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AUTOMATIC DATA GENERATION FOR MC/DC TEST CRITERION USING METAHEURISTIC ALGORITHMS

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To my parents, Souraya et Avedis, Thank you.

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Résumé

Le test de logiciel a traditionnellement été l'une des principales techniques contribuant à la haute fiabilité et à la qualité des logiciels. Les activités de test consomment environ 50% des ressources de développement de logiciel, ainsi toute technique visant à réduire les coûts du test est susceptible de réduire le coût total de développement du logiciel. Le test complet d'un logiciel est souvent impossible à réaliser à cause des exécutions infinies nécessaires pour effectuer le test et le prix élevé par rapport aux limitations du budget.

Les systèmes informatiques de fiabilité élevée sont souvent des systèmes appartenant aux domaines réglementés tels que le domaine aérospatial et le domaine médical. Dans de tels domaines, l'assurance de la qualité et les activités de test de logiciel sont imposées par la loi ou exigées par des normes obligatoires, telles que le DO-178B, DO-254, EN-50128, IEEE/EIA 12207, ou ISO/IEC i2207. Ces normes et règlements imposent normalement des activités de vérification et de validation, ainsi qu'ils spécifient les critères de test exigés.

Proposé par la NASA en 1994, la couverture modifiée des décisions et des conditions (MC/DC) est une stratégie de test requise, entre autres, par le RTCA DO-178B. MC/DC est un critère de test en boîte blanche qui vise à prouver que chacune des clauses (expression booléenne ne contenant aucun opérateur logique tel que le $z < x + y$) impliquée dans une décision influence correctement la valeur de cette décision. Le critère MC/DC englobe d'autres critères structurels bien connus tels que la couverture des instructions et des décisions.

Le travail présenté dans se mémoire applique des techniques d'optimisation de la recherche au problème du test. Nous explorons la façon d'intégrer la distance des branches, les dépendances de contrôles et les dépendances de données dans la recherche pour mieux la guider. Le but serait la génération automatique des données de test pour le critère MC/DC appliqué au niveau des méthodes.

Notre approche est organisée en deux étapes. D'abord, pour chacune des décisions dans le code à tester, nous calculons les ensembles des cas de test nécessaire pour couvrir le critère MC/DC pour cette décision. Cet ensemble de cas de test formera alors un ensemble d'objectifs pour la recherche. Dans la deuxième étape, nous appliquons des stratégies de recherche méta-heuristiques pour produire des données de test, assignant des valeurs booléennes vraies et fausses aux clauses des décisions de sorte qu'un objectif de test calculé dans la première étape soit satisfait.

Nous proposons une nouvelle fonction de coût qui sert à guider efficacement la recherche pour la génération des données test pour le critère MC/DC. En particulier nous nous inspirons de la méthode d'enchaînement qui intègre les dépendances de données dans la fonction coût. Nous avons étendu l'algorithme proposé par McMinn pour la fonction de la distance des branches, en l'adaptant au critère MC/DC.

Afin d'évaluer la faisabilité de notre approche, nous avons implémenté un prototype d'un outil d'automatisation des tests pour du code écrit en Java. Nous avons utilisé deux programmes bien connus, Triangle et NextDate. Nous rapportons des preuves de la supériorité de la nouvelle fonction coût proposée dans ce travail. En effet, cette fonction a permis d'éviter les plateaux menant à la dégradation de la technique de recherche en une recherche aléatoire comme dans le cas des fonctions traditionnelles utilisées dans le test structurel. Les contributions principales de ce travail peuvent alors être récapitulées comme suit :

- Nous proposons d'utiliser une technique de recherche afin de générer les données de test pour le critère MC/DC ; Nous appliquons la technique des problèmes de logiciel basée sur l'optimisation de la recherche au problème de la génération des donnes de test.

- Nous proposons une nouvelle fonction coût dans laquelle nous intégrons des dépendances de données par l'intermédiaire des dépendances de contrôles afin de l'adapter au critère MC/DC.

- Nous poussons plus loin l'algorithme de détection des dépendances afin de s’assurer que la nouvelle fonction coût prend en considération l’interaction mutuelle possible entre les dépendances de données et les dépendances de contrôles.

Abstract

Testing has traditionally been one of the main techniques contributing to high software dependability and quality. Testing activity consumes about 50% of software development resources, so any technique aiming at reducing software-testing costs is likely to reduce software development costs. Indeed, exhaustive and thorough testing is often unfeasible because of the possibly infinite execution space or high cost with respect to tight budget limitations. High dependability computerized systems are often software intensive systems belonging to regulated domains such as aerospace and medical application domain. In such domains, quality assurance and testing activities are enforced by law or required by mandatory standards, such as DO-178B, DO-254, EN-50128, IEEE/EIA 12207, or ISO/IEC i2207. These standards and regulations enforce verification and validation activities and they specify the required testing coverage criteria.

Proposed by NASA in 1994, the Modified Condition/Decision Coverage (MC/DC) criterion is a testing strategy required, among other practices, by the RTCA DO-178B. MC/DC is a white box testing criterion aiming at proving evidence that all clauses (Boolean expression not containing any logical operator such as $z > x + y$) involved in a predicate can influence the predicate value in the required way. It subsumes other well-known coverage criteria such as statement and decision coverage.

This work explores the way search techniques can be integrated with branch distance, control and data dependencies to generate MC/DC test input data at method level. Our approach is organized in two steps. First, for any given predicate, we compute the sets of test cases that would cover the MC/DC criterion for this predicate. In the second step, we apply meta-heuristic search strategies to generate test input data assigning true and false Boolean values to clauses so that one of the MC/DC test case computed in step one is satisfied.

We propose a novel fitness function to efficiently generate test input data satisfying the MC/DC criterion. In particular we draw inspiration from the Chaining approach integrating data dependencies in the fitness design and evaluation. We extended the algorithm proposed by McMinn for the branch distance fitness adapting it to MC/DC.

To assess the feasibility of our approach we implemented a prototype of a test automation tool for code written in Java and applied it to the well-known ‘Triangle’ and ‘NextDate’ programs. We report evidence of the superiority of the new fitness function that is able to avoid plateau leading to the degradation of the optimisation search techniques to a random search as in the case of traditional white box fitness functions. The primary contribution of this work can be summarized as follows:

- We propose a search based approach to generate MC/DC test input data; applying the Search Based Software Engineering problem techniques to testing.

- We propose a novel fitness function in which we integrate data dependencies via control dependencies in a new fitness function tailored for MC/DC.

- We extend the algorithm to define the fitness function to cope with mutually interacting data and control dependencies.

Condensé en Français

Le logiciel est au cœur des infrastructures informatiques et de communication modernes, ainsi la confiance dans l'intégrité de l'infrastructure exige la confiance dans son logiciel. Le logiciel est sujet habituellement à plusieurs types de méthodes de vérification et de test. Toutefois, chaque année des défauts de logiciel sont rapportés. En Août 2008, plus de 600 vols d'une ligne aérienne américaine ont été sensiblement retardés en raison d'une incohérence dans une base de données causant un problème de logiciel dans le système de contrôle du trafic aérien des États-Unis. Dans un système de sûreté critique, les erreurs ne peuvent pas être tolérées parce que soit les vies de personnes dépendent du système, soit les erreurs peuvent avoir des conséquences très néfastes. L'échec d'Ariane 5, une fusée lancée en 1996 par l'agence spatiale européenne en Kourou, Guyane, est un exemple d'échec d'un logiciel dans un system critique qui a amené une fusée de 7 millions de dollars à exploser juste quelques secondes après son lancement. La cause de l'échec était une erreur de logiciel. Un débordement dans une conversion d'une virgule flottante de 64 bits en nombre entier de 16 bits a amené l'ordinateur de la fusée à s'arrêter pendant quelque secondes et donc à perdre tout contact avec la station de base.

L'assurance qualité (QA) a été introduite comme une étape important dans le cycle de vie d'un logiciel; tout logiciel critique (ou pas) doit être validé avant d'être mis sur le marché. Dans les domaines réglementés, tel que le domaine Aérospatiale, le logiciel doit être conforme aux normes du document RTCA/DO-178B intitulé « Les considérations de logiciel dans les systèmes aéroportés et la certification d'équipement », qui traite de l'évaluation de la sécurité des systèmes. Le document fournit un ensemble obligatoire d'activités de vérification et de test pour chaque niveau de criticité d'un logiciel. Ne pas se conformer aux normes du DO-178B mène à un déni de l'approbation de l'Administration Fédérale de l'Aviation des États-Unis et par conséquent le logiciel ne peut pas être utilisé sur le marché aérospatiale. La couverture modifiée de condition et de décision (MC/DC) auquel on s'intéresse est un des critères de test requis par le DO-178B pour les systèmes de haute criticité.

Le but de l'assurance qualité est de s'assurer que le projet sera complété selon les spécifications, les normes et les fonctionnalités décrites dans la documentation du projet, sans aucun défaut. L'QA présente plusieurs avantages, dont l'augmentation de la fiabilité du logiciel, la diminution du taux d'échec, la diminution du coût de la maintenance, parfois très élevé, une meilleure satisfaction des clients et une meilleure réputation de l'entreprise et du produit.

Le contrôle de la qualité (CQ) est un processus de l'assurance qualité qui débute après que le code soit fini. Les activités du CQ visent à détecter les erreurs dans le code et à les corriger; Le CQ est donc orienté vers la 'détection' (Quality Assurance and Software Testing, 2008). En général, le contrôle de la qualité se compose de la vérification, de la validation et des tests de logiciels. Le test de logiciel a toujours été l'une des principales techniques contribuant à la haute fiabilité et qualité des logiciels. Le test exécute un système dans des conditions contrôlées et compare les résultats obtenus avec ceux attendus. Nous pouvons principalement diviser les stratégies de test en deux familles : test boîte noire ou fonctionnel et test boîte blanche ou structurel.

Dans le cas du test boîte noire, les tests effectués sont basés sur les exigences fonctionnelles du logiciel, sans aucune visibilité du code du logiciel ou de sa structure interne. Cette famille englobe le test fonctionnel, le test système, le test d'acceptation et le test d'installation. La stratégie de test boite blanche est basée sur la connaissance de la logique interne du code et la structure interne du logiciel. Cette famille comporte plusieurs critères de couvertures telles que la couverture d'instructions, la couverture des branches, la couverture de conditions et la couverture modifiée de conditions et de décisions (MC/DC).

Alors que le test logiciel est très important pour s'assurer que le logiciel est prêt à être mis sur le marché, les activités de test peuvent être très longues. En fait, 40 à 50% de l'effort de développement logiciel est alloué aux tests (Saha, 2008) et il est demandé à 91% de développeurs d'enlever des fonctionnalités principales tard dans le cycle de développement afin d'allouer du temps pour tester les fonctionnalités déjà développées et respecter la date de livraison du logiciel (Dustin, Rashka & Paul, 1999).

Une solution pour réduire le temps de test est l'automatisation des tests, qui peut être réalisée de deux façons. La première est d'écrire des scripts qui peuvent être exécutés en parallèle sur plusieurs machines et plusieurs environnements (Geras, Smith, & Miller, 2004). Cette méthode peut sauver beaucoup de temps de test manuel mais nécessite toujours l'écriture manuelle des suites de tests.

Une méthode plus poussée d'automatisation est de générer les cas de test et les données de test pour un certain critère de couverture de façon automatique. Des scripts peuvent ensuite exécuter les tests sur le logiciel. Un tel outil d'automatisation est complexe et nécessite un cycle de vie en lui-même, mais il peut permettre un énorme gain de temps une fois fini. En fait, puisqu'un logiciel est habituellement examiné plusieurs fois avant qu'il ne soit livré, le coût de développement de l'outil d'automatisation est parfois regagné avant même que le logiciel ne soit livré (Volokh, 1990). De plus, un outil d'automatisation est généralement développé indépendamment du logiciel ou du système à tester et, donc, il peut être utilisé pour différents systèmes. En d'autres termes, la longue durée de vie d'un outil d'automatisation compense en général son coût initial et résulte en une grande diminution du coût de test de logiciel dans le futur.

