the channel requirements. Since 3G networks is intended to provide not only voice but also data services, it is interesting to investigate the effect of mixed traffics on 3G radio access network capacity, coverage and investment cost, for example, 10% of TPs is web-browsing traffics, 20% data services, 70% voices. As we know, each type of traffic needs different WCDMA spreading factors, different *SIR* requirements, etc..

**Table 3.2 3G downlink cell planning and optimization system data**

| Parameters | Values |
|---|---|
| Mobile antenna height | 1.8 m |
| BS antenna height | {10, 20, 30}m |
| BS antenna maximum transmit power | {20, 40, 80, 120}w |
| Frequency | 2 GHz |
| Mobile antenna gain | 0 db |
| BS antenna gain | 14 db |
| BS costs with transmit power{20, 40, 80, 120}w ($K) | {100, 150, 200, 250} |
| $SIR_{min}$ | 0.009789 |
| $E_b/I_o$ | 7 db |
| Processing gain | 512 |
| Mobile receiver sensitivity | -110 dBm |
| WCDMA orthogonality factor | 0.7 |
| Thermal noise density | -130 dBm/Hz |
| Annual revenue for each channel($) | 10,000 |

In our fictitious realistic-sized planning scenario, there are 800 demand nodes ($n$) uniformly distributed over the 2 km × 2 km geographical area, and each demand node channel requirement $\mu_i$ randomly takes a value from the set {1, 2, 3, 4} for each $i \in I$.

There are 150 potential candidate BS locations ($m$) which are randomly generated with an uniformly distribution. For the purpose of simplicity, each potential location can accommodate an omnidirectional BS antenna with its maximum transmit power and height as configuration decision variables. COST 231 Hata urban propagation model is used to generate propagation gain matrix $\boldsymbol{G}$. Table 3.2 contains important planning input data necessary to compute capacity, coverage, load factor, *SIR*, location, final investment cost, and other configuration parameters.

### 3.4.2 Algorithm performance comparison

We randomly generate an initial configuration of the fictitious realistic-sized planning scenario, in a way that the number of initial solutions is half the total number of potential locations (150), that is 75. The values of antenna powers and heights are randomly assigned to each selected BS. The demand assignment algorithm of section 3.3.3 is used to allocate 800 TPs to BSs. We choose tabu search tenure $K$ = 7 and candidate list size $V$ = 10; simulated annealing cooling rate $\delta$ = 0.9 and homogenous Markov chain length $\tau$ = 50. Table 3.3 shows the experimental results of the average performance of tabu search and its comparison to simulated annealing and the greedy algorithm for the deployment the realistic-sized planning scenario over its five test cases. Our purpose here is to maximize total profit realization as shown in section 3.2.3.3. Please note that the power-based power control mechanism is incorporated in the optimization process. For each set of comparisons, each test case runs for 10 times, each time consisting of 1,000 iterations for each algorithm. We execute the C++ programs on computers with P4 1.8 Ghz. For the purpose of simplicity, we assume the antenna height (20m) is the same for each selected BS, , the feasible power set of {20, 40}[w] and its corresponding cost of {100, 150}[K], and each site cost of 100 [K]. Table 3.3 reports the results obtained with the three algorithms. For each algorithm, the first column means average percentage of served traffic, the second and third columns mean average numbers of the first and second power level BSs selected respectively. Each demand node takes the number of channels from the set {1, 2, 3, 4}. The second column of the Table 3.3 represents the channel requirement for each generated case.

**Table 3.3 Simulation results obtained with tabu search, simulated annealing, and greedy algorithm for very large sized instances with $m$ = 150, $n$ = 800, and total average 2000 channel requirement**

| | Total channel required | Tabu search | | | Simulated annealing | | | Greedy algorithm | | |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 2107 | 57.63% | 6.11 | 4.80 | 57.78% | 7.45 | 5.00 | 57.09% | 10.40 | 3.20 |
| 2 | 2002 | 61.12% | 5.22 | 9.60 | 58.93% | 4.00 | 9.20 | 58.89% | 9.37 | 5.50 |
| 3 | 1999 | 59.34% | 6.27 | 6.34 | 57.10% | 3.85 | 7.35 | 57.82% | 9.00 | 5.02 |
| 4 | 1981 | 62.89% | 4.66 | 7.18 | 59.53% | 7.55 | 2.50 | 58.84% | 4.67 | 7.25 |
| 5 | 2114 | 60.07% | 6.05 | 6.50 | 57.78% | 6.45 | 5.00 | 57.09% | 8.40 | 4.20 |

The performance measures are: (1) best objective value, (2) worst objective value, and (3) average objective value. The three different search algorithms are compared with each other for their performance on the 3G downlink cell planning and optimization problem. Figure 3.1 is a bar chart comparing the performance of greedy algorithm, simulated annealing, and tabu search. These algorithms are compared for the same neighborhood. The figure shows that the tabu search algorithm performs on average all five test cases better than simulated annealing and the greedy algorithm. Figure 3.2 shows that the maximum, average, minimum final objective function values obtained by each search technique for test case 2 in Table 3.3. We observe that the result of greedy algorithm shows a high variance indicating that it has a tendency to get trapped in local minima, and the performance of simulated annealing both in terms of variance and mean is better than greedy algorithm. The performance of tabu search is observed to be the best of them all, both in terms of average value and variance. From these experiments, it is clear that tabu search is best-suited for this cell planning and optimization problem. In term of average computing time, approximately 12 minutes are needed for each single run of greedy algorithm, 1:40 hours for each single run of simulated annealing, and 2:10 hours for each run of tabu search. The computing time here does not make a big difference between tabu search and simulated annealing.

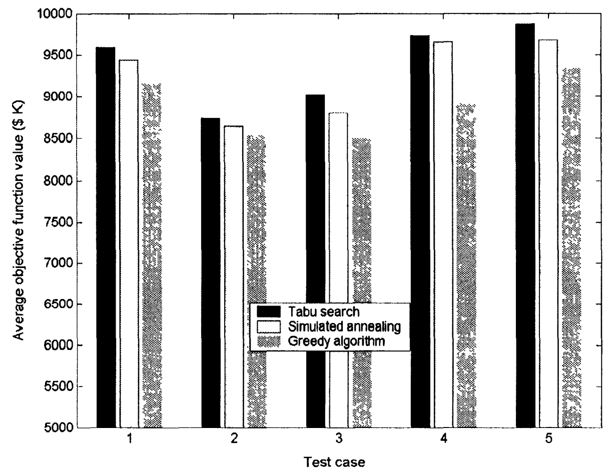



**Figure 3.1 Average performance of three algorithms for five test cases**

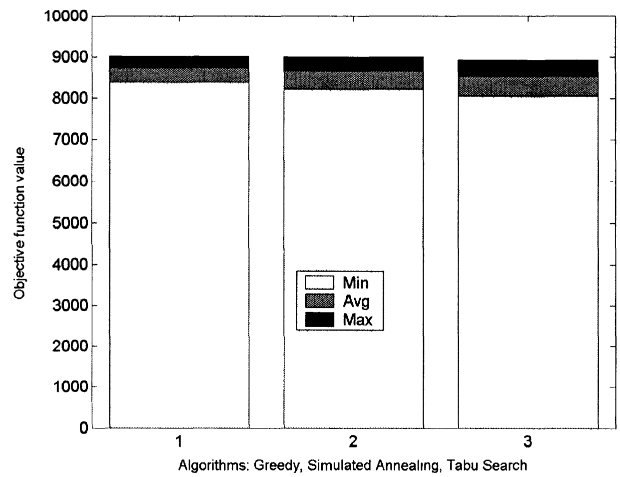



**Figure 3.2 Performance of greedy algorithm, simulated annealing, and tabu search measured by the min, avg, and max objective values for test case 2**