Un des critères structurels non automatisé aujourd'hui dans l'industrie est le critère MC/DC. Ce critère documenté dans la norme DO-178B est obligatoire pour les logiciels de niveau A dans le domaine aérospatial. Un logiciel de niveau A est décrit par la NASA comme étant un logiciel où un échec peut provoquer ou contribuer à une panne catastrophique du système de contrôle de vol de l'avion (Hayhurts & al, 2001). **Aucun outil d'automatisation des tests pour le MC/DC n'existe aujourd'hui dans l'industrie avionique (ou autres) qui est capable de générer automatiquement les cas de test et les données de test pour ce critère, cela forme alors notre objectif et motivation principale dans ce travail de recherche.**

La génération des données de test est un travail complexe et parfois impossible à faire manuellement. Couvrir un critère de test consiste à trouver les données appropriées pour satisfaire les cas de tests pour ce critère. Le testeur peut normalement manipuler les paramètres x et y par exemple du logiciel à tester et non pas les variables locales qui pourraient être utilisées dans la condition à tester. De plus, si x et y peuvent prendre n'importe quelle valeur entière, alors le testeur doit 'deviner' la combinaison gagnante de x et y entre 2^{32} x 2^{32} possibilités, ce qui est impossible à faire manuellement. Par conséquence, un outil de recherche est utile dans ce cas-là.

Les problèmes du génie logiciel basés sur les techniques d'optimisation dans des espaces de recherche (Search Based Software Engineering, SBSE) visent à appliquer des algorithmes d'optimisation à des problèmes issus du génie logiciel, tel que la génération de données de test. Les algorithmes d'optimisation utilisés sont des techniques méta-heuristiques telles que l'algorithme génétique, la recherche locale et d'autres. Ces algorithmes utilisent une fonction de coût pour guider leur recherche, généralement dans un espace large de solutions possibles. L'application des techniques SBSE dans le domaine du test de logiciel est référée par le terme SBST. Puisque les algorithmes méta-heuristiques ont besoin d'une fonction de coût représentant le problème combinatoire pour guider la recherche, le critère de test est alors transformé en une fonction de coût. Pour la couverture d'un nouveau critère de test, il suffit de le transformer en une nouvelle fonction de coût pour que l'algorithme méta-heuristique soit adapté à ce nouveau problème (Lakhotia, Harman, & McMinn, 2008).

Pour chaque problème résolu en utilisant des techniques méta-heuristiques, il existe généralement deux principales décisions de mise en œuvre. La première décision est le codage de la solution, par exemple sa structure, et la deuxième décision est la transformation du critère de test en une fonction de coût. Deux types de recherche méta-heuristiques ont été utilisés dans la littérature pour le problème d'automatisation des tests structurels, la recherche locale et les algorithmes évolutionnaires.

La fonction de coût utilisée dans la plupart des méthodes de recherche méta-heuristiques pour la couverture des critères de test structurel est composée de deux éléments : la fonction d'approchement et la fonction de distance des branches. La fonction d'approchement mesure la proximité avec la cible en termes structurels pour la donnée de test générée. La fonction est donc le compte du nombre de nœuds critiques dans le graphe de flot de contrôle entre la cible et le nœud où l'exécution a divergé (Baresel, Sthamer, & Schmidt, 2002). Cette fonction se base sur les dépendances de contrôles dans un code. La fonction de distance de branche est la proximité de la donnée de test générée de satisfaire soit la cible soit la branche où l'exécution a divergé. Elle permet alors de guider la recherche vers des données qui satisferont la branche ou la cible en général à tester (McMinn, 2004).

La fonction de coût traditionnelle telle que présentée a une limitation majeure quand des variables booléennes sont présentes dans les conditions ou quand des variables utilisées dans les conditions dépendent d'autres variables dans le code, le cas de dépendance de donnée. Alors, la génération de données de test avec cette fonction de coût se dégénère en une génération aléatoire.

En 2005, Liu et al. ont essayé de résoudre le problème des variables booléennes utilisées dans les conditions. L'approche propose d'intégrer un coût pour la dépendance de données des variables booléennes dans la fonction de distance de branche traditionnelle (Liu, Liu, Wang, Chen, & Cai, 2005). Cette approche aide la recherche pour les données de test dans ce cas. Le désavantage de cette approche est qu'elle se limite au problème de variables booléennes et ne résout pas le problème de variables locales ayant des dépendances de données. Une autre approche consiste à éliminer les variables booléennes dans un code à l'aide des techniques de transformation de code (Harman, Hu, Hierons, Baresel, & Sthamer, 2002). Bien que les résultats de cette approche soient prometteurs, on ne peut effectuer une transfomation de code pour la couverture du critère MC/DC qui se basent essentiellemnt sur la structure des conditions dans le code. De plus, une transformation de code doit être certifié par le FAA avant d'être effectué sur le code.

Le travail le plus influent dans notre domaine de recherche est la méthode d'enchainement proposée par McMinn en 2006, qui est en fait une extension du travail de Korel de 1990. L'approche propose d'utiliser les dépendances de données dans la fonction d'approchement au lieu des dépendances de control pour résoudre le problème de dégénération de la génération de données de test en une génération aléatoire. La méthode génère des séquences d'événements contenant les chemins possibles à exécuter afin de satisfaire une cible, chaque chemin modifiant essentiellement les variables critiques du code d'une façon différente. Une variable critique est définit comme un nœud problème pour lequel la recherche n'arrive pas à trouver des données de test appropriées. Cette méthode permet d'atteindre une couverture de 95% pour le critère des branches et 0% avec la fonction de coût traditionnelle. Toutefois, cette méthode présente une limitation quand des variables critiques contrôlent structurellement les dépendances de données. On propose alors d'intégrer mutuellement les dépendances de contrôle et de données dans la fonction de rapprochement, permettant de résoudre ce problème.

Dans notre travail de recherche, nous appliquons deux techniques de recherche méta-heuristiques à la génération de données de tests automatique pour le critère MC/DC, la recherche évolutionnaire et la recherche locale. En SBST, une solution est une donnée de test et la fonction de coût est la fonction d'évaluation du but de test. Pour chaque condition dans le code, il y a plusieurs cas de tests MC/DC et chacun a une fonction coût appropriée. Par conséquent, pour chaque objectif de test, une fonction coût différente doit être évaluée pour les données générées lors de la recherche. Cette fonction est utilisée pour comparer les solutions générées par rapport au but global de la recherche.

Les algorithmes évolutionnaires consistent principalement à évoluer toute une population de solutions possibles. Un tel algorithme choisit aléatoirement sa première population, ensuite choisit les n meilleurs individus pour produire une nouvelle génération. Deux opérations principales sont effectuées par la suite sur les paires de parents choisis, le croisement et la mutation. Le croisement, également appelé recombinaison, consiste à combiner les parties des parents pour générer les enfants, et la mutation modifie légèrement une partie des enfants. La nouvelle population des enfants remplace alors la population précédente. En général, les parents ayant les meilleures fonctions coûts ont plus de chance d'être choisis pour la reproduction. L'algorithme itère ainsi jusqu'à ce que l'un de ses critères d'arrêt soit atteint. Si la recherche génère une solution qui satisfait le but du test, dans ce cas la fonction coût est zéro, la recherche est arrêtée. Sinon, si après un nombre maximal d'itérations la recherche n'a toujours pas trouvé une bonne solution pour le but du test, l'algorithme est forcé de s'arrêter et un échec est reporté. Nous avons implémenté l'algorithme génétique (AG) de la famille évolutionnaire, vu qu'il est le plus utilisé dans la littérature. L'AG est surtout utile lorsque l'espace de recherche est vaste et aucune analyse mathématique n'est disponible pour le problème. Afin d'appliquer AG à notre problème, nous devons modifier légèrement son critère d'arrêt. En fait, chaque condition dans le code a plusieurs cas de tests et donc plusieurs fonctions coûts. Par conséquence, AG selecte un premier but de test comme but de recherche et commence ses itérations. Lorsqu'un des critères d'arrêts est atteint, GA selecte un nouveau but de test et recommence les itérations. De plus, lors de l'évaluation de la fonction de coût pour une solution, le programme à tester est effectivement exécuté avec la donnée de test générée et les résultats du programme sont utilisés pour l'évaluation de la fonction coût. Notre GA est élitiste et implémente un croisement arithmétique approprié aux solutions de valeurs réelles et une mutation uniforme.

La deuxième famille méta-heuristique utilisée dans notre travail de recherche est la recherche locale. Nous avons implémenté une méthode de descente stricte (HC) avec relance aléatoire. Elle est basée sur la notion de voisinage de la solution courante. Un algorithme de recherche locale crée une solution et l'évolue à chaque itération, essayant de l'optimiser. HC génère une solution initiale aléatoire, ensuite génère pendant un nombre d'itérations des voisins de la solution courante, le premier voisin trouvé ayant une meilleure fonction de coût remplace la solution courante et la recherche recommence. Si par contre après un certain nombre d'itérations la recherche converge vers une solution optimale ayant une fonction coût différente de zéro, donc qui ne satisfait pas le but de la recherche, une relance aléatoire est effectuée. Cela empêche la recherche de bloquer et permet d'explorer différentes régions de l'espace de recherche. Vu qu'une solution est une donnée de test, elle est alors formée des paramètres du programme à tester. Dans notre méthode de voisinage, on sélectionne au hasard un premier paramètre, on le modifie avec un pas ϵ, généré uniformément avec une moyenne nulle et un écart type σ. Le paramètre est modifié n fois, ensuite un second paramètre est choisit et son voisinage est exploré, etc. Lorsqu'un critère d'arrêt est atteint pour le présent but de recherche, un second cas de test MC/DC est sélectionné et ainsi un nouveau but de recherche est établi.

Selon le critère MC/DC, une condition est une expression booléenne ne contenant aucun opérateur booléen. Une décision est une expression booléenne composée d'une ou de plusieurs conditions connectées par des opérateurs booléens, par exemple un 'if'. Une clause majeure est la condition dont le test vise à démontrer qu'elle affecte correctement le résultat de la décision, tandis que les clauses mineures sont toutes les autres conditions dans la décision. Ainsi, pour générer les cas de test pour la couverture du MC/DC, la clause majeure prend les deux valeurs possible, vrai et faux, alors que les clauses mineures restent fixes, et le résultat de toute la décision varie en fonction de la clause majeure. Par exemple, les cas de test d'une décision (A && B) seront VV, FV et VF (ou V = vrai et F = faux).

Afin d'automatiser la génération des données de test pour MC/DC, une analyse de code est nécessaire. Nous nous basons alors sur le graphe de flux de contrôle (CFG). Le CFG est un graphe représentant la structure du programme à tester et il sert à détecter le flux d'exécution dans le programme. Notre approche comporte alors les étapes suivantes. Premièrement, une analyse du code est effectuée. Une analyse syntaxique extrait les décisions du code, ensuite un analyseur syntaxique transformera la structure de chaque décision en un arbre abstrait de la décision (ADT). La deuxième étape utilise des ADT pour générer pour chacun, le set des cas de tests nécessaires pour couvrir le critère MC/DC. La couverture de ces cas de test sert comme but de recherche des outils méta-heuristiques. La troisième étape de notre approche consiste à formuler les fonctions coûts pour chaque décision. Notre fonction coût se compose de la fonction d'approchement et de la fonction de distance des branches. La fonction d'approchement intègre les dépendances de contrôles et de données dans sa formule. Les dépendances de contrôles sont extraites du code à l'aide du CFG. Les décisions qui peuvent modifier le flux d'exécution du programme pour le diverger de la décision visée par le test sont dites critiques par rapport à la décision visée. On dit que la décision visée a une dépendance de contrôle sur ses décisions critiques. Si la couverture de la décision visée dépend des valeurs de variables ultérieurement modifiées dans le code, alors la décision visée a une dépendance de donnée sur ces variables. Pour intégrer les deux dépendances ensemble, un algorithme commence par la décision visée, trouve ses dépendances de contrôles C1 et les variables utilisées V1 dans cette décision. Ensuite, l'algorithme remonte dans le code pour collecter de nouveau les dépendances de contrôles et de données pour C1 et pour V1. L'algorithme itère jusqu'à ce que toutes les dépendances soient trouvées. Le résultat est plusieurs séquences de dépendances, chacune comportant un chemin critique dans le code qui déterminera le flux d'exécution et les modifications apportées aux variables critiques utilisées dans la décision visée. La dernière étape de notre approche consiste à instrumenter le code afin de pouvoir tracer son exécution pour chaque donnée de test.

Des tests sont effectués sur deux programmes écrits en Java. Des résultats préliminaires montrent la supériorité de la nouvelle fonction coût, qui est en mesure d'éviter le plateau menant à un comportement proche de la recherche aléatoire de la fonction traditionnelle du test structurel. Le premier programme testé est un programme de classification de triangle (Triangle). C'est un problème bien connu et utilisé comme référence dans de nombreux travaux de test. Ce programme prend trois réels en entrée représentant les longueurs des côtés du triangle et décide si le triangle est irrégulier, scalène, isocèle ou équilatéral. Il compte 80 lignes de code. Le second programme, NextDate, prend une date en entrée, la valide et détermine la date de la prochaine journée. L'entrée est donc formée de trois entiers, un jour, un mois et une année. L'espace de recherche est tout le domaine admissible des paramètres, le domaine des entiers. Deux expériences ont été menées sur les deux programmes dans le but de générer des données de test pour couvrir le critère MC/DC pour toutes les décisions dans les deux programmes. La fonction coût utilisée dans la première expérience est la fonction traditionnelle se basant sur les dépendances de contrôles seulement, alors que la nouvelle fonction coût proposée dans notre travail est utilisée dans la deuxième expérience. Dans les deux expériences, nous avons aussi conduit deux essais, premièrement nous avons limité le nombre maximal d'évaluations de la fonction coût à 5 000 évaluations par cas de test, ensuite nous avons remonté ce nombre à 10 000. Le but est de vérifier si la couverture augmente avec le nombre d'itérations. La population du AG comprend 100 individus et 400 générations peuvent être produites au maximum. La probabilité de croisement est 0.7 et la probabilité de mutation est 0.05. Pour HC, le nombre maximal de relances aléatoires est 16, avant chaque relance, 100 itérations sont faites, et pendant chacune de ces itérations, 100 autres itérations par paramètre de la solution sont effectuées pour la limite d'évaluation de la fonction coût de 5 000 et 200 itérations par paramètre de la solution pour la limite d'évaluations de la fonction coût de 10 000. L'écart type de la fonction de voisinage est définit à 400 pour les trois paramètres du programme Triangle, et à 5, 10 et 50 pour les trois paramètres jour, mois et année du programme NextDate.

Nous comparons nos résultats à un générateur aléatoire de données (RND). Il génère de façon aléatoire un triplet de nombres entiers et l'évaluation de la fonction coût pour ce triplet se fait en utilisant le même ensemble de but de recherche. Si la valeur de la fonction coût est zéro, la donnée de test générée a atteint le but, cette donnée est alors retournée et un nouveau but de test est sélectionné. Si la valeur de la fonction coût n'est pas nulle, l'algorithme ne profite en aucune manière de cette valeur pour guider la recherche, plutôt il génère un nouveau triplé de manière aléatoire. Le nombre maximal d'itérations est le même fixé pour HC et AG.

Les résultats obtenus montrent premièrement que la couverture de test atteinte en utilisant la nouvelle fonction coût est meilleure que celle atteinte en utilisant la fonction traditionnelle. En effet pour une limite de 5 000 évaluations, AG couvre 81% des tests avec la nouvelle fonction de coût contre 55% avec la fonction traditionnelle, environ 30% d'amélioration, HC couvre 47% contre 39% avec la nouvelle et traditionnelle fonction de coût respectivement, 8% d'amélioration. Le générateur aléatoire atteint une couverture de 40%. Il est à noter qu'AG et HC atteignent 55% et 39% avec la fonction traditionnelle, qui est a peu près le même pourcentage de couverture du générateur aléatoire qui couvre 40%. Cela montre l'effet des dépendances de données qui mène la recherche méta-heuristique à se dégrader en une recherche aléatoire quand elles ne sont pas prises en considération pour guider la recherche. Avec la nouvelle fonction, AG performe le mieux entre les trois algorithmes. En fait, HC n’arrive pas à atteindre un pourcentage de couverture élevé qui peut être reporté à sa fonction de voisinage.

Les résultats obtenus pour une limite maximale de 10 000 évaluations de la fonction coût sont similaires. Nous concluons alors que 5 000 évaluations sont suffisantes pour atteindre la couverture maximale.

D’autre part, NextDate ne contient pas de dépendances de donnée entre ses décisions. Notre fonction coût est toujours performante. Les résultats obtenus montrent que plus le nombre d’évaluations de la fonction coût est élevé, plus le pourcentage de couverture est élevé. Avec 5 000 évaluations, GA atteint 85% de couverture, HC atteint 78% et RND atteint 73%. GA encore a la meilleure couverture.

Des travaux futurs pourront se consacrer à mieux définir un voisinage pour HC vu que celui mis en œuvre actuellement ne semble pas bien adaptée à profiter de l'intégration des dépendances de données dans la fonction coût lorsque les paramètres d'entrée du programme Triangle sont sélectionnés sur tout le domaine des valeurs entiers.

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Initials and Abbreviation

QA	Quality assurance
QC	Quality control
MC/DC	Modified Condition / Decision Coverage
SBSE	Search Based Software Engineering
SBST	Search Based Software Testing
ET	Evolutionary testing
GA	Genetic algorithm
HC	Hill climbing
SA	Simulated annealing
RND	Random generator
CFG	Control flow graph
AST	Abstract syntax tree
ADT	Abstract decision tree
σ	Standard deviation
FAA	Federal Aviation Administration

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Chapter 1: Introduction

Software is at the heart of modern information and communication infrastructures. Trust in the integrity of the infrastructure requires trust in the underlying software; in other words, users must trust that the software meets its requirements and is available, reliable, secure, and robust. Quality assurance is a process used to help assess the correctness, completeness, security, and quality of the developed computer software.

The importance of software correctness and robustness varies with the criticality of the system used, from systems where failures generated can be repaired with no damage i.e. a website showing games results, to critical applications where failures can cause serious damage. Software is usually subject to several types and cycles of verification and test. Nevertheless, defects still occur sometimes in released products leading to serious consequences; indeed every year, software defects are reported. In January 2009, a large health insurance company was banned by regulators from selling certain types of insurance policies due to problems in its computer system resulting in denial of coverage for needed medications and spurious overcharging or cancelation of benefits. The regulatory agency stated that the problems were posing "a serious threat to the health and safety" of beneficiaries (Hower, 2009). In August 2008, more than 600 U.S. airline flights were significantly delayed because of a database mismatch resulting in a software glitch in the U.S. FAA air traffic control system (Hower, 2009). In August 2006, a software defect in a US Government student loan service made public the personal data of as many as 21,000 borrowers on its web site. The government department subsequently offered to arrange for free the credit monitoring services for those affected. Two months earlier, June 2006, 11,000 customers of a major telecommunication company were over-billed up to several thousand dollars each, due to a software bug. The bug was fixed within days but correcting the billing errors took much longer (Hower, 2009).

Moreover, in a safety-critical system, errors cannot be tolerated as people's lives depend on it. The Therac-25 is a computerized radiation therapy used in the late 80s; its built-in software monitored the safety of the machine. Between 1985 and 1987, six accidents involved massive overdoses given to patients causing death and sever injuries. The cause of the problem was an unanticipated, non-standard user inputs (Leveson & Turner, 1993). Another example is the failure of Ariane 5, the rocket launched in 1996 by the European Space Agency that exploded just forty seconds after its lift-off from Kourou, French Guiana. The rocket was on its first voyage, and its development cost $7 billion. The cause of the failure was an overflow in a conversion from a 64 bit floating point to a 16 bit integer. The overflow caused the rocket computer to shut down for few seconds and loose all contact with the ground station.

Quality assurance is therefore a major component in the software development life cycle. Software should be validated before it is released into the market. The level of validation is however proportional to the system criticality and dependability and requires different levels of software validation and testing. For example, in regulated domains such as the Aerospatiale domain, software should be compliant with the RTCA/DO-178B standard document entitled "Software Considerations in Airborne Systems and Equipment Certification", which treats system safety assessment. The document categorises software based on its safety criticality and provides an obligatory set of verification and testing activities for each software level. Failing to comply with the DO-178B standard leads to a denial of the Federal Aviation Administration approval and the software cannot be released in the Aerospatiale market. In our work, we will focus on one of this document's criteria that we will discuss later.

It is important to note that quality assurance is not a one stage activity; instead, it is involved in the project from the beginning till the end and consists of means of monitoring the entire software engineering process and methods used throughout the software life cycle to ensure quality. We will start by describing briefly the different activities involved in a software development cycle, and then we will describe how quality assurance integrates in this cycle to ensure expected software quality.

1.1. Quality Assurance

1.1.1. Software Development Process

A software life cycle that includes the development process describes the life of a software product from its inception to its implementation, delivery, use and maintenance as shown in *Figure 1.1* (Pfleeger, 1998).

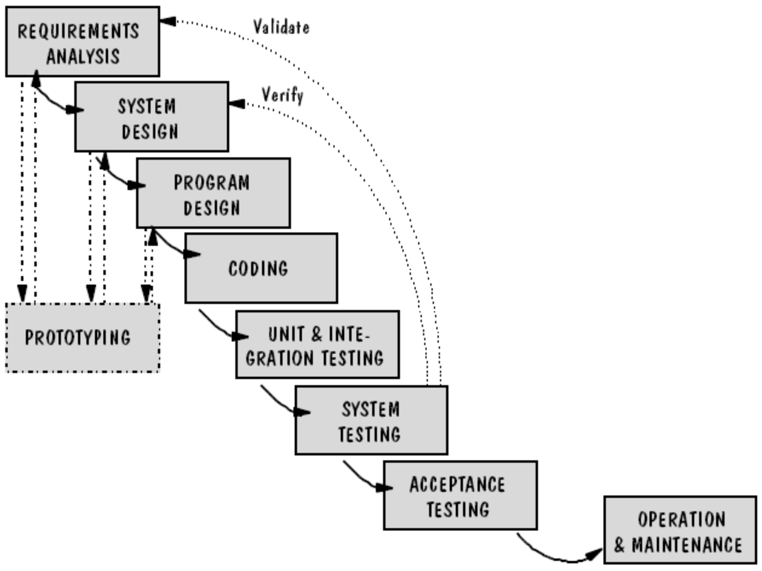


Figure 1.1: The waterfall model (Pfleeger, 1998)

The first stage of the software development process is requirements analysis and definitions; it starts by meeting with the customer, eliciting the system requirements and analyzing the requirements document to determine the scope of the project. A requirement is a feature of the system or a description of something the system is capable of doing in order to fulfill the system's purpose (Pfleeger, 1998). There are many types of requirements such as interface, functionality, data, security or performance requirements. Requirements describe system behaviour, and there are usually functional and non-functional requirements. Functional requirements describe an interaction between the system and its environment, while non-functional requirements or constraints describe a restriction on the system that limits our choices for constructing a solution for the problem. Both types are elicited from the customer in a more or less formal, careful way (Pfleeger, 1998). Even though requirements documents are done at the first stage of the development cycle, they can be redefined and updated as the development project progresses, with the consent of the client.

The next step in the software life cycle is to write a precise and detailed software specifications document for the project, which is the system design. The specifications document restates the requirements definition in technical terms appropriate for the development of a system design; it is the technical counterpart to the requirements definition document, and it is written by requirements analysts. Specifications can be presented using different techniques such as use cases, data flow diagrams, event tables, decision tables, UML flow charts, patterns, drawings, etc. There are also different types of written specifications such as system or software requirements specification, software design specification, software test specification, software integration specification, etc.

The third step in a software life cycle involves the program design. It consists of planning for a software solution, where software engineers develop a plan for a solution for the project. The plan includes an architectural view of the software, low-level components as well as any possible algorithm implementation issues.

At this point, the software requirements, specifications and design documentation are done and thus in general the software is ready for the actual implementation stage. One or more software engineers develop the code following the documentation.

The code will then be subject to a quality control procedure including validation and testing, encapsulating the stages unit and integration testing, system testing and acceptance testing. The quality control might include code inspection, formal method validation and/or several types and levels of testing. An important quality assurance activity is to present a plan to identify the types of validation and-or testing, the features to be validated, the personnel and the schedule to do it (Software Testing Life Cycle, 2006).

At this stage, the software is ready for deployment on the client side and testing of the installation. The cycle then extends to software maintenance as new discovered problems might emerge and need to be fixed or new functionalities are required to be added to the original system (Software Testing Life Cycle, 2006).

1.1.2. Quality Assurance Activities

In order to ensure the good quality of a product, quality assurance is all about making sure that the project will be completed accordingly to the agreed upon specifications, standards and functionalities required without any defects. For this reason, quality assurance (referred to as QA) should be involved in the project from its earlier stages. QA refers to the planned processes continuously monitoring the software life cycle activities. It helps the teams communicating and understanding problems and concerns, and plan, ahead of time, the testing environment required. It is mainly said to be oriented to "prevention" (Quality Assurance and Software Testing, 2008).