### 3.4.3 *SIR*-based power control *vs* Power-based power control

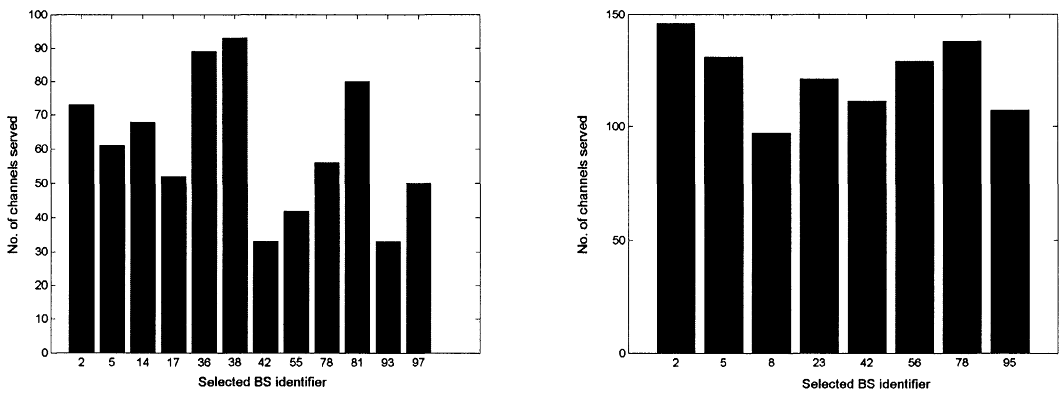
In this subsection, we compare the effects on the network capacity, coverage, and investment requirement between *SIR*-based power control mechanism and power-based power control mechanism by using tabu search algorithm. Intuitively, the *SIR*-based power control mechanism is more sophisticated and yields a more involved mathematical programming model since the received power of TP $i$, $p_i$, required to make a good quality connection to a candidate site it is assigned to, must be considered as an explicit variable. The received power $p_i$ can be freely adjusted provided they do not exceed the maximum power a candidate site can assigned to TP $i$.

Because the large sized problems take too much computing time, here we choose a smaller planning scenario for examining *SIR*-based power control model. Assume that there are 500 demand nodes ($n$) uniformly distributed over the 1.5 km × 1.5 km geographical area, and each demand node channel requirement $\mu_i$ randomly takes a value from the set {1, 2, 3} for each $i \in I$. We assume that each demand node has the same type of conversional traffic. There are 100 potential candidate BS locations ($m$) which are randomly generated with an uniformly distribution. For the simplicity of comparison, we assume that all selected locations choose the same type of BS, having the same height (10m) and the same maximum transmit power (20w). Other parameters are assumed to be the same as those used in Table 3.2. Each test case runs for 5 times, each time consisting of 1,000 iterations for each power control mechanism. Table 3.4 illustrates that *SIR*-based power control mechanism is much efficient than power-based power control mechanism.

**Table 3.4 Simulation results obtained for both power based and *SIR*-based power control mechanisms, with $m$ = 100, $n$ = 500, average 1000 channel requirement**

| | Channel need | Power-based power control | | *SIR*-based power control | |
|---|---|---|---|---|---|
| | | Traffic coverage rate | No. of required BSs | Traffic coverage rate | No. of required BSs |
| 1 | 1001 | 73.45% | 11.23 | 95.34% | 7.13 |
| 2 | 1034 | 68.99% | 10.20 | 90.25% | 7.76 |
| 3 | 988 | 76.80% | 12.72 | 99.19% | 8.38 |
| 4 | 1017 | 64.35% | 9.89 | 97.10% | 7.02 |
| 5 | 996 | 77.51% | 12.71 | 100% | 9.35 |

We can say that power-based power control is not adequate for the downlink direction, because it requires larger number of BSs selected and much lower coverage, compared to those obtained with a model with *SIR*-based power control. We make a single run of the test case 1 in Table 3.4. The results are listed in Figure 3.3, which shows that *SIR*-based power control can allow each BS to serve more traffic. In terms of average tabu search computing time, about 6 hours are needed for each *SIR*-based power control model, compared to about 50 minutes for each power-based power control model. This clearly indicates that considerable additional computational load required to compute the transmit power values at each run.




(a) (b)

**Figure 3.3 Comparison of capacity and coverage between power-based and *SIR*-based power control mechanisms: (a) power-based, (b) *SIR*-based**

This significant difference is mainly due to the fact that the emission powers in *SIR*-based power control are selected in order to have a signal quality exactly equal to $SIR_{tar}$. The interference is thus substantially lower than in a model with a power-based power control mechanism, and this leads to solutions having excellent coverage with a smaller number of BS selected.

### 3.4.4 Planning with alternative objectives

In pure capacity maximization planning, the network cost is not included in the optimization process, which may result in network configurations with unnecessarily high cost. In pure cost minimization planning, the capacity is not included in the optimization process, which may result in network configurations with unacceptable low capacity. Our purpose with the following quantitative examples is to illustrate the tradeoff between capacity and cost.

Let us assume that the task is to design a 3G downlink radio access network (cell deployment pattern) to provide conversational service over a predefined urban working area 1.5 km $\times$ 1.5 km. There are 500 demand nodes ($n$) uniformly distributed, and for the purpose of simplicity, each demand node channel requirement $\mu_i$ take one value from the set $\{1, 2, 3\}$ for each $i \in I$. There are 100 potential candidate BS locations ($m$) which are randomly generated with a uniform distribution. Assume that annual site non-configuration cost is \$100k for each potential site. BS antennas are assumed to be omnidirectional at every site. For the sake of presentation clarity, we define the feasible power- and antenna height sets for all sites uniformly. The three power and height values, as well as their associated configuration costs are shown in Table 3.5. For simplicity, we assume the power-based power control mechanism is adopted, because it requires much less computational effect.

**Table 3.5 Feasible values for antenna power, height with their respective cost**

| Max transmit power | | BS antenna height | |
|---|---|---|---|
| Permitted values (watts) | Cost (unit K) | Permitted values (m) | Cost (unit K) |
| 20 | 100 | 10 | 10 |
| 40 | 150 | 20 | 20 |
| 80 | 200 | 30 | 30 |

From Table 3.5, intuitively, BS antenna height configuration costs are not significant when compared to other cost components. This means that the antenna heights are not important in cost optimization, but important in capacity optimization, because antenna heights are a dominating factor in determining coverage area and received power strengths at traffic demand node points. We apply tabu search to solve the above planning problem, but using alternative objective functions, according to the following three scenarios:

- *Capacity optimization* (*CO*): cost is completely disregarded during the optimization, the objective function is formulated in relation (3.30) to maximize the served traffic in the working area (or minimize the number of unserved traffic points where the some constraints are not satisfied (outage). For simplicity, we call this scenario *pure capacity optimization*.

- *Cost optimization* (*COST*): capacity factor is completely ignored during the optimization, the objective function is formulated in relation (3.29) to minimize the total cost and hopefully find the cheapest feasible network configuration during the optimization process.
- *Combined cost and capacity optimization* (*COM*): cost is part of the objective function, according to relation (3.31). The weighing factor $\theta$ allows us to give priority to either minimizing cost or maximizing capacity. To find an appropriate value for $\theta$, a number of alternative values have been applied, and the results are subject of comparison based on a large number of independent tabu search executions. Figure 3.4 summaries the results of four representative values, $\theta = 0.1$, 1.0 and 10.

Low $\theta$ value results in low success in terms of finding high capacity feasible network configurations, which can be attributed to the possibility to sacrifice one or more traffic demand nodes to obtain a cheaper network configuration. This phenomenon is demonstrated by the low traffic service ratio (capacity) as well as by the apparently low total cost figures, as it is exemplified by the $\theta = 0.1$ case in Figure 3.4. The simulation results are ordered by means of simply ranking (no. of hits). The number of hits represents the frequency of occurrence of different simulation output values. The $\theta = 1$ case already represents a situation where network configurations have on average a higher capacity and cost than feasible configurations with low network cost. The $\theta = 10$ case makes solutions cluster than $\theta$ =1. Increasing $\theta$ further does not lead to additional capacity improvement (not shown here).