In QA, records are kept concerning identified problems, which is an advantage since steps can be taken in the future to avoid the same problems for the same or different projects. This reduces significantly the total cost of a project as problems can be eliminated in earlier stage, when the software is still under construction, and even before the actual testing phase (Ruso, 2008).

Software verification and validation increase the reliability and dependability of the product resulting also in decreased failure rates. It also decreases the maintenance cost of the software that represents sometimes a large percentage of the total cost, due to necessary corrective patches, software updates and service packs. In 2003, it was reported that the relative cost for maintaining software and managing its evolution represent more than 90% of its total cost (Seacord, Plakosh, & Lewis, 2003).

Another advantage of QA is an improved customer satisfaction. Because the process of QA is designed to prevent defects, customers will be better satisfied with their products leading to positive customer testimonials and thus a better company or product reputation. In fact, the quality of the final software product can be a very decisive factor in the market success or failure of a company.

QA activities start at the earlier stage of writing the requirements document. In fact, most of the problems encountered in a software development are due to incomplete requirements, lack of user involvement and unrealistic expectations (Pfleeger, 1998). Thus, the first quality assurance process is to review the requirements document and detect any possible problems, errors, inconsistency or ambiguity, anticipating and deleting this way a large amount of possible software defects (Ruso, 2008). This QA activity will also lead to success in accurately validating the resulting software to correct user requirements.

Another QA main task is Process and Product Quality Assurance audits (PPQA), which is an objective audit of each step of the software development to make sure it is compliant with relative standards and process description. The QA team would document any inconsistencies or problems and report it to the project staff (CMMI Product Team, 2007). Audits are usually backed by standards as the ISO 9000 (a standard that concerns quality systems that are assessed by outside auditors), CMMI (a model of 5 levels of process maturity that determine effectiveness in delivering quality software) or others.

QA activities include also monitoring the quality of the processes such as the software design, the coding standards, code reviews, release management and any change management that might be needed in the software platform. QA also encompasses the quality control stage in the software life cycle. It consists of planning, documenting and following the quality control outputs.

1.1.2.1. Quality Control

Quality control is a set of activities designed to evaluate the project output with respect to its specifications. It starts after the code is done and it aims at proving that the code is correct and error free. It is thus oriented to “detection” (Quality Assurance and Software Testing, 2008). In general, quality control consists of verification, validation, and software testing; it includes activities such as walkthroughs, reviews, code and document inspections, formal method verification, several types of testing, etc. It is the responsibility of QA people to plan and document all these steps, to determine where the interdependencies are and reduce the information into standard patterns for future use.

Software validation ensures that the final product has implemented all of the requirements, so that each system function can be traced back to a particular requirement in the specification (Pfleeger, 1998).

Software verification ensures that each function works correctly. Validation makes sure the developer is building the right product and verification checks the quality of the implementation (Pfleeger, 1998). Verification typically involves testing and code evaluations through walkthroughs, inspections, checklists, etc. (Hower, 2009).

Testing is a process of executing a system with several input values with the intent of finding errors and correcting them. In this master's thesis, we focus on software testing as a mean for quality control, which is part of the quality assurance process. In the following section, we will explain briefly what might cause failures in software, and we will define some errors terminology. Then, we will discuss in details the different types of software testing.

1.1.3. What Causes a Software Failure?

There are several possible causes for a software failure that we will discuss in this section. But first we will define the used terminology for a better understanding of the problem:

- An error is committed by people, developers.
- A fault is the result of such an error in software documentation, code, etc.
- A failure in the system occurs when a fault is executed.
- An incident is the consequence of a failure, but may or may not be visible to the user.
- A test case is an input and its expected software output.
- Testing is executing test cases to find faults.

There are several possible reasons for software failures, the first one being a miscommunication between customers and developers, especially in the presence of a poorly elicited system requirements and specifications. In this case, the system is delivered based on a wrong understanding of the requirements, thus generating lot of failures from the user point of view.

Another possible reason for software failure is the software complexity. As the complexity of current software applications increases, it becomes more difficult for non-experienced developers to manage complex software development tools. Multi-tier distributed systems, system applications utilizing multiple remote Web services, enormous relational databases, security complexities, and large systems have all contributed to the exponential growth in software/system complexity.

A third possible reason for software failure is of course development errors. Programmers are humans and can make errors while coding. While some of these errors are detected fast by the developer's test, some of them can stay hidden and require more advanced testing techniques.

Another and very important possible cause can be the continuously changing requirements or evolution of software. It is specially the case in poorly documented software where, under time pressures, developers are required to do lot of guesswork regarding an implemented feature when they are asked to modify, maintain, or add to it.

For this reason, QA is a key element to detect as much as possible of software errors and prevent software failures. Companies that fail to implement QA standards and adequately define the software testing plan for an application can destroy brand credibility, sabotage the overall project, and create a cost blowout. We will discuss in the next section the different testing strategies and types.

1.1.4. Software Testing

Software testing has traditionally been one of the main techniques contributing to high software dependability and quality. It provides confidence in the system developed and establishes the extent that the requirements have been met, i.e., what the users asked for is what is delivered to them. Testing involves execution of a system under controlled conditions and comparing the results with expected ones. The controlled conditions should include both normal and abnormal conditions to determine any software failure under non expected situations (Hower, 2009).

1.1.5. Testing Techniques

In a conventional program testing situation, a program P is executed on a set of input values X and then the correctness of the output Y is examined. In the life cycle of software though, there are several stages of testing, each having a different kind of input values X and different goals or parts of P to test.

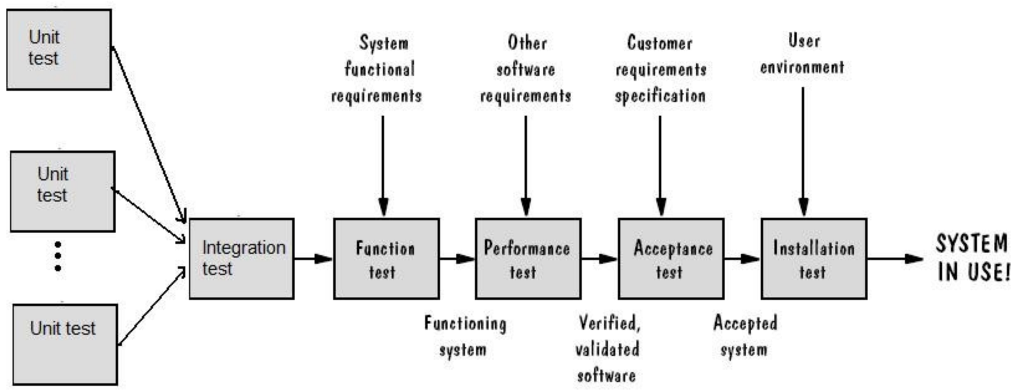


Figure 1.2: Testing activities (Pfleeger, 1998)

The testing stages illustrated in *Figure 1.2* are:

- Unit testing is the most 'micro' scale of testing; it consists of testing functions or code modules. It is based on module specifications and has complete visibility on the code details.
- Integration testing tests the modules or classes combined to determine if they function correctly together. It is based on interface specifications representing how

a whole set of classes should interact together and thus it has visibility of the integration structure.

- System testing is based on the overall requirements of the whole system brought together and it has no visibility of the code. It is based on the requirements and functionalities of the system. It can be divided into two sub-testing types:
    - The functional testing of the whole system to make sure the system matches the system functional specifications.
    - The performance testing of the software final measurable performance characteristics.
- Next, the system should be tested from a user perspective. Acceptation testing is usually done by the customer or buyer of the system. It is based on the end-user requirements to make sure the software answers the users' specifications and requirements.
- Finally installation testing is performed to test the software in the user's environment. In some cases, an initial release of the software is provided to an intended audience to secure a wider range of feedback. This is commonly called beta testing.
- Another kind of testing is the regression testing that consists of re-testing after fixes or modifications of the software or its environment.

We can mainly divide testing strategies into two families: black box testing and white box testing. The main difference between black box and white box testing is that the underlying code of the software is used to determine the test-data in white box testing. In contrast, in black-box testing, the test inputs and expected outputs are derived solely from the functional specifications.

Black box testing is also known as functional, behavioural, opaque-box, or closed-box testing; the tests done are based on the functional requirements of an application and there is no visibility of the application code or internal structure. This kind of testing is usually performed by a testing team different from the development team. The types of testing under this strategy focus on testing functionalities of the product. The base of the black box testing strategy lies in the selection of appropriate data as per functionality and testing it against the functional specifications to check for normal and abnormal behaviour of the system.

The testing stages usually done using the black box family techniques include functional testing, system testing, user acceptance testing, sanity or smoke testing, beta testing etc.

The main advantage of black box testing is that it allows checking the conformance of the system with the specifications and thus it allows detecting missing functionalities. It also scales up in the sense that it is used for different types of testing at different granularity levels. However, the disadvantage of this strategy is that it depends on the specifications and, thus, on the degree of details in the specifications. In other words, poorly documented specifications can lead to poor functional testing. The other weakness of black box is that it does not detect unexpected functionalities. If the system performs unwanted behaviour for non specified input, the black box testing will not be able to detect it because it selects test data based on the wanted behaviour in the documentation.

The other testing strategy is white box testing. It is also known as structural, glass-box, and clear-box testing. It is based on knowledge of the internal logic of the code as well as its internal structure. Thus, tests are based on the code structure; there are several white box coverage criteria:

- Statement coverage: every statement in the code should be executed at least once, since errors cannot be discovered if the parts containing them are not executed. The problem with this criterion is that it doesn't ensure high dependability; for instance it does not test the false outcome of an "if" statement with no else branch.
- Branch coverage: all branches in the code are tested at least once. Branches are basically parts of code under an "if", "else", "while", "for" loops, etc. Representing the code as a control flow graph, branch testing, or what is also called edge testing, is generating test data to ensure each edge in the graph is

executed at least once. The problem is that while a certain input can make an “if” true and thus traverse its branch, we will not be sure that this decision is 100% correct. Other input might lead this decision to give unwanted result, and such error will not be detected using this coverage.

- Condition coverage: it is a strengthened branch testing. Each edge in a control flow graph should be executed at least once, but also, if a decision is a compound of several conditions, all possible values of the constituents conditions are exercised at least once.
- Modified Condition / Decision coverage: this criterion is in turn a strengthening of the condition coverage. It consists of proving that every condition in a decision affects the result of the decision in the desired way. Such criterion is able to prove that a decision is correct and if an error exists, it is able to detect which part of the decision generated the error. The focus of this Master’s thesis is the automation of this criterion that we will describe in details in the following sections.

The main advantage of white box testing is that it allows developers to be confident about code coverage. It is also based on data and control flow and thus can rigorously test every detail in the code. However, the main disadvantage of white box testing is that it can miss cases omitted in the code; testing the code, developers cannot detect required functionalities that were not included in the code.

In general, an understanding of the software lifecycle and the testing process in the quality control stage is essential to any commercial software company. Implementing best practice standards is part of the ongoing commitment of industry professionals to the continual improvement paradigm. Still, no absolute certainty can be gained from testing. Malicious errors can still go undetected. For this, testing should be integrated with other verification activities, e.g., code inspection, formal verification, and other possible techniques.

1.2. Problem Definition

1.2.1. Automating Testing

While software testing is very important to make sure the developed software is ready to be released on the market, testing can be very time consuming. It is reported that 40 to 50% of software development effort is allocated for testing (Saha, 2008). A survey done in 2002 by InformationWeek revealed that software testing consumes up to 50% of the total cost of the software development; this survey was followed by a second one in 2002 in the province of Alberta, Canada, showing that only up to 30% of test automation is done on the unit level, and the percentage drops even more for system and integration level (Geras, Smith, & Miller, 2004).

There are several reasons why testing is time consuming. Let us consider an application counting millions line of codes; the white box testing techniques alone require lot of time to cover all the selected test criteria, which can cause a problem for competing companies on the market. In fact, today, software managers and developers are often asked to deliver complex software with ever-shrinking schedules and with minimal resources. As a result, 90% of developers miss the deadlines and 91% are asked to remove key functionalities late in the development cycle, allowing time to test the functionalities already developed and release it on time. The reason is that often getting a product to the market as early as possible can make the difference between the product survival and death (Dustin, Rashka & Paul, 1999).

A solution to this problem is the automation of testing. Automating software testing can be done mainly in two ways. The first way would be to create scripts with all the required test cases embedded in them. This is extremely advantageous in the regression testing, which consists of redoing all tests on the entire system after every small change to make sure that the change didn't affect other working functionalities in the system. In this case, it is extremely costly to redo manually the same tests over and over again, when the scripts can be re-launched and the system is tested automatically. A second advantage of automating testing with scripts is that it provides proof that the tester did all the tests and no test was forgotten (Geras, Smith, & Miller, 2004). Another advantage is the ability to run the scripts in parallel on different machines instead of doing manual testing sequentially on one machine and thus to save lot of time, or even let the scripts run all the tests all night long and report errors found without the need to be supervised (Crestech Software Systems, 2008). Moreover, if the software is environment-dependent, such as operating systems dependent, but has the same external behaviour, then the tests should be performed on all the different possible environments, which is of course very costly when done manually.

There are test automating tools in industry today that will create automated scripts to test a system; the test cases should be provided to automate them. One example is the TestComplete tool from Automated QA, promoted as “a tool designed to free developers and QA departments from the massive drain on time and energy required by manual testing”. The advantage is to run nightly scripts and collect the tests later (AutomatedQA, 2009). Another example is the Test Plant tool that uses a scripting language to automate the tests as well (TestPlant Ltd., 2008).

The second test automation method is to develop a tool that would automatically generate test cases and run them on the application or system to be tested. Such a tool is required to analyse the code under test, generate the test cases for a certain test criterion and then generate the test data (Crestech Software Systems, 2008). Scripts can then execute the application with the test data and check the output against expected results. Such an automation tool is complex to develop and requires a software life cycle by itself; however it can provide a huge time saving once it is done. In fact, since a program is usually tested several times before it is released, the cost of writing the test suite is sometimes regained before the program is even released (Volokh, 1990). More importantly, an automation tool is usually done independently of the application or system to test, and thus it can be used for different applications and systems. In other words, the long life of an automation tool usually compensates its initial cost and results in a big decrease in the software testing cost on the long run.

In general, automating test is easier to implement on white box testing techniques than black box techniques. In white box techniques, the test cases to be generated rely on the code itself, and thus it is possible to use code analysis techniques to extract the necessary information needed to generate the test cases and the test data. In most black box techniques, the test cases should be generated based on functionalities written in natural language such as English or French. It is more difficult to create techniques with the ability to analyse such languages and to extract the necessary information required to generate the adequate test cases.

It is important to have automation tools engineered in an independent way of the application to be tested. With the growing demand for rapidly developed and deployed Web applications, we cannot afford to do and redo all the tests manually on the applications, nor can we afford to reengineer automation frameworks for each and every new application. Thus, it is an advantage to have a single tool for each test criterion that will grow and continuously improve with each application and every diverse project that challenges us; which is what we aim in this masters' thesis, developing an automation tool for the MC/DC test criterion that would be applicable on Java programs; such a tool does not exist in industry today.

1.2.2. Modified Condition/Decision Coverage Criterion

As stated above, avionic regulated domains should be compliant with the DO-178B safety assessment document to get the approval of the Federal Avionic Administration (FAA) for any software before its release in the avionic market. Because of the importance and criticality of software in this domain, failures are non-affordable. One testing criterion stated in the DO-178B document is the Modified Condition/Decision Coverage criterion (MC/DC) for level A software. The document divides the software into four levels, from level A to D, in a decreasing order of safety criticality; level A being defined as "Where a software/hardware failure would cause and-or contribute to a catastrophic failure of the aircraft flight control systems" by the FAA (Hayhurts & al., 2001). No test automation tool exists currently for the MC/DC criterion; for this reason we choose to develop such a tool for the test data generation for MC/DC.

The goal of MC/DC testing is to make sure that each condition in a decision in the application code affects correctly the outcome of this decision. This way, not only the developers will test all the decisions in a code, but also every part of these decisions. Later, we will describe in details how to generate test cases to cover this testing criterion.

The MC/DC criterion is detailed in the report published by NASA, entitled “A Practical Tutorial on Modified Condition/Decision Coverage” (Hayhurts & al., 2001), but no implementation is provided. To the best of our knowledge, no automatic tool exists today in the avionic industry (or other industries) that is able to automatically generate test cases and test data for this criterion. This forms our main motivation to develop a tool that would automatically test applications to cover the MC/DC criterion, first by analysing the code under test, second by generating the appropriate test cases, and third and most importantly by generating the appropriate test data for each test case. For instance, if a program contains the decision “if (speed > 100 && force < 200)”, the MC/DC criterion requires to prove that each part of the decision (speed > 100) and (force < 200), called conditions, will affect correctly the outcome of this decision; i.e., the outcome of the decision is as expected. Thus, the MC/DC test cases to generate would make the first condition (speed > 100) once true and once false while (force < 200) is fixed to true to show the effect of the first condition on the entire decision. The same way, the second condition should be once true and once false while the first condition is fixed to true. These test cases are generated automatically for the decision. The next step would be to automatically generate the appropriate values of the variables “speed” and “force” to satisfy the test cases, i.e., for the test case (speed > 100) false and (force < 200) true, the tool should find a value for “speed” less than 100 and a value for “force” less than 200.

1.2.3. Test Data Generation

Generating test data is a complex task. Let us consider that we want to test a program that has two integer parameters x and y, and let us consider for now that we are trying to generate the test data manually, the tester has usually a set of test cases to write to cover the MC/DC or any other testing criterion. Covering a test criterion consists of finding the appropriate test data, x and y, that would satisfy the criterion. If a test case consists of making a condition in the middle of a code true, the tester can only manipulate the parameters x and y of the program under test, and not any local variables that might be used in the condition to be tested and their possible relationship with x and y. Moreover, the admissible range for x and y in this case is the entire integer range, and thus the tester has to guess the appropriate values for x and y from a $2^{32}x2^{32}$ possibilities. As a result, searching for the test data manually can sometimes be impossible; an automated code analysis technique is needed to extract the dependencies in the code and then an automated search technique such as the meta-heuristic algorithms is needed to search iteratively for the data in large search spaces.

In the following section, we summarize the activities required to attain the MC/DC automation.

1.2.4. Extracting Code Dependencies

MC/DC criterion consists of testing every decision in the code. Thus we need to locate the decisions in the code and extract their structure to generate the appropriate test cases for them. We developed a parser to extract the decisions structure, as well as a code instrumentation tool to trace the execution of the program for each test datum. A third tool is needed to extract the dependencies in the code between the decisions. Dependencies can be in two forms:

- Control dependencies between nested decisions. In this case, if a decision is nested into the true branch of an earlier decision, we say that the first decision has control dependency on the second decision.

- Data dependencies on the other hand are between the variables used in the decision and prior variables in the code or with the program parameters.

Most suggested techniques for structural testing consider control dependencies, ignoring data dependencies. This can cause a serious lack of guidance for the search in some cases. On the other hand, a work done by McMinn in 2004 suggests data dependencies as the appropriate tool to guide the search for data. This technique alone may lead to incompleteness of guidance, and thus we worked to fully integrate both control and data dependencies in the code analysis and be able to come up with an improved technique to guide much more effectively the search for automatic test input data generation. As a result, we propose a new and improved guidance function, also called fitness function, for the generation of test cases and test data for the MC/DC criterion.

1.2.5. Meta-heuristic Algorithms

In today's literature, several works use meta-heuristic algorithms as search tools to automate the data generation. Due to the computational complexity of the search problem, exact techniques like linear programming are mostly impractical for large scale software engineering problems and manual search is mostly impossible. Thus, Search-based software engineering (SBSE) is an approach to apply meta-heuristic search techniques like genetic algorithms, simulated annealing, and taboo search to seek solutions for combinatorial problems at a reasonable computational cost. In SBSE, we apply search techniques to search large search spaces, guided by a fitness function that compare solutions with respect to the search goal and determine which is the better solution and thus to direct the automated search into potentially promising areas of the search space (McMinn, 2004).

For test data generation, this involves the transformation of test criteria to objective functions. For each test criterion, a family of different objective functions is needed. The algorithm iterates then to generate the appropriate data to make the fitness function as close as possible to zero, meaning the algorithm found the data for the test case.

1.2.6. Objectives and Contributions

SBSE are used in literature to automate the data generation for structural testing such as statement testing and branch testing, however none explored the problem of generating test input data for the MC/DC criterion. We use two meta-heuristics algorithms, the genetic algorithm and the hill climbing algorithm, to automate the test data generation, and we propose an improved cost function to better guide the search. We test the automatic test and data generation on two benchmarks. We also use a random generator that tries randomly selected data from the entire search space. The test data generation is performed with the new cost function with integrated data dependencies and with the traditional cost function relying solely on control dependencies. Results show the superiority of the new fitness function. For the first program, we are able to achieve 81% vs. 55% coverage with the genetic algorithm with data dependencies and without respectively, 47% vs. 39% coverage with the hill climbing and 40% coverage with the random (in this case nor data or control dependencies influence the random generation of the data).

Overall, we are able to develop a testing automation tool that would first analyse the code under test and collect all necessary information about control and data dependencies of the code, second, generate a new improved fitness function for each decision in the code, and third, use the fitness function as a guide to meta-heuristic search algorithms to automate the test data generation for the MC/DC testing criterion.

We published our work at the **2009 Genetic and Evolutionary Computation Conference.** The article published is entitled 'MC/DC Automatic Test Input Data Generation**'**, by Zeina Awedikian, Kamel Ayari and Guiliano Antoniol.

Chapter 2: Related work

2.1. Search Based Search Engineering

Search Based Software Engineering (SBSE) applies search based optimization algorithms to problems drawn from software engineering. The optimization algorithms are used to identify optimal solutions and to yield insight. SBSE techniques can be used for multiple objectives and-or constraints where the potential solution space is large and complex (Harman, 2007). Such situations are common in software engineering, leading to an increasing interest in SBSE.

The search based optimization algorithms used in SBSE are meta-heuristic algorithms such as Genetic Algorithms, Hill climbing, Simulated Annealing, Random, Taboo Search, Estimation of Distribution Algorithms, Particle Swarm Optimization, Ant Colonies, LP, Genetic programming, Greedy algorithms. The search mechanism of these algorithms in large search spaces is guided by a fitness function that captures properties of the acceptable software artefacts we seek.

In the past five years, SBSE techniques were used for several applications such as Regression testing (Li, Harman, & Hierons, 2007), model checking (Ferreira &al. 2008), maintenance (Antoniol, Di Pentan & Harman, 2007), test generation (McMinn & Holcombe, 2006), etc. We are mostly interested in the application of SBSE to software testing.

2.1.1. Search Based Software Testing

We use the term Search Based Software Testing (SBST) throughout our work to indicate the application of SBSE to the testing problem. A major issue in software testing is the automatic generation of the testing inputs to be applied to the program under test.

To cover a test criterion, a set of test cases should be met. For each test case, the parameters of the application or the system under test should be generated in a specific way to satisfy the test case, which is called test data generation. One way to generate the data is to explore the entire parameter's space in order to find the appropriate combination of values. However, for applications with several parameters, exploring the entire parameter's space can increase exponentially, and an exhaustive search becomes impossible. For instance, aerospatiale applications can take up to 10 or more parameters; in such cases, if the parameters are integers, the parameter's space is $2(^{10*32})$. A solution to this problem is to use a heuristic technique which is use an approximation algorithm to search for the data. Such a technique risk to either not find a solution, when there exists one, or to find a non optimal solution. However, it allows searching for the data in a reduced search space and in a reduced search time.

A number of approaches based on heuristic search methods have been developed; in general SBST uses search based optimization techniques to formulate the test data generation problem as a search problem (Lakhotia, Harman, & McMinn, 2008). This problem is then addressed using search methods; it can also be formulated as a constraint optimisation problem or a constraint satisfaction problem (Sagarna & Yao, 2008).

The meta-heuristic search techniques used in SBST are high-level frameworks that use heuristics to find solutions to combinatorial problems at a reasonable computational cost. Since meta-heuristic algorithms need a fitness function representing the combinatorial problem to guide the search; the testing criterion is transformed into the fitness function. The search space is the space of possible inputs to the program under test.

SBST has proved to be effective partly because it has a wealth of optimization techniques upon which to draw and because the generic nature of the approach allows it to be adapted to a wide range of test data generation problems; in principle, all that is required to adapt a search based technique to a different test adequacy criterion is a new fitness function (Lakhotia, Harman, & McMinn, 2008).

Works on search based approaches to software engineering testing problems date back to as early as 1976, when Miller and Spooner used optimisation techniques for test data generation (Miller & Spooner, 1976). In 1992, Xanthakis et al. were the first to apply meta-heuristic optimization search for test data generation (Xanthakis et al., 1992). In recent years, several approaches that use meta-heuristic search techniques to automatically obtain the test inputs for a given test criterion have been proposed. We are mainly interested in works done on structural testing since the MC/DC is a structural testing criterion.