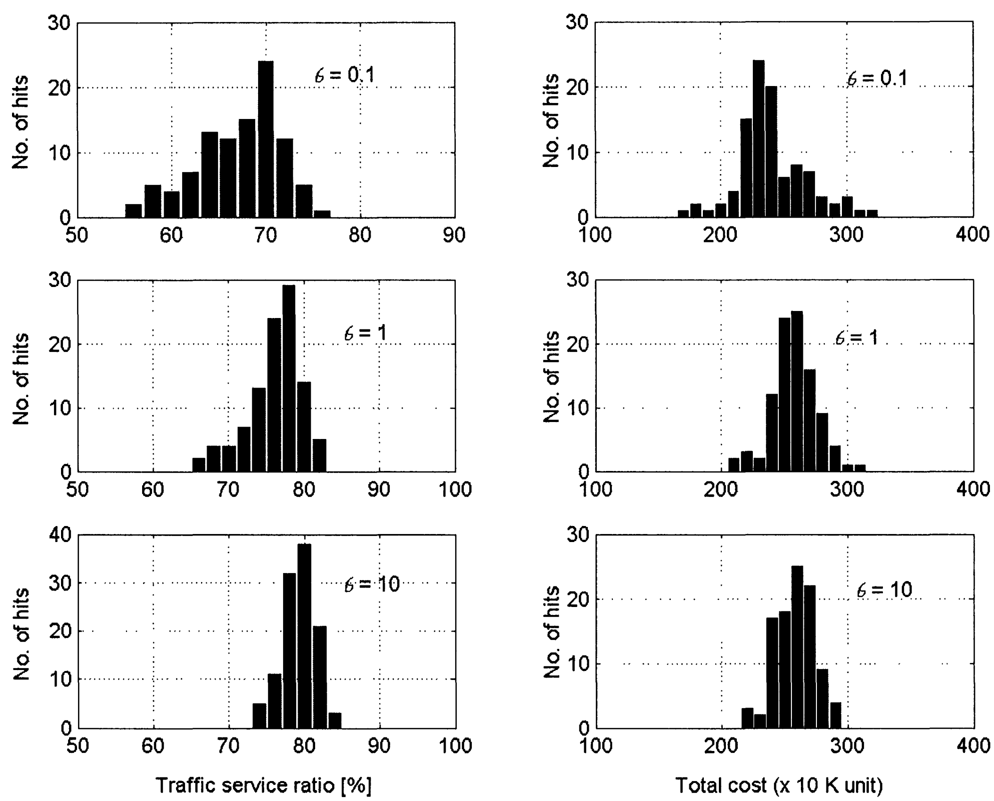



**Figure 3.4 Resulting overall traffic service ratios and total cost histograms for three different capacity weighting factors, $\theta$= 0.1, 1 and 10.**

Figure 3.5 summaries the results of the three optimization cases *CO*, *COST*, *COM* in terms of the total cost of the obtained network configurations. The histograms are generated from the results of 100 independent tabu search runs for each of the three cases. We use the same parameters and test cases as above for *CO*, *COST*, and *COM*, and apply $\theta$ =1 for *COM*. It can be seen that pure cost optimization case yields considerable cost reduction when at least 40% traffic demand must be satisfied. It is believed that pure cost optimization case would not select any BSs if we did not specify a minimum traffic satisfaction requirement. Likewise, pure capacity optimization yields considerable cost increase. Here we assume that the budgetary constraint allows no more than 20 BS sites installed. The combined cost and capacity optimization case lies somewhere between two extreme cases, striking a meaningful tradeoff. For explanation we can look at Table 3.6,

**Table 3.6 Summary of allocated resources for scenarios *CO*, *COST*, *COM***

| Optimization case | *CO* | | *COST* | | *COM* ($\theta$= 1) | |
|---|---|---|---|---|---|---|
| | best | mean | best | mean | best | mean |
| No. of BS transmitters | 12 | 14.78 | 5 | 6.60 | 8 | 10.71 |
| Total power [dBm] | 56.81 | 57.29 | 53.98 | 55.46 | 55.05 | 56.17 |
| Average power / BS [dBm] | 46.02 | 45.59 | 46.99 | 47.27 | 46.23 | 45.87 |
| Average height / BS [m] | 17.05 | 16.08 | 22.00 | 22.12 | 17.50 | 17.48 |
| Total cost [× K unit] | 3060 | 3745 | 1410 | 1866 | 2040 | 2727 |

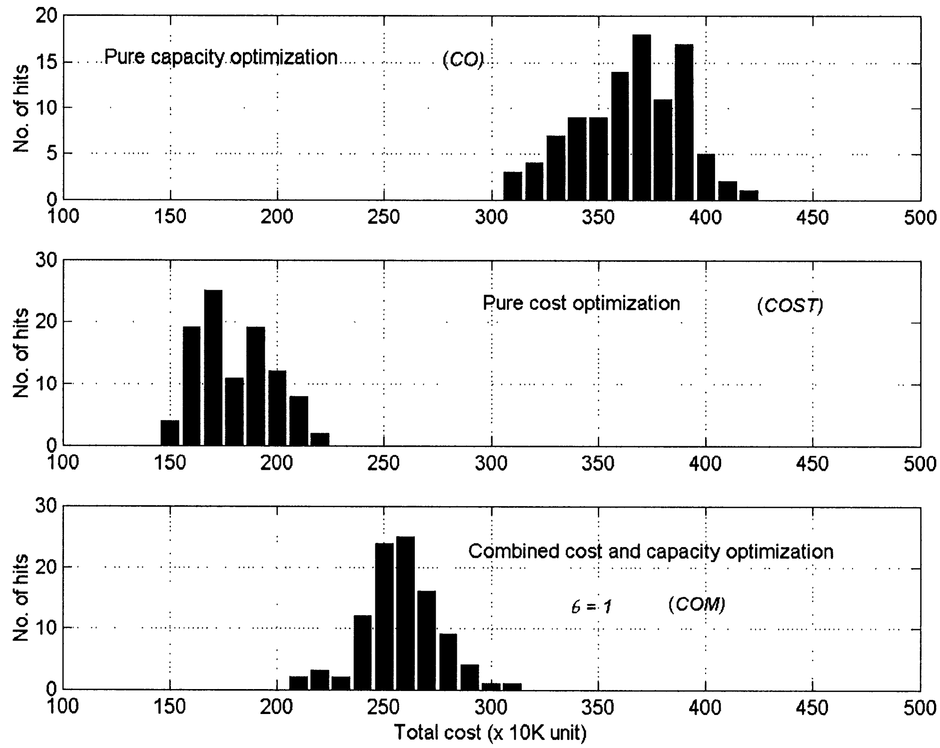



**Figure 3.5 Resulting total cost values for pure capacity optimization, pure cost optimization, combined cost and capacity optimization ($\theta$= 1).**

which contains that statistical results of 100 resulted network configurations found by tabu search for each objective (*CO*, *COST*, *COM*). The resource utilization of the networks is measured by the average number of BS transmitters in the networks, average total power, average height of antennas in the networks and by the average cost. Besides the average values over the 100 runs we indicate the parameters of the best found network in terms of cost.

Comparing the statistical values, the total power usage of these three case are very similar. In pure capacity optimization the results favor networks with a larger number of lower BSs. In contrast to that, networks of the pure cost optimization contain fewer BSs with higher structural antenna.

Comparing the best achievable results of *CO* and *COM*, the total power usage (i.e., *CO*, 56.81 dBm and *COM*, 55.05 dBm) and the average antenna height (*CO*, 17.05 m and *COM*, 17.50 m) are approximately the same for both objectives, but the number of BSs is decreased from 12 (*CO*) to 8 (*COM*). This result indicates that the network remains "over-provisioned" under *CO*, that is, the optimization does not attempt to remove unnecessary BSs, neither to cut back excessive power.

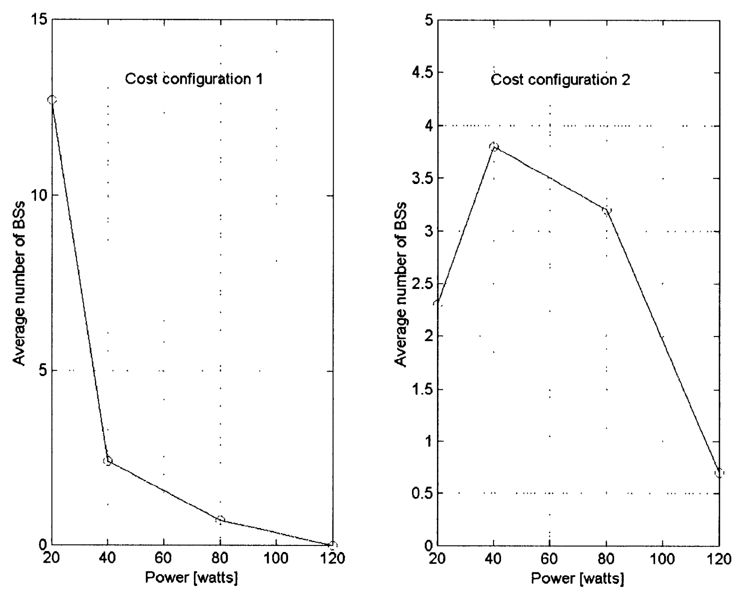
### 3.4.5 Cost sensitive network planning

In this section, we present some of the effect of different cost configurations in the same planning problem. The trials are performed in a 3G downlink cell planning and optimization task. Assume that power-based power control mechanism is adopted. In this case, the urban area is 1.5 km $\times$ 1.5 km. There are 500 demand nodes ($n$) uniformly distributed, and for the purpose of simplicity, each demand node channel requirement $\mu_i$ take one value from the set {1, 2, 3} for each $i \in I$. There are 100 potential candidate BS locations ($m$) which are randomly generated with an uniformly distribution. Assume that annual site non-configuration cost is $100k for each potential site. BS antennas are assumed to be omnidirectional at every site. For simplicity, we assume that all BS antennas have the same height (10 m), because in 3G cell planning and optimization the BS antenna height cost is negligible compared to other cost components, e.g., BS equipment cost (power related). The feasible set of power values is $P = \{20, 40, 80, 120\}$ [w]. Two different cost configurations are applied during the optimization as defined by

Table 3.6 (The cost figures are fictitious and for illustration purpose only). The objective function of this optimization is *COM* with $\theta = 1$.