In the following section, we present two main works done in this field, the first one is by Miller and Spooner, as it was the first work to use search based optimisation techniques for test data generation (Miller & Spooner, 1976). The second work done by Korel is the first to use data analysis to help the heuristic search (Korel, 1990). In the next section entitled Meta-heuristic search algorithms, we will present more recent work that use different search approaches for SBST problems.

2.1.2. Structural Testing

Automation of structural coverage criteria and structural testing has been the most widely investigated subjects. The first strategy used to automate the test data generation for structural testing is a local search used by Miller and Spooner back in 1976 (Miller & Spooner, 1976). Their goal was to automate the generation of input data to cover particular paths in a program. They formulated the problem as a numerical maximization problem and they used a “heuristic” approach to solve it. However, they were only interested in generating floating point data to cover the test cases of the branch testing criterion. The used approach fixes any integer parameters in the program, and tries to generate values for the remaining floating point parameters for each possible path in the program. Since each program execution takes the form of a straight line program, it is possible to collect any path constraints for a given execution. The collected constraints form the search fitness function. Then, starting from an initial random point, the approach applies numerical techniques for constraint maximization. The search iterates until the fitness function become positive. Since the goal here is to make the fitness function positive, and any point with positive fitness is equivalent, there was no need to consider the cases of local optima (Miller & Spooner, 1976).

This approach has two drawbacks. First it only targets floating points parameters; second, often infeasible paths are selected; as a result, significant computational effort is wasted analyzing these paths and trying to find data covering them.

This work was later extended by Korel in 1990 (Korel, 1990). While the first work relies on the static constraints in the program execution to form the fitness function guiding the search, Korel uses a dynamic technique that relies on the actual execution of the program with input data. The goal is again to cover the branch testing criterion. Initially the program is executed with arbitrary input. During each execution for a targeted branch, a search procedure determines whether the execution should continue through the current branch or an alternative branch should be taken. This decision is made based on the control flow graph of the program, determined prior to the execution of the program. Branches are classified into categories, critical branches, required branches, semi-required branches, and non-required branches. These categories represent the control dependencies between branches. Thus, if the execution flow is diverging from the targeted branch, a real valued function is associated with this branch; the fitness value. A minimisation search algorithm is then used to automatically generate data to change the flow of execution at this branch. In order to speed up the search, Korel uses a data flow analysis technique to determine input variables that are responsible for the undesirable program behaviour. The technique is used for programs with a high number of parameters such as big size arrays, and it aims at detecting which of the input influences more the targeted branch. Thus, if $T=<n_{kl},n_{k2},...,n >$ is a path traversed on a program input x, where x can be an array of 30 elements, the technique determines the influence of the elements of x on the nodes in the path in terms of used variables, and the influence of each node n_k on the node following it until the targeted branch is reached. This way, for a certain target branch, the author only considers the influential input variables (elements of the array in our example) in the search procedure (Korel, 1990).

Though this approach presents improvements on the previous work (Miller & Spooner, 1976), it does not present an implementation of the data flow analysis. On the other hand, the data flow analysis is used only to select the input variables influencing the branch to test and thus starting the search of required data for these variables. However, the author does not take advantage of dependencies to actually guide the search using the data flow analysis information. This is what we call data dependencies between the nodes of the program, and it can actually help the search converge faster to the required solution.

The local search used to find the test data can lead to local optimum solutions in the search space when trying to minimize the fitness function. In order to overcome this problem, researchers investigated more sophisticated search techniques such as the simulated annealing, hill climbing, and evolutionary search algorithms. We will discuss the work done on these algorithms in the following section.

2.2. Meta-heuristic Used To Automate Test Data Generation

For each problem solved using meta-heuristic techniques, there are usually two main decisions of implementation. The first one being the encoding of the solution, i.e., the structure (e.g., array, tree), how many variables it has, their types, etc, and the second main decision is the transformation of the test criteria into a fitness function. The fitness function, models the closeness of the input data to cover the criterion tested. It is usually calculated at the end of each algorithm iteration and it compares and contrasts the solutions with respect to the overall search goal to guide the search into a promising neighbourhood of the search space.

There are several types of meta-heuristic algorithms that were used in literature to automate the data generation. We will describe here works based on the simulated annealing algorithm and the evolutionary techniques, such as the genetic algorithm.

2.2.1. Simulated Annealing

To overcome the limitations associated with local search optimum, Simulated Annealing (SA) was used as another type of meta-heuristic search algorithms. Tracey et al. proposed in 1998 an optimisation-based framework to be applied to a number of structural testing problems (Tracey et al., 1998). Tracey's work focuses on branch coverage. Their goal is to search for program input which forces execution of the desired part of the software under test. For the search to succeed, a fitness function is needed to guide the search, relating a program input to a measure of how "good" the input is to achieve a certain test target. The fitness function returns good values for test-data that nearly executes the desired statement and bad values for test-data that is a long way from executing the desired statement. In general, the input domain of most programs is likely to be very large, and given the complexities of systems it is extremely unlikely that the fitness surface would be linear or continuous. The size and complexity of the search space therefore limits the effectiveness of simple gradient-descent or neighbourhood searches as they are likely to get stuck in locally optimal solutions and hence fail to find the desired test-data (Tracey et al., 1998). Thus a more sophisticated approach is needed such as the SA. SA allows movements which worsen the value of the fitness function based on a control parameter known as the temperature. At the early stage of the search iterations, inferior solutions are accepted with relative freedom, but as the search progresses, accepting inferior solutions becomes more and more restricted. The aim of accepting these inferior solutions is to accept a short term penalty in the hope of longer term rewards.

The fitness function designed by Tracey et al. evaluates to zero if the branch predicate evaluates to the desired condition and positive otherwise. It is designed based on the structure of the system under test; for each predicate controlling the target node, if the target node is only reachable if the branch predicate is true then the fitness of the branch predicate is added to the overall fitness for the current test-data otherwise the fitness of ¬(branch predicate) is used. For loop predicates, the desired number of iterations determines whether the fitness of the loop predicate or ¬(loop predicate) is used. The simulated annealing search uses this to guide its generation of test-data until either it has successfully found test-data or until the search freezes and no further progress can be made (Tracey et al., 1998).

The automation framework was tested on small Ada 95 programs to cover the branch coverage criterion. The programs ranged from 20 to 200 lines of codes. The reported coverage percentage is 100% for all but one case; the failing case achieved 100% branch coverage in 40 out of the 50 trials. The search time of SA is 2 to 35 seconds. Unfortunately, the programs tested are not available and thus we were unable to verify their structural complexity. Moreover, no comparison with other search techniques performance is presented. Still, this work provides an automated platform for structural testing. We aim in our work to build a similar platform, however achieving the MC/DC coverage and not the branch coverage.

2.2.2. Genetic Algorithm

Evolutionary approaches are search algorithms tailored to automate and support testing activities, i.e., to generate test input data. They are often referred to as evolutionary based software testing or simply Evolutionary Testing (ET). Genetic algorithm (GA) is an ET algorithm.

2.2.2.1. Real Time Testing

In 1997, GA was used by Wegener & al. to test real-time systems for functional correctness. A common definition of a real-time system is that it must deliver the result within a specified time interval and this adds an extra constraint to the validation of such systems, namely that their temporal correctness must be checked (Wegener, Sthamer, Jones, & Eyres, 1997). The standard technique for real-time testing is the classification-tree method; it was used to generate the test cases forming the objective of the search. The genetic algorithm aimed to find the longest execution time, and then the shortest of the real system response time. Wegener et al. concluded from their work that genetic algorithms are able to check large programs and they show considerable promise in establishing the validity of the temporal behaviour of real-time software (Wegener, Sthamer, Jones, & Eyres, 1997).

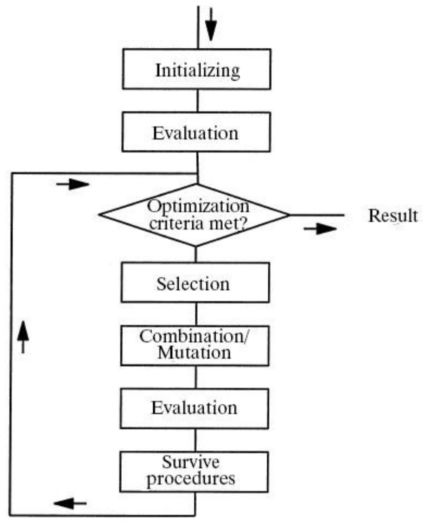


Figure 2.1: Block diagram of the genetic algorithm (Wegener & al., 1997)

The used GA's block diagram is illustrated in *Figure 2.1*; the algorithm iterates with a population of candidate solutions. It initialises with a randomly generated population then it evolves by combining and mutating the current generation in order to generate possible solutions. An evaluation is performed on the newly generated solutions and a selection technique is then used to transmit only the fittest individuals into the next generation. The algorithm iterates until a solution is found to satisfy the optimisation criteria.

2.2.2.2. Data Flow Testing

A recent work by Ghiduk et al. in 2007 applies GA to search for test data to satisfy the data-flow coverage criteria; which is a structural criterion, by generating a test suite to cover the all-uses coverage criterion. Data flow analysis determines the definitions of every variable (statement where the variable is defined) in the program and the uses (statement where the variable value is used) that might be affected by these definitions. Thus, the all-uses criterion consists of generating a set of test cases T, such that for every variable v in the program, T contains at least one definition clear path from every definition of v to every reachable use of v. The genetic algorithm used is fed with one test goal $t \in T$ at a time and generates the test data satisfying this test goal. To generate the appropriate fitness function for each test goal, the technique uses the control flow graph of the code under test. The control flow graph is mostly used to detect the nodes where variables are defined and used, and then the genetic algorithm tries to find input data to cover the pairs of (definition, use) for each variable v. The program under test is executed for each test data and the path of the execution is recorded. The path is then used to calculate the closeness of the input data to the clear path sought; a clear path being a path with no modification applied on the variable between its definition and its use. In the search process, parameters are encoded into binary values and the crossover and mutation is applied on binary values. The resulted individuals are decoded back into the real parameters types (Ghiduk, Harrold, & Girgis, 2007).

The technique was tested on nine programs ranging between 20 and 60 lines of code, and between 11 and 88 def-use pairs. The results of the work can be summed as follows:

- On average the genetic algorithm needs 79 seconds, 628.56 iterations, and 4112.56 test cases to satisfy 93.25% of the test requirements of all programs to cover all-uses criterion
- A random search technique needs 180.22 seconds, 1251.56 iterations, and 6879.11 test cases to satisfy 79.81% of the test requirements of all programs.

The results show the superiority of the GA search. However, two important threats to validity can be summarized as follows, first, the programs tested are small and do not represent a random selection over the population of programs as a whole. The second threat to validity is that results are compared to a random data generator that is usually not sufficient to evaluate the reliability of the technique (Ghiduk, Harrold, & Girgis, 2007).

2.2.2.3. Class Testing

A recent contribution by Tonella in 2004 has demonstrated ET applicability to the problem of object-oriented testing, more precisely to unit testing of classes. Unit testing is a white box technique that considers one class at a time, executing the class with different input values and verifying the expected results. The class is isolated from the rest of the software and required classes are made available using stubs. The complexity of class testing in an object oriented environment is caused by the object state, the many possible usage scenarios of an object and the large search space.