**Table 3.7 Comparison of two different cost configurations**

| Max transmit Power | Cost configuration 1 | Cost configuration 2 |
|---|---|---|
| Permitted values [watts] | Cost [× K unit] | Cost [× K unit] |
| 20 | 100 | 100 |
| 40 | 250 | 150 |
| 80 | 400 | 200 |
| 120 | 500 | 250 |




**(a)** **(b)**

**Figure 3.6 (a) BS participation for case 1. The average BS number in a network is 15.83. (b) BS participation for case 2. The average BS number in a network is 10.15**

For both cost configurations, the optimization is performed by tabu search algorithm, 100 runs. The resulting network configurations are evaluated by the frequency of the BS antennas with power values of *P*. The statistics presented in Figure 3.7 follow the cost configurations. In the first case the cost of antenna power drastically increase for larger values and the site cost relatively low. According to the expectations, the resulting BS antenna assignment in Figure 3.7 (a) is featured with a large number of BS antennas, on average 15.83, with low antenna power.

In the second case we repeat the optimization with a modified cost configuration where the BS antenna power is relatively cheap. As the results show in Figure 3.7(b), the optimization reacts with different solution to the inversed input. The average number of BS antennas is 10.15. Due to the cost configuration and its relation to the size of the coverage are per BS, the middle size BS antennas are preferred. The use of large BS antennas requires also some small gap filling BS antennas. Due to the high cost for $P =$ 80, 120 w, the number of BS antennas with these power values is low.

# CHAPTER 4
# 3G UPLINK CELL PLANNING AND OPTIMIZATION

In this chapter, we focus on the efficient 3G uplink radio networks planning. We formulate the 3G cell uplink planning problem as a discrete optimization problem, where base station location and configuration are basic decision variables. An uplink scenario occurs when the maximum uplink load is reached prior to the BS running out of transmit power. This means that no additional users can be supported without degrading the planned service coverage performance. This is likely to occur in environments where the capacity requirements are relatively low and the network has been planned with a low uplink cell load to maximize cell range and thus reduce the requirement for sites. The traffic associated with an uplink scenario is generally relatively symmetric.

Uplink and downlink are not operated in an identical condition, and their performance characteristics are vastly different. Both directions are ultimately limited by interference, but there are large dissimilarities, since the downlink access is of one-to-many type and uplink is of many-to-one type. It is apparent that the downlink is limited by the total BS transmit power and the power limit per radio link, while the uplink is limited by individual mobile transmit powers [56]. In this chapter, the uplink direction is examined. It is not studied closely which link limits the system capacity and coverage in a particular WCDMA system, but some general attention needs to be paid to the unbalance of downlink and uplink, though.

For solving such a difficult optimization problem, we apply tabu search algorithm. The detailed implementation of tabu search algorithm is given in Section 3.3.6. Our goal [121,127] is twofold: on the one hand to suggest efficient tabu search algorithm for 3G uplink cell planning and optimization, on the other hand to discover inherent features of 3G uplink base station configuration with the help of optimization.

## 4.1 Uplink cell planning as an optimization problem

In this section, we define the decision variables, design constraints and objective function for profit-maximized 3G uplink cell planning and optimization, and formulate the task as a discrete integer optimization problem.

### 4.1.1 Decision variables

It is natural to model the available BS sites as a discrete set of geographical locations. In this case, there are some limitations on the antenna height depending on the tower height and the occupancy of the tower by other services. The antenna height of a BS can affect the area and shape of the cell coverage. The emitted power of the BS antennas is also confined to a range of permitted values. In 3G, there is basically no need to do frequency planning. Other BS antenna configuration parameters are also considered. The antenna downtilt can reduce the interference to the neighboring cells and enhance the coverage for the weak spots within the cell. The directional antennas in a sectored cell can reduce co-channel interference and enhance system capacity.

The primary objective of our uplink cell planning and optimization is to configure a radio access network such that the capacity requirements of all traffic demand TPs in the working area and the signal quality for each TP are satisfied as much as possible. A traffic demand node TP can be served by a BS only if the signal emitted from the TP and measured at a BS receiver meets a system-specific requirement. Therefore, the number of BSs and their configurations in a solution will depend not only on the total required capacity demand of all TPs, but also on the signal quality constraint for each connection. We introduce an integer variable $x_{ij}$ to represent a capacity assignment at BS site $j$ for service of TP $i$.

Let us define the two basic classes of decision variables, which do not consider the BS configurations:

$$x_{ij} = \begin{cases} 1 & \text{if TP } i \text{ assigned to a BS } j \\ 0 & \text{otherwise} \end{cases} \quad (4.1)$$

$$y_j = \begin{cases} 1 & \text{if a BS installed at site } j \\ 0 & \text{otherwise} \end{cases} \quad (4.2)$$

for $i \in I$ and $j \in S$. Suppose we consider directive BSs with three identical 120 degree sectors and with an omnidirectional antenna diagram along the horizontal axis. Let the index set $I_j^\sigma \subseteq I$ denote the set of all TPs, that fall within the sector $\sigma$ of the BS installed in site $j$. obviously, for each j, $I_j^1 \cup I_j^2 \cup I_j^3 = I$ and the index sets $I_j^\sigma$ with $\sigma = 1, 2, 3$ are disjoint.

We now turn to the general setting in which a BS antenna can be in one out of $q$ different configurations, denoted by set $L = \{1,\ldots, q\}$ A configuration represents a sextuplet BS = (location, type, height, tilt, azimuth, power). This accounts, for instance, for a variable tilt selected out of a set of possible angles with respect to the vertical axis, and for a variable height selected from a finite set of values with respect to the ground level. Since propagation gains depend on the BS antenna configuration, we denote by $g_{ij}^w$ the propagation gain from TP $i$ to potential site $j$ if the BS antenna is in configuration $w$. For the general setting, extended decision variables are needed for each configuration:

$$x_{ijw} = \begin{cases} 1 & \text{if TP } i \text{ assigned to a BS } j \text{ with configuration } w \\ 0 & \text{otherwise} \end{cases} \quad (4.3)$$

$$y_{jw} = \begin{cases} 1 & \text{if a BS with configuration } w \text{ installed at site } j \\ 0 & \text{otherwise} \end{cases} \quad (4.4)$$

for $i \in I$, $j \in S$ and $w \in L$. Once these basic decision variables have been determined, other dependent variables, such as loading factors and *SIR* for each BS, etc., can be easily derived from.

### 4.1.2 Design constraints

Constraints (4.5) below make sure that each TP $i$ is assigned to at most one BS.

Note that by restricting the assignment variables $x_{ijw}$ to take binary values, it is required that in every feasible solution all active connections must be assigned to a single BS.

$$\sum_{j \in S} \sum_{w \in L} x_{ijw} \leq 1 \tag{4.5}$$

If the left terms of constraints (4.5) were forced to be equal to one, that is, each TP must connect to a BS, the results would be too demanding for network resources. In some cases, a feasible solution would not able to be found. Therefore, in our implementation, constraints (4.5) are relaxed and intentionally allow some TPs not to be assigned.

Another set of constraints are common for both power-based power control model and *SIR*-based power control model. This set of constraints are called minimum service requirements as described in Section 3.2.2. The minimum service restrictions are handled by the following set of constraints:

$$\sum_{j \in S} \sum_{w \in L} \sum_{i \in I} \mu_i x_{ijw} \geq \beta . \sum_{i \in I} \mu_i \tag{4.6}$$

The constraints ensure that service is available in the working area that have at least proportion $\beta$ of all traffic demand nodes.

In our model, the cost of a BS involves the cost of site installation and cost of the configuration:

$$C_j(y_{jw}) = C_j^S + C_j^L \tag{4.7}$$

The over cost of a radio access network in the predefined working area, $C(\boldsymbol{y})$, is the sum of the non-configuration cost of each BS antenna $C_j^S$, and its associated configuration cost $C_j^L$, i.e., $C(\boldsymbol{y}) = \sum_{w \in L} \sum_{j \in S} y_{jw} . C_j(y_{jw})$. Cost is an extremely important factor for choosing an adequate network configuration. Denote $C_{max}$ an externally given ceiling cost, or a budgetary limit in total monetary investment. In most cases, it is practical to consider the budget constraints as follows:

$$\sum_{w \in L} \sum_{j \in S} y_{jw} . C_j(y_{jw}) \leq C_{max} \tag{4.8}$$

#### 4.1.2.1 Constraints with power-based power control model

Constraints (4.9) correspond to the most stringent constraints among the coherence

$$x_{ijw} \leq \min\left\{1, \frac{g_{ij}^{w} P_{\max}}{P_{tar}}\right\} y_{jw} \tag{4.9}$$

constraint $x_{ijw} \leq y_{jw}$, which ensures that TP $i$ is only assigned to site $j$ if a BS with configuration $w$ is installed in $j$, and the power limit on a single connection from a mobile terminal in TP $i$ to BS $j$:

$$\frac{P_{tar}}{g_{ij}^{w}} x_{ijw} \leq P_{\max} y_{jw} \tag{4.10}$$

where $P_{max}$ is the maximum emission power of a mobile terminal in TP $i$, for the connection from TP $i$ to site $j$, and $P_{tar}/ g_{ij}^{w}$ corresponds to the emission power required by a mobile terminal in TP $i$ to guarantee the target received power $P_{tar}$ at BS $j$. For each pair of site $j \in S$ and TP $i \in I$, constraints (4.10), which is active only if TP $i$ is assigned to BS $j$ (i.e., $x_{ijw} = 1$), corresponds to the signal strength requirement. Please note that the subscripts $i \in I$, $j \in S$ and $w \in L$ are applicable to all the constraints in this Chapter, unless otherwise stated.

In addition to the constraints (4.5), (4.6), (4.8), and (4.10), the quality of service constraints should be emphasized. Since in a power-based power control mechanism $P_{tar}/ g_{ij}^{w}$ is the power that needs to be emitted from a mobile terminal at TP $i$ to guarantee a received power of $P_{tar}$ at the BS with configuration $w$ in site $j$. For each triple of candidate $j$, configuration $w$ and sector $\sigma$, the power-based $SIR$ constraints can be expressed as follows:

$$\frac{P_{tar}}{\sum_{h \in I_{jw}^{\sigma}} \mu_h g_{hj}^{w} \sum_{t \in S} \sum_{z \in L} \frac{P_{tar}}{g_{ht}^{z}} x_{htz} - P_{tar}} \geq SIR_{\min} y_{jw} \qquad (4.11)$$

where the index set $I_{jw}^{\sigma}$ denotes the set of all TPs in $I$ that fall within the sector $\sigma$ of the BS installed in $j$, with configuration $w$.

For each triple of candidate $j$, configuration $w$ and sector $\sigma$, the numerator of the left-hand-side term in constraints (4.11) corresponds to the power of the relevant signal received at the BS from TP $i$, while the denominator amounts to the total interference due to all other active connections in the working area. Indeed, the first summation term expresses the total interference received at BS $j$ due to all connections and the $P_{tar}$ term that is subtracted amount to the received power associated to a signal connection assigned to BS $j$. Note that for any TP $h$, the only term of the inner summation (over index $t$ and $z$) that is nonzero corresponds to the site to which TP $h$ is assigned. Thus the contribution to the outer summation of any TP $h$ assigned to site $j$ amount to $\mu_h P_{tar}$.

#### 4.1.2.2 Constraints with *SIR*-based power control model

For each connection, the emission power is adjusted so as to guarantee a signal quality level that is equal to or greater than a target value $SIR_{tar}$. This is a more sophisticated power control mechanism. Since the emitted power from each mobile terminal $p_i$, $i \in I$, must be considered as an explicit decision variable. Indeed, if TP $i$ is assigned to a site $j$, $p_i$ is not taken to be equal to $P_{tar} / g_{ij}$ , but to be enough to have $SIR = SIR_{tar}$ at the serving BS $j$. In the presence of an *SIR*-based power control mechanism, the emission power values $p_i$ can be freely selected provided they do not exceed the maximum transmit power $P_{max}$ that a mobile terminal is allowed to transmit. Constraints (4.12) state that a TP $i \in I$ can be assigned to a BS $j \in S$ only if a BS with a configuration $w \in L$ has been installed in $j$:

$$x_{ijw} \leq y_{jw} \tag{4.12}$$

Since the transmit power must be nonnegative and there exist an upper bound on the maximum power $P_{max}$, we have:

$$0 \leq p_i \leq P_{max} \tag{4.13}$$

Given the *SIR*-based power control mechanism, for each set of candidate $j$, configuration $w$, sector $\sigma$ and TP $i$, the *SIR* constraints can be expressed as follows:

$$\frac{p_i g_{ij}^w}{\sum_{h \in I_{jw}^{\sigma}} \mu_h g_{hj}^w \sum_{t \in S} \sum_{z \in L} p_h x_{htz} - p_i g_{ij}^w + \eta_0} \geq SIR_{tar} x_{ijw} \tag{4.14}$$

which makes sure that the *SIR* of any active connection between BS $j$ and TP $i$ (i.e., $x_{ijw}$ = 1) is equal to or greater than $SIR_{tar}$. The term $p_i g_{ij}^w$ is the power of signal received at BS $j$ from TP $i$. Note that constraints (4.14) are trivially satisfied whenever $x_{ijw}$ = 0. As we shall know, the thermal noise $\eta_0$ plays here an important role and cannot be omitted as in the model with power-based power control mechanism.

Constraints (4.14) are the most difficult to solve in the optimization process. Given a current set of active BSs $\boldsymbol{y}$ and assume each TP has to be assigned to its closest BS in terms of its corresponding propagation gain, an initial capacity assignment pattern $\boldsymbol{x}^o$ can be easily found out. Once we find out an optimal assignment $\boldsymbol{x}$, which satisfies all the above mentioned constraints, it will be very easy to compute most of cell planning and optimization parameters, such as the objective function value $f(\boldsymbol{x}, \boldsymbol{y})$, coverage ratio, investment requirement, and loading factor, etc. In order to find out $\boldsymbol{x}$, we start with the initial assignment pattern $\boldsymbol{x}^o$, which assume all TPs are initially assigned to their closest BSs, that is, the coverage ratio at this stage is 100%, and go through the capacity assignment algorithm described in Section 3.3.3. Because the core here is to compute the emitted powers $p_i$, it would be necessary to solve the corresponding linear algebraic equations from the inequalities (4.15) as formulated below:

$$x_{ijw}\left(\sum_{h\in I_{jw}^{\sigma}}\mu_h g_{hj}^{w}\sum_{t\in S}\sum_{z\in L}p_h x_{htz}-p_i g_{ij}^{w}+\eta_0\right)=\frac{p_i g_{ij}^{w}}{SIR_{tar}} \tag{4.15}$$

If we do not consider the BS configuration in the optimization process, the constraints (4.15) can be simplified as follows:

$$x_{ij}\left(\sum_{h\in I}\mu_h g_{hj}\sum_{t\in S}p_h x_{ht}-p_i g_{ij}+\eta_0\right)=\frac{p_i g_{ij}}{SIR_{tar}} \tag{4.16}$$

Since the resulting linear algebraic equations contain $n$ constraints (4.16) in the $n$ variables $p_i$, a solution satisfies all of them with equality. Assume that TPs are assigned to closest active BSs, the linear algebraic equations can then be simplified by reducing the number of variables as well as the number of equations. For each given active BS $j$, the equations corresponding to all TPs $i$ assigned to BS $j$ are equivalent when considered as functions of $p_i g_{ij}$. Denoting the power received from any such TP $i$ by $p_j^{'} = p_i g_{ij}$, the single equation associated with each $j$ in active BS $\boldsymbol{y}$ can be rewritten as

$$\sum_{h\in I}\mu_h g_{hj}\sum_{t\in S}\frac{p_t^{'}}{g_{ht}}x_{ht}+(\frac{1}{SIR_{tar}}-1)\cdot p_j^{'}+\eta_0=0 \tag{4.17}$$

The size of the resulting linear algebraic equations are, thus, equal to the number of active BSs which is at most $m$ and usually much smaller than the number $n$ of TPs. This size reduction plays an important role in making tabu search work well. Please note that the tabu search for uplink is much faster than those of downlink. In downlink, we have to consider as many as power variable $p_i$ as there are TPs, while in uplink it suffices to consider a single received power for each BS. After we solve this simple linear algebraic equations and have the solution $p^{'}$, the emission powers at the TPs are derived by setting $p_i = p_j^{'}/g_{ij}$. We then apply the constraints (4.13) to each resulting $p_i$. If $p_i$ is not satisfied with the correponding constraint, the corresponding TP $i$ is assumed to be put into outage, that is, $x_{ij} = 0$, or interfrequency handover to another carrier if there is one (in our model, we assume that there is only one carrier).