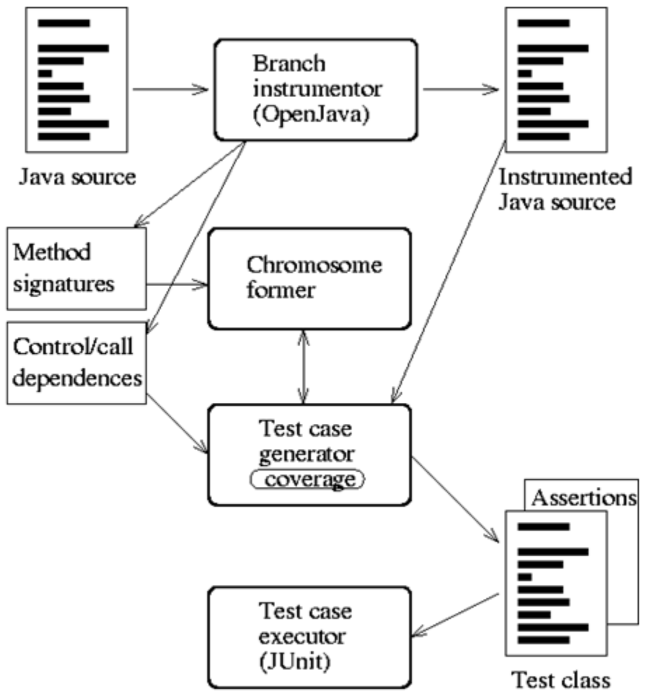


Figure 2.2: Automation of test cases generation using ET (Tonella, 2004)

In Tonella's approach, the functionalities of classes are tested first by testing the total outcome of the methods, then code coverage is targeted, using structural coverage, and data flow coverage. Thus, the fitness function is build based on the state of the objects in a class, each object's parameter, action and value, as well as each method signature, call and parameter contribute to form a chromosome reprensenting the fitness function. ET is then used to automate the test case generation. The mutation used in the genetic algorithm is a one-point mutation, where either a parameter value is changed, or a method signature, or a method call insertion, etc (Tonella, 2004).

The algorithm was tested on seven classes taken from the java.util library with the number of line of codes ranging from 100 to 1,000 approximately and having between 6 and 26 public methods. Artificial errors were inserted in the classes. The results showed an average test coverage of 95% and the tests were able to find an average of 77% of the inserted errors. The method was able to find powerful and compact test suites, however it was not fully automated. It needed manual tweaking and annotation, and no oracle was available to use as a comparison tool (Tonella, 2004).

2.3. Search Fitness Function

2.3.1. Traditional Fitness Function

ET has proved its effectiveness in searching for test data (Wegener, Baresel, & Sthamer, 2001). In most evolutionary approaches for structural testing, the traditional fitness function is composed of two components:

$$f(x) = \textit{approach level} + \textit{branch distance}$$

The first component accounts for control dependencies and it is often referred to as the approach level, or approximation level. It measures how close in structural terms the input is from reaching the target. Thus, it is usually the count of critical nodes in the control flow graph between the target and the node where the execution diverged (Baresel, Sthamer, & Schmidt, 2002).

For example, *Figure 2.3* presents a simple code for the Calc method. The statement at line 17 depends on the ’if’ statements at lines 12, 13 and 16: the ’if’ statements at lines 12, 13 and 16 control the execution of line 17. Control flow nodes in the program Control Flow Graph (CFG) corresponding to those ’if’ statements are called the critical branches because they can cause the flow to diverge to unwanted code regions. The approach level for a test input datum is computed by subtracting one from the distance in critical branches. Going back to the target line 17, if the flow diverges at line 13 (two control nodes in between), the approach level assign a fitness value of one. Thus, approach level measures how close we are to line 16 “if”, the last controlling statement (McMinn, 2004).

```
1     public int Calc (int x, int y, int z) {
2           int result = -1;
3           bool Fail = false;
4           if (x < 0 || y < 0 || z < 0 )
5                 Fail = true ; //illegal parameter value
6           else
7                 Fail = false;
8           if (not Fail) {
9                 x = y //overwrite x by a new value
10                result = 0;
11          }
12          if (result == 0) {
13                if (z == 0 )
14                      result = x + y;
15                else {
16                      if (z > x && z > y && z > x + y)
17                            result = z;
18                      else
19                            result = x + y;
20                }
21          }
22          return result;
23    }
```

Figure 2.3: Example of code under test

The second component of the fitness function is the branch distance. It is computed either at the branch where the input diverged (Baresel, Sthamer, & Schmidt, 2002), or at the target node if the input x did not achieve the test case at this node. It is used to overcome the limitation of the first fitness component; if the search generates input data leading to the target without satisfying the test case at the target, all critical branches are satisfied and thus the approach level fitness is zero, also if two input values diverge at the same critical node, the approach level is the same for both of them. In these two cases, the approach level is no longer effective in guiding the search and the branch distance is needed. The later calculates how close the input is from satisfying either the target or the branch where it diverged (McMinn, 2004). A work presented by

Bottaci in 2003 explores how to calculate effective branch distance functions (Bottacci, 2003).

This fitness function has a limitation when the code under test contains flag conditions or data dependencies between the variables of the code. In this case, the fitness function fails to guide the search, leading to a random search. We will discuss this issue in details in the next two sections.

2.3.2. Fitness Function For Flag Conditions

In 2005, Liu and al. addressed the problem of flag conditions in the code under test. While ET proved its effectiveness in automatically generating test data, the presence of flag variables makes the search degenerates into a random search for structural testing. The problem in such techniques is that they rely on a fitness function solely derived from the control dependencies between nodes based on the control flow graph. When the target statement is controlled by an "if" containing flags and these having data dependencies from prior statements not contained in the control dependencies predicates of the target, the fitness function is no more effective in guiding the search.

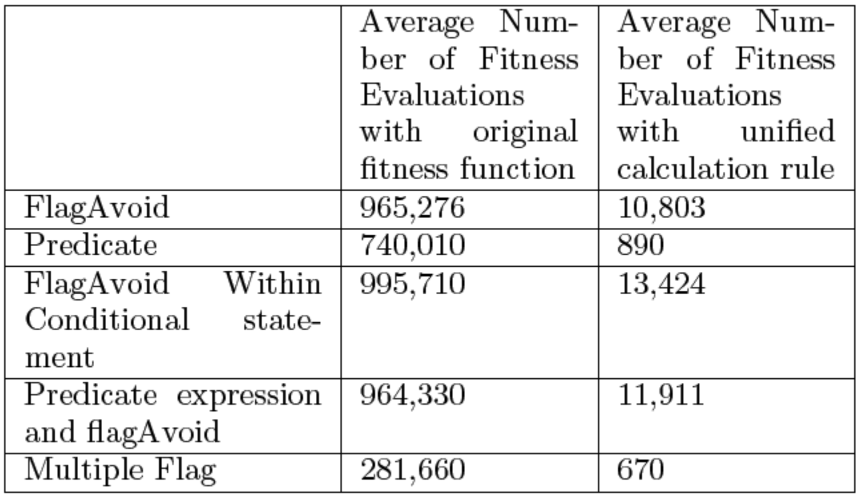
```
void flagCondition(int x, int y){
1:   bool flag = false;        7: ... // no flag assignment
2:   if( x > 4)                8: if(y > 6)
3:     flag = true;            9:   flag = true;
4:   if( x == 2)              10: if(flag)
5:     flag = false;          11:   //target
6:   if(x != 0)                }
```

Figure 2.4: A simple example of flag conditions (Liu et al., 2005)

For example a flag variable use is illustrated in *Figure 2.4* at line 10. While the "if" at line 10 contains the "flag" variable, and the value of "flag" depends on its modification in prior statement, there is no mean to make its value true based on the control dependencies that the "if" has (in this example it has none).

In general, flag variables only hold two values, either true or false; thus the fitness function can no more differentiate the degree of closeness and the fitness landscape becomes plateaux (Liu, Liu, Wang, Chen, & Cai, 2005). Liu and al. presented a new fitness function composed of two parts, the first is the same approach level and the second is flag cost function related to the flag definition statements. Since the flag value is defined by its definition statements (example flag = true at line 9 in *Figure 2.4*), it is required to consider the data dependence relationship between the use of the flag and its definitions, to calculate the branch distance. Each flag has a definition set D_f=<d_1,d_2,...,d_m>, where each node in this set is a definition statement of the flag. Also, each feasible path to the target has a conditional statement set C_f=<C_1,C_2,...,C_m>. When C_i is true, an assignment statement of f will be executed, whereas, when C_i is false, the assignment statement fails to be executed. Generally, at the ith conditional statement C_i, if branch d_i assigns true to the flag, the condition Si which keeps the flag true at C_{i+1} is $S_{i-1} \vee C_i$. For example, in *Figure 2.4*, in order to make flag true at the conditional statement of line 10, $S(1) = x > 4$, $S(2) = S(1) \wedge \neg$ (x= =2), S(3) = S(2) $\vee$ (y > 6) (Liu, Liu, Wang, Chen, & Cai, 2005).

An empirical study was conducted on different programs with flag. The approach uses a genetic algorithm with a population size of 49, crossover probability of 0.2 and mutation probability of 0.02. The algorithm stops when the test data are found or after 10,000 iterations. The algorithm runs using the traditional fitness function, then using the new fitness function. Also, the authors compare their approach to the flag avoid approach that we will present next. In the later approach, the code under test is modified in a way to avoid the flag use. For example, the code: if (a == 0) {flag = true} is replaced by: flag = (a[i] == 0). The results show a tremendous decrease in the number of fitness evaluations with the use of the new fitness function, *Figure 2.5* sums the results.

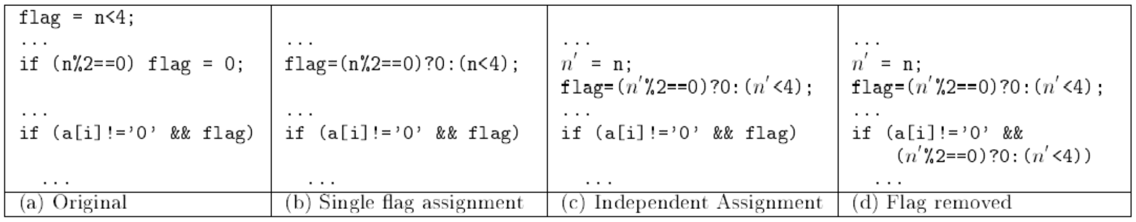


	Average Number of Fitness Evaluations with original fitness function	Average Number of Fitness Evaluations with unified calculation rule
FlagAvoid	965,276	10,803
Predicate	740,010	890
FlagAvoid Within Conditional statement	995,710	13,424
Predicate expression and flagAvoid	964,330	11,911
Multiple Flag	281,660	670

Figure 2.5: Results of flag problem approach (Liu et al., 2005)

Even though this approach presents a large improvement in the data generation for code with flag problems, it is specialized to flags and does not scale to the problem of data dependency between any types of critical nodes. For instance, a local variable can be modified several times in a code and then used in a predicate (for example at line 8 of *Figure 6* instead of y>6), the traditional fitness function leads to a random search, because the new fitness function proposed by Liu does not apply the data dependence analysis on non flags variables.

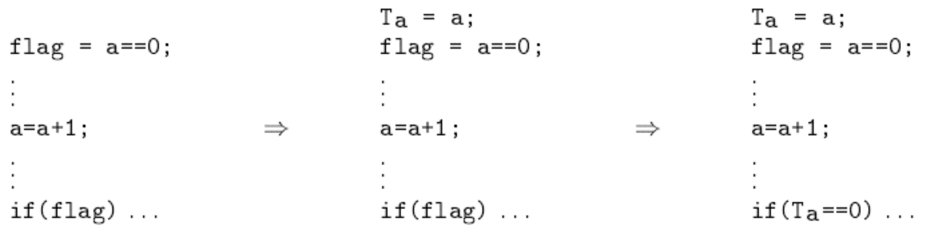
Another approach to solve the flag problem is the flag avoid approach that transforms code with flags into flag free codes (Harman, Hu, Hierons, Baresel, & Sthamer, 2002). The purpose of this approach is to also overcome the problem of flattened fitness landscape. Evolutionary testing is used to generate test data to cover certain structural criteria. An example of a transformation is illustrated in *Figure 2.6*.



flag = n<4;			
...	...	...	...
if (n%2==0) flag = 0;	flag=(n%2==0)?0:(n<4);	n' = n;	n' = n;
		flag=(n'%2==0)?0:(n'<4);	flag=(n'%2==0)?0:(n'<4);
...	...	...	...
if (a[i]!='0' && flag)	if (a[i]!='0' && flag)	if (a[i]!='0' && flag)	if (a[i]!='0' &&
			(n'%2==0)?0:(n'<4))
...	...	...	...
(a) Original	(b) Single flag assignment	(c) Independent Assignment	(d) Flag removed

Figure 2.6: Flag removal example (Harman et al., 2002)

Column (d) is equivalent to the original code in column (a) but easier to test because the flag is replaced by an expression that denotes its value at the point of use. Columns (b) and (c) are intermediate transformation steps introducing a temporary variable to capture the value of the variable “n”. The approach also treats the cases where there is no clear definition path between the flag definition and its use in the condition as illustrated in *Figure 2.7*.



```
                          Ta = a;                    Ta = a;
flag = a==0;              flag = a==0;               flag = a==0;
:                         :                          :
a=a+1;            ⇒       a=a+1;            ⇒        a=a+1;
:                         :                          :
if(flag) ...              if(flag) ...               if(Ta==0) ...
```

Figure 2.7: Flag removal example 2 (Harman et al., 2002)

Results were presented for experiments conducted on two flag-based programs to generate test data before and after the transformation, the Triangle program used as benchmark in our work as well, and a Calendar program. For the Triangle program, 40,000 fitness evaluations were not able to attain coverage of 86%, where 25,000 fitness evaluations were enough to attain the 86% on the transformed code. Also the maximum coverage is attained only on the flag-free code. For the Calendar program as well, the maximum achieved coverage is attained on the transformed program.

This work was extended in 2007 to cover the issue of function-assigned flags (Wappler, Baresel, & Wegener, 2007). A new approach is used, injecting a distance calculation function in the code to capture how far the flag is from being assigned true or false.

original program	transformed program
int callee(int b)	double callee_t(int b)
{	{
if(b == 0)	if(b == 0)
return TRUE;	return dist(1.0, <b==0>, 1);
else	else
return FALSE;	return dist(0.0, <b==0>, 1);
}	}
void fa_flag(int a, int b)	void fa_flag_t(int a, int b)
{	{
int flag = FALSE;	double flag = FALSE;
if(a == 0)	if(a == 0)
flag = callee(b);	flag = map(callee_t(b), 2);
	else
	flag = dist(flag , <a==0>, 2);
if(flag)	if(flag >= 0)
// target A	// target A
else	else
// target B	// target B
}	}

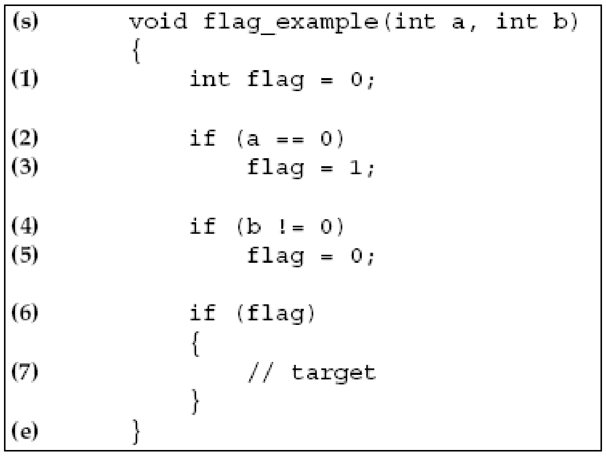
Figure 2.8: Flag removal for function (Wappler, Baresel, & Wegener, 2007)

In the example of *Figure 2.8*, a branch completion is performed on the code; "else" branches are added. The intention of this addition is to make a flag assignment occur regardless of the control path taken during execution of the program. Also, local instrumentation is performed on the flag definitions, where a distance function is called on the right hand operator of the flag assignment. This distance function is replaced by the "map" function when the flag assignment contains a function. Test data generation was performed on four flag-based examples and the results show that the successful rate of the data generation on transformed codes with fitness evaluations ranging from 1,200 to 24,000 approximately, while coverage for non transformed programs failed after 40,000 fitness evaluations trials.

The code transformation approach presents a solution for flags used in conditions and leading to a total loss of guidance for the evolutionary search. However, it is argued that there is a risk to modify the logic of a program while doing code instrumentation; a transformation of a condition might not be equivalent to the original one. Moreover, the structure of the conditions is the sole information for MC/DC coverage and thus an approach relying on the transformation of the conditions to logically equivalent ones but structurally different cannot be used for MC/DC. The generated test cases would not satisfy the coverage criterion.

2.3.3. Chaining Approach Integrating Data Dependencies

As stated above, the search algorithms can degrade to a random search due to a lack of guidance to the required test goal. Often this happens because the traditional fitness function does not take into account data dependencies within the program under test, and because certain program statements need to have been executed first in order to reach the target statement (McMinn & Holcombe, 2006).



```
(s)     void flag_example(int a, int b)
        {
(1)         int flag = 0;

(2)         if (a == 0)
(3)             flag = 1;

(4)         if (b != 0)
(5)             flag = 0;

(6)         if (flag)
            {
(7)             // target
            }
(e)     }
```

Figure 2.9: Code with one problem node (McMinn & Holcombe, 2006)

Figure 2.9 is an example of a code where the target in line 7 relies on a flag variable "flag" that was modified in prior statements. The traditional fitness function, relying solely on the control dependencies of predicate at line 6, fails to guide the search as the predicate has no control dependencies.

To overcome this problem, McMinn proposed in 2004 and 2006 to integrate data dependencies in test data generation to improve the search process, extending the chaining approach of Korel (Korel, 1990). If the search fails to find test data that directly executes the target, the Chaining Approach performs data flow analysis to identify intermediate statements that may determine whether the target will be reached or not. By incorporating data dependencies into ET, the evolutionary search can be directed into potentially unexplored, yet promising areas of the test object's input domain (McMinn & Holcombe, 2006).

In the chaining approach, an event sequence is a sequence of events, < e1, e2, ... ek >, where each event is a tuple $e_i = (n_i, C_i)$ where n_i is a program node and C_i is a set of variables referred to as a constraint set (Ferguson and Korel, 1996). The constraint set is a set of variables that must not be modified until the next event in the sequence. That is to say, a definition-clear path must be executed between two events e_i and e_{i+1} with respect to each variable v in C_i.

McMinn defines a problem node as a branching node for which the search cannot find inputs. The set of nodes that can have an immediate effect on a problem node is the set of last definitions of variables used at that problem node. A last definition i is a program node that assigns a value to a variable v which may potentially be used by a node j. For the node to qualify as a last definition, a definition-clear path must exist between node i and node j with respect to v. In the example of *Figure 2.9*, the path < 4, 6 > is definition-clear with respect to the variable flag, but < 4, 5, 6 > is not, bacause flag is defined at node 5.

The Chaining Approach first introduced by Korel begins with an initial sequence E0 = < (s, φ), (t, φ) > that contains the start node s and the target node. Both events have empty constraint sets. The test data search may fail to find inputs to execute the event sequence, with the flow of execution diverging down an unintended branch at some node p1. In our example, input data may not be found to take the true branch from node 6 so that node 7 is executed, due to the existence of a flag variable in the predicate at node 6. Therefore, node 6 is declared as a problem node. Node p1 (node 6) is then inserted into the event sequence: < (s, φ), (p1, φ), (t, φ) >. For the problem node p1, the set of last definition nodes *lastdef(p1)* are found for the set of variables used at p1. For each last definition di ϵ lastdef(p1), a new event sequence is generated containing an event associated with that last definition:

E1 = < (s, φ), (d1, {def(d1)}), (p1, φ), (t, φ) >

E2 = < (s, φ), (d2, {def(d2)}), (p1, φ), (t, φ) >

. . .

EN = < (s, φ), (dN, {def(dN)}), (p1, φ), (t, φ) >

The addition of the last definition variable into the constraint set specifies that it will not be modified again until the problem node is encountered; ensuring the effect of that last definition on the problem node is not destroyed (Korel, 1990).

In *Figure 2.9*, the last definition nodes for node 6 are identified as nodes 1, 3 and 5 and the three new generated event sequences are:

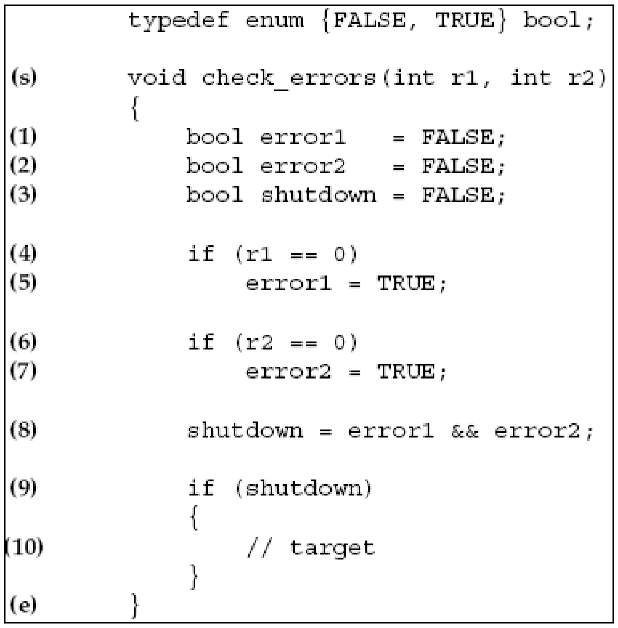
E1 = < (s, φ), (1, {flag}), (6, φ), (7, φ) >

E2 = < (s, φ), (3, {flag}), (6, φ), (7, φ) >

E3 = < (s, φ), (5, {flag}), (6, φ), (7, φ) >.

The constraint set contains the variable "flag". In event sequence E1, this means that the false branch must be taken from nodes 2 and 4 to prevent flag being redefined before node 6. E2 requires flag to be set to true at node 3. This requires node 2 to be executed as true and so the search can use the branch distance information at this node to find a value of "a" for this to happen. This branch distance information explicitly directs the search to the zero value of the "a" variable. Such guidance was not available from the branching condition at node 6, which depends only on the flag variable (McMinn & Holcombe, 2006).

The Chaining Approach selects one of the event sequences and tries to find inputs for which it is successfully executed. If such an input is found, then test data to execute the test goal has been found. If not, new event sequences need to be generated. In the original approach proposed by Korel, the new sequences are generated based on the same problem node, tracing back in the last definitions of this node. This approach then has limitations when more than one problem node is encountered in a feasible path, i.e., when the last definition of the current problem node depends on the use of another problem node. To overcome this limitation, McMinn extended the chaining approach to generate new event sequences based on newly found problem nodes.



```
        typedef enum {FALSE, TRUE} bool;

(s)     void check_errors(int r1, int r2)
        {
(1)         bool error1   = FALSE;
(2)         bool error2   = FALSE;
(3)         bool shutdown = FALSE;

(4)         if (r1 == 0)
(5)             error1 = TRUE;

(6)         if (r2 == 0)
(7)             error2 = TRUE;

(8)         shutdown = error1 && error2;

(9)         if (shutdown)
            {
(10)            // target
            }
(e)     }
```

Figure 2.10: Code with multiple problem nodes (McMinn & Holcombe, 2006)

Based on the initial chaining approach, the event sequences generated are:

E1 = < (s, φ), (3, {shutdown}), (9, φ), (10, φ) >

E2 = < (s, φ), (8, {shutdown}), (9, φ), (10, φ) >

E1 is infeasible, E2 on the other hand is feasible, but node 9 remains problematic, because it requires node 8 to be executed. This node is always executed, but no new information is added to the fitness function, whose landscape is still flat. To handle this problem, an extension is made to the event sequence generation algorithm, using the concept of *influencing sets*. An influencing set consists of all variables that could potentially affect the outcome at the problem node. Thus, the event sequence generation process is forced to consider definitions for all variables that can potentially affect the problem node. For a newly identified problem node, the influencing set is simply the set of variables involved in evaluated, but unsatisfied conditions, at the problem node. Beginning with the current problem node s_n, the initial influencing set I, and the event prior to the problem node event in the event sequence e = (n, C), the algorithm traces its way backwards through the nodes of the program. Returning to E2 =< (s, φ), (8, {shutdown}), (9, φ), (10, φ) >, node 9 is still problematic. In event sequence generation, node 8 is encountered tracing backwards from node 9. The influencing set is then the uses of variables at node 8: {error1, error2}. This means that further event sequences can be generated:

E21 = < (s, φ), (5, {error1}), (8, {shutdown}), (9, φ), (10, φ) >

E22 = < (s, φ), (7, {error2}), (8, {shutdown}), (9, φ), (10, φ) >

Tracing back from the definitions and uses of error1 and error2, the following event sequence will be generated from both E21 and E22:

< (s, φ), (5, {error1}), (7, {error1, error2}), (8, {shutdown}), (9, φ), (10, φ) >

This event sequence requires nodes 5 and 7 to be executed before node 8, which in turn assures that the true branch is taken from node 9, and that node 10 will eventually be executed (McMinn & Holcombe, 2006).

Experimental studies were conducted on 7 synthetic test objects and one real program. The codes included flag problem, counter problem, and multiple flag problems. They used a genetic algorithm with the traditional fitness function, then with the fitness function derived from the extended chaining approach. The results obtained showed a substantial improvement, where the search resulted in 0% success rate in most of the programs tested with the traditional fitness function, and an average of 95% success rate with the new fitness.

While this approach is very promising, it has one main limitation. When the flag definition is a condition, the approach