### 4.1.3 Problem formulation

Our aim is to formulate the 3G cell uplink planning problem as an optimization problem. The available cell sites ($S$), the traffic demand nodes ($I$) with capacity requirements, configuration set ($L$) are fixed input parameters. Here, we are only interested in the profit maximization scenarios. The following variables are the basic decision variables:

- The number of selected base stations and their configuration, denoted by multi-dimensional vector $\boldsymbol{y}$,
- The capacity assignment matrix, $\boldsymbol{x}$,
- The power assignment vector (mobile transmitter participation), $\boldsymbol{p}$.

Based on these basic decision variables, most of radio access network parameters can be derived from.

This formulation explicitly considers the trade-off between the revenue potential of each site with its cost of installation and configurations. This trade-off is subject to $QoS$ constraints in terms of sufficient $SIR$ ratios. The objective of the model is to maximize the total annual profit generated by the cellular network operator, which is equal to the total annual revenue minus the costs. Mathematically we have:

$$\text{maximize} \quad \varepsilon \sum_{w \in L} \sum_{j \in S} \sum_{i \in I} \mu_i x_{ijw} - \sum_{w \in L} \sum_{j \in S} y_{jw} . C_j(y_{jw}) \tag{4.18}$$

subject to (power-based power control model)

(4.3), (4.4), (4.5), (4.6), (4.8), (4.9), (4.11).

Or ($SIR$-based power control model)

(4.3), (4.4), (4.5), (4.6), (4.8), (4.12), (4.13), (4.14).

$\varepsilon$ denotes the annual revenue ($) generated by each channel equivalent utilized in the working area.

## 4.2 Numerical simulations

Numerical experiments are made for 3G uplink cell planning and optimization. System performance evaluations are based on 3G WCDMA system specification. The optimization strategies used in these experiments are also applicable to other systems (e.g., TD-SCDMA, CDMA 2000). We will present in detail a realistic planning scenario in this section.

### 4.2.1 Input data

We choose a planning scenario from the one in Section 3.4.3. As downlink cases, We assume that there are 500 demand nodes ($n$) uniformly distributed over the 1.5 km × 1.5 km geographical area, and each demand node channel requirement $\mu_i$ randomly takes a value from the set {1, 2, 3} for each $i \in I$. We assume that each demand node has the same type of conversational traffic. There are 100 potential candidate BS locations ($m$) which are randomly generated with a uniform distribution. For the simplicity of comparison, we assume that all selected locations choose the same type of BS, having the same height (10m) and the same maximum transmit power (20w). Other parameters are assumed to be the same as those in Table 4.2.

In this chapter, four different traffic scenarios have been analyzed. First case is 7.5 kbps speech traffic only. Second case is to dimension a network traffic scenario with circuit switched data of 64 kbps for each mobile terminal. Third case is packet switched data of 144 bps for each mobile terminal. The last case is to dimension the mixed traffic scenario with 70% 7.5 kbps of voice traffic, 20% 64 kbps data, and 10% 144 kbps data. Assume mobile terminals are stationary. To make analysis easier, assume each demand node can have only one mobile terminal, that is, demand node channel requirement $\mu_i$ takes only the value of 1. Assume other parameters are the same as described in this section, the exact traffic information used in the mixed traffic scenario is presented in Table 4.1.

**Table 4.1 The traffic information used in mixed traffic scenario**

| Data rate | Percentage | Total users |
|---|---|---|
| 7.5 kbps | 70% | 350 |
| 64 kbps | 20% | 100 |
| 144 kbps | 10% | 50 |

Note that in the uplink case, the maximum emission powers of the various BSs play no role. For the purpose of simplicity, each potential location can accommodate an omnidirectional BS antenna with its maximum transmit power, height and other configuration parameters as fixed. Our implementation can be easily extended to take into account a number of different BS configurations. COST 231 Hata suburban propagation model is used to generate propagation gain matrix $\boldsymbol{G}$. Table 4.2 contains important planning input data necessary to compute capacity, coverage, load factor, *SIR*, location, final investment cost, and other configuration parameters.

**Table 4.2 3G uplink cell planning and optimization system data**

| Parameters | Values |
|---|---|
| Mobile antenna height | 1.8 m |
| BS antenna height | 20 m |
| Frequency | 2 GHz |
| Mobile antenna gain | 0 db |
| BS antenna gain | 14 db |
| BS site costs ($ K) | 100 |
| $SIR_{min}$ (for voice only) | 0.00619 |
| $E_b/I_o$ | 5 db |
| Processing gain for voice traffic | 512 |
| BS receiver sensitivity | -110 dBm |
| Thermal noise density | -130 dBm/Hz |
| Annual revenue for each channel($) | 10,000 |

### 4.2.2 *SIR*-based power control *vs* Power-based power control

In this subsection, we compare the effects on the network capacity, coverage, and investment requirement between *SIR*-based power control mechanism and power-based power control mechanism. Intuitively, the *SIR*-based power control mechanism is more sophisticated and yields a more involved mathematical programming model since the emitted power of TP $i$, $p_i$, required to make a good quality connection to a candidate site it is assigned to, must be considered as an explicit variable. The emitted power $p_i$ can be freely adjusted provided they do not exceed the maximum power a mobile terminal can have [127].

Table 4.3 shows the numerical results for the five test cases. Comparing the number of selected BSs yields by the power-based power control model with that obtained by the *SIR*-based power control model, we observe that the latter one allows for a saving of around 17% in investment in BSs and an improvement in traffic coverage by around 9%. These results illustrate that *SIR*-based power control mechanism is much efficient than power-based power control mechanism in the uplink environment.

**Table 4.3 Simulation results between power-based and *SIR*-based mechanism**

| | Channel need | Power-based power control | | *SIR*-based power control | |
|---|---|---|---|---|---|
| | | Traffic coverage rate | Ave no. of required BSs | Traffic coverage rate | Ave no. of required BSs |
| 1 | 1001 | 85.43% | 14.72 | 92.35% | 11.70 |
| 2 | 1034 | 81.72% | 14.11 | 87.60% | 12.33 |
| 3 | 988 | 89.17% | 15.89 | 95.52% | 13.86 |
| 4 | 1017 | 77.26% | 12.35 | 93.22% | 10.37 |
| 5 | 996 | 94.12% | 16.64 | 100% | 15.00 |

This significant difference in traffic coverage and investment cost is mainly due to the fact that the emission powers in *SIR*-based power control are selected in order to have a signal quality at BSs exactly equal to $SIR_{tar}$. The interference is thus substantially lower than in a model with a power-based power control mechanism, and this leads to solutions having excellent coverage with a smaller number of BS selected. These claims are evidenced by comparing the *SIR* values at each selected BS and the received powers for each connection. Figure 4.1 shows the *SIR* values measured in each active BS by using the power-based power control model and *SIR*-based power control model. Notice that all achieved *SIR*s at BSs in *SIR*-based power control model are naturally 5 dB, because 5 dB is the threshold value in optimization process for solving linear programs as described in Section 4.1.2.2, whereas, only a few BSs have a *SIR* close to the required threshold value 5 dB and for many BSs the service quality is far above the required level. Thus, the emitted powers are higher than needed in power-based power control model and as a result the interference levels are higher and the scarce radio resources are not used as efficiently as they could.

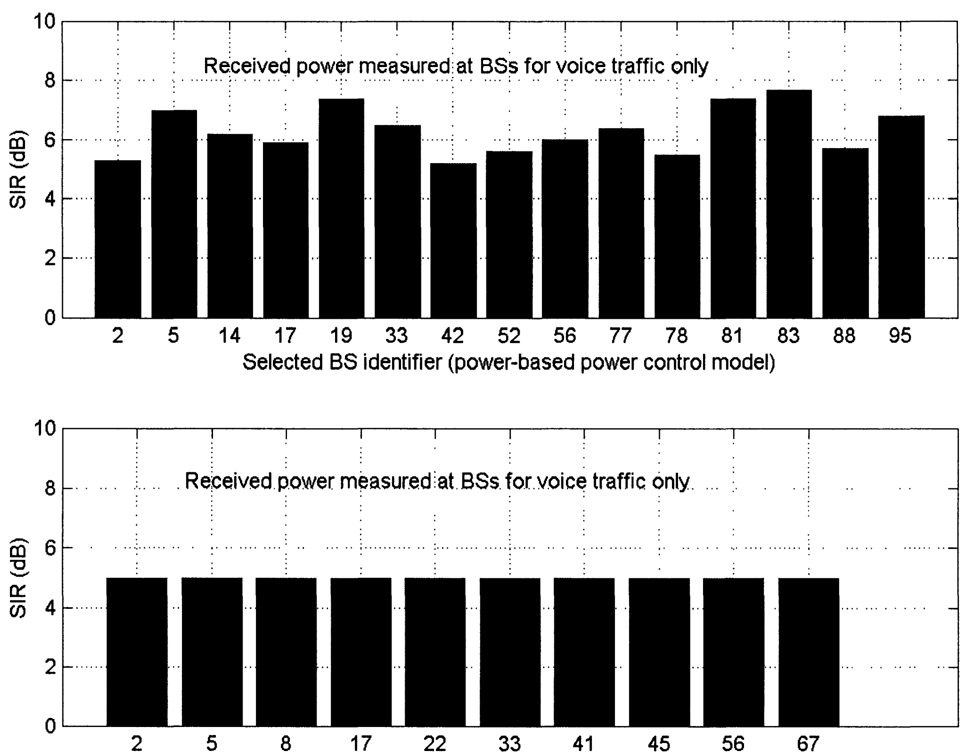
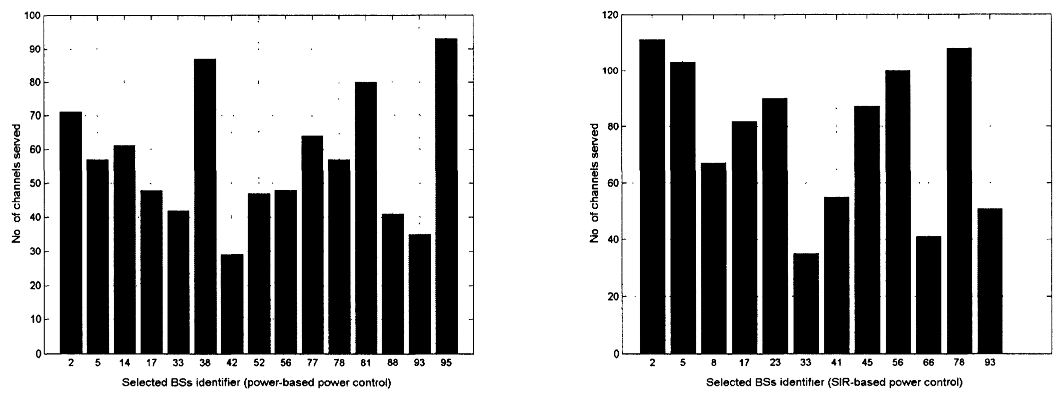



**Figure 4.1** ***SIR* values measured in each active BS by using the power-based and *SIR*-based power control mechanisms.**

Interesting insight on the inefficiency of the power-based power control model is provided by the distribution of the number of active connections assigned to each active BS. A sample run of test case 2 in Table 4.3 is shown in Figure 4.2. In the case of *SIR*-

based power control model, a substantial increase in the number of active connections for each active BS (average 78 channels per active BS) from that in the power-based power control model (average 57 channels per active BS).




(a) (b)

**Figure 4.2 Comparison of capacity and coverage between power-based and *SIR*-based power control mechanisms: (a) power-based, (b) *SIR*-based**

### 4.2.3 Comparison between downlink and uplink for voice traffic scenario

For a fair comparison of capacity and coverage between downlink and uplink, we apply tabu search to all five test cases in Table 4.3 for both uplink and downlink with the same number of total iterations (100) in optimization.

**Table 4.4 Results with SIR-based power control for uplink and downlink**

| Test case | Channel need | Downlink SIR-based power control | | Uplink SIR-based power control | |
|---|---|---|---|---|---|
| | | Traffic coverage rate | Ave no. of required BSs | Traffic coverage rate | Ave no. of required BSs |
| 1 | 1001 | 95.34% | 7.13 | 92.35% | 11.70 |
| 2 | 1034 | 90.25% | 7.76 | 87.60% | 12.33 |
| 3 | 988 | 99.19% | 8.38 | 95.52% | 13.86 |
| 4 | 1017 | 97.10% | 7.02 | 93.22% | 10.37 |
| 5 | 996 | 100% | 9.35 | 100% | 15.00 |

Table 4.4 shows in *SIR*-based power control situations that with the balanced traffic (e.g., voice calls) the uplink direction is the most stringent one from the point of

view of coverage as well as of the number of BSs used. This is primarily due to the low intracell interference that TPs experiment in the downlink direction because each BS uses orthogonal spreading codes. Note that the downlink model yields substantial improvements: higher traffic coverage ratio and smaller number of BSs used.

### 4.2.4 Impact of multi-service scenarios on 3G capacity and coverage

A major differentiation of 3G over 2G networks is the provision of multi-data-rate services. It is interesting to investigate the capacity and coverage on multi-service scenarios with both voice and data users with different traffic rates, different $E_b/I_o$ requirements, and processing gains, as listed in Table 4.5. The other parameters are the same as in Table 4.2. In this section, only uplink direction is explored.

**Table 4.5 Traffic scenarios and QoS requirements**

| **Date rate (kbps)** | **7.5 (voice)** | **64 (data)** | **144 (data)** |
|---|---|---|---|
| $E_b/I_o$ target (dB) | 5 | 4.1 | 3.9 |
| Processing gain | 512 | 60 | 26.67 |
| Scenario 1 | 100% | | |
| Scenario 2 | | 100% | |
| Scenario 3 | | | 100% |
| Scenario 4 | 70% | 20% | 10% |

The required $E_b/I_o$ is the ratio between the received energy per information bit and the total effective noise and interference power density needed to satisfy the quality objectives for a specific services. $E_b/I_o$ in the FDD uplink is defined in Constraints (4.19) (assume $SIR$-based power control mechanism is adopted)

$$\frac{p_i g_{ij}^{w}}{\sum_{h \in I_{jw}^{\sigma}} \mu_h g_{hj}^{w} \sum_{t \in S} \sum_{z \in L} p_h x_{htz} - p_i g_{ij}^{w} + \eta_0} \geq SIR_{tar} x_{ijw} \tag{4.19}$$

In fact, $SIR_{tar}$ = $E_b/I_o$ * $R/W$, where $W$ is the transmission bandwidth (3.85 Mcps in UMTS), and $R$ is the data rate. The ratio of transmitted bandwidth to data rate is called the processing gain (or spreading factor). Take the voice (7.5 kbps) as example, its processing gain is 512, and $E_b/I_o$ target is 5dB ( = 3.17), then $SIR_{tar}$ = 3.17/500 = 0.00619. This result means that the voice signal power strength received at a BS receiver can be 0.00619 times under the total interference and thermal noise power. Note that within given channel bandwidth (chip rate 3.84 Mbps) we will have a higher processing gain for lower user data bit rates than for high bit rates as shown in Table 4.5. For multi-service scenarios, Constraints (4.19) can be rewritten equivalently as in Constraints (4.20) for each individual traffic demand node $i$ and each individual connection $x_{ijw}$, with different service (denoted by the data bit rate $R_i$) and QoS requirement (denoted by $(E_b/I_o)_i$).

$$\frac{p_i g_{ij}^w}{\sum_{h \in I_{jw}^\sigma} \mu_h g_{hj}^w \sum_{t \in S} \sum_{z \in L} p_h x_{htz} - p_i g_{ij}^w + \eta_0} \cdot \frac{W}{R_i} \geq \left( \frac{E_b}{I_o} \right)_i \cdot x_{ijw} \tag{4.20}$$

To illustrate the effects of multi-service traffic, processing gain, QoS requirements on the 3G radio access network configuration, coverage, and capacity, we perform the optimization on the problem defined in Table 4.1 in Section 4.2.1. We randomly generate a test case for the problem with an uniform distribution of demand nodes and BSs, and apply, in the optimization process, the parameters summarized in Table 4.2 and Table 4.5. We consider four scenarios as defined in Table 4.5, using the same generated test case. For each scenario there are 10 independent tabu search runs executed. The best network configurations in terms of the objective function for first two scenarios are presented in Table 4.6 (illustrating other two scenarios is omitted because much more space is needed to show the detailed assignment patterns). In Table 4.7, the average results of coverage ratios, number of served users, and number of required BSs, over all cells are collected.

**Table 4.6 Maximum profit radio access networks for scenario 1-2**

| BS id. | Served users |
|---|---|
| 3 | 50 |
| 5 | 65 |
| 11 | 76 |
| 38 | 85 |
| 39 | 24 |
| 52 | 31 |
| 73 | 88 |
| 90 | 81 |

Scenario 1

| BS id. | Served users | BS id. | Served users |
|---|---|---|---|
| 1 | 24 | 58 | 26 |
| 5 | 21 | 69 | 17 |
| 11 | 13 | 73 | 13 |
| 17 | 28 | 80 | 14 |
| 19 | 22 | 82 | 25 |
| 22 | 17 | 83 | 7 |
| 27 | 14 | 85 | 16 |
| 30 | 15 | 86 | 18 |
| 35 | 9 | 88 | 19 |
| 38 | 21 | 90 | 10 |
| 41 | 23 | 93 | 19 |
| 52 | 17 | 94 | 16 |
| 54 | 10 | 98 | 8 |
| 55 | 8 | 99 | 12 |

Scenario 2

**Table 4.7 Simulation results for each scenario. Only the average results (averaged over all the cells) are included.**

| | **Scenario 1 (voice)** | **Scenario 2 (64 bps)** | **Scenario 3 (144 bps)** | **Scenario 4 (mixed traffic)** |
|---|---|---|---|---|
| Number of served users | 62.5 | 15.6 | 7.8 | 20.6 voice<br>4.9 data (64 kbps)<br>2 data (144 kbps) |
| Coverage ratio | 100% | 91.2% | 80.7% | 100% voice<br>83.8% data (64 kbps)<br>69% data (144 kbps) |
| Number of required BSs | 8 | 29.2 | 51.7 | 17.1 |

# CHAPTER 5

# CONCLUSION

This thesis proposes realistic planning models and develops a few optimization strategies for designing the 3G cell assignment and cell planning and optimization problems arising from 3G mobile network design practice. These problems are NP-hard and involve numerous constraints. In this work, several contributions have been produced to achieve the research goal. Major contributions are summarized in Section 5.1. Based on the results of this research, Section 5.2 identifies the limitation of this work and outline the promising research areas within which further work may be beneficial.

## 5.1 Summary of contributions

This research makes four contributions to the state of the art in research in 3G mobile network planning and optimization:

- hierarchical 3G cell planning and optimization downlink model,
- 3G cell planning and optimization uplink model,
- system performance criteria accurately expressed by constraints, and
- integrated multi-objective search and decision making.

We summarize these four individually in the following subsections.

### 5.1.1 Hierarchical 3G cell planning and optimization downlink model

We focus on the efficient 3G downlink radio networks planning providing multi-services over a predefined service area. We formulate the 3G cell downlink planning problem as a discrete optimization problem, where the emitted power, antenna heights and base station locations are basic decision variables. In order to efficiently solve this NP-hard problem, we test different search algorithms and compare with each other on large size problem instances. Tabu search is found to be the best method among the tested search algorithms. The main contributions of our model are five-fold: first, instead of just minimizing the cost as most previous works do, we consider alternative objectives, which better reflect the dynamics of the various requirements of potential mobile operators. We also present the sensitivity studies about the effect of different cost configurations on the radio access network configurations. Secondly, the decision variables and traffic capacity are embedded in the objective function and are optimized in a single integrated step. This can result in the tradeoff between the cost reduction and the capacity improvement, compared with approaches where they are considered separately. Thirdly, the model represents three-tier hierarchical cell structure that contains macrocell, microcell and picocell, because at each selected base station location, the network can use different equipment types to generate coverage areas corresponding to different cell sizes. Fourthly, because the optimal 3G radio network configuration is mainly a function of the geographical traffic demand features of the target service area, we incorporate different traffic classes, such as voice and data, into our model. Finally, we compare the effects on the radio access network capacity, coverage, and investment cost requirement between the *SIR*-based power control mechanism and the power-based power control mechanism by using tabu search algorithm.

### 5.1.2 3G cell planning and optimization uplink model

Classic coverage models, adopted for 2G cellular systems, are not suited for planning 3G cell deployment, because they are only based on signal predictions and do not consider the traffic distribution effects, the signal quality requirements, and the power control mechanism. For 3G cell planning and optimization, we propose discrete optimization models and algorithms aimed at supporting the decisions in the process of planning where to locate base stations, how to configure the selected base stations. These models consider the signal-to-interference ratio as quality measurement and capture at different levels of detail the signal quality requirements and the specific power control mechanism of the wideband CDMA air interface. As in downlink experiments, we compare the effects on the radio access network capacity, coverage, and investment cost requirement between *SIR*-based power control mechanism and power-based power control mechanism in the uplink environment. More importantly, we also investigate the radio access network capacity, coverage, and investment cost, considering multi-service scenarios with both voice and data uses with different traffic rates, different $E_b/I_o$, and processing gains.

### 5.1.3 System performance criteria accurately expressed by constraints

3G cellular system performance criteria are addressed by local constraints and global constraints. Local constraints, including the traffic load and the interference, are defined on each single cell, while global constraints are defined on the whole system (a set of cells), including the coverage area, capacity, and financial cost. Our models are more realistic, because we explicitly consider the intercell interference and accurately incorporate it into SIR constraints. Therefore, the optimization results better reflect the realistic radio environment than the simplified and commonly used models, which assume that the intercell interference can be expressed as a fraction of the intracell interference in the *SIR* constraints [162].

### 5.1.4 Integrated multi-objective search and decision making

3G cell planning and optimization is a typical multi-objective optimization problem as several objectives need to be considered simultaneously. After analyzing the insufficiency of classical methods, we propose an approach for solving multi-objective problems by integrating the search and decision-making processes. The different search algorithms are compared with each other for their performance on the problem using the best parameters from the previous experiments. The best overall solution in these experiments is found using tabu search.

## 5.2 Limitations and future work

Several open issues are seeking for further research. According to our trial of genetic algorithm in the 3G cell planning and optimization problem, it is found that standard genetic algorithm performs no worse than tabu search and simulated annealing. The only problem is computing time. We believe that the standard genetic algorithm can be significantly improved and made more efficient. Parallelization of the genetic algorithm could provide great enhancement. Since the objective functions are computationally intensive for cell planning and optimization problems, the computational time would be significantly reduced if individuals can be evaluated in parallel.

Our 3G cell planning and optimization approach considers the case where the traffic demand node configuration is fixed, i.e., it does not change in time. On the other hand, it can be expected that the multi-services traffic demand in 3G mobile networks will show dynamic fluctuations both in time and space. A mobile network that can adapt dynamically to the changing conditions will be appealing. Several improvement are possible, all of which require further feasibility and performance analysis. One possibility is to introduce adaptivity to periodically reconfigure the network cell configurations according to the statistically predicted traffic demand distributions. This will require very fast optimization methods.

So far, the cell planning and optimization models we propose are mainly concerned with greenfield mobile radio access design problems. What happens if the traffic demand increases? What should we do if the existing cells can not afford the scaled-up traffic? This is the so-called growth planning problem. The growth planning problem should be studied in the future. As networks grow, large number of base stations along with base station controllers are added to support mobile traffic growth and demand. How to deploy this equipment and optimize certain criteria is a complex problem, which calls for sound and useful methodologies. The key here is to model mobile users' behavior and demand, which determines how networks will perform as the traffic grows and the network evolves.

Although this thesis has investigated many aspects of cell planning and optimization, a lot still remains to be done in this area. For the purpose of investigation of various algorithms, a benchmark test problem suite needs to be built in consideration of different design scenarios. Further development can be done for cell planning and optimization taking into account more parameters, such as the antenna downtilt, uptilt, type, azimuth, in addition to the location, antenna height and transmit power. As the mobile communications system evolves, the modeling methodology and algorithms presented in this thesis may be applied to WLAN and 4G wireless networks.

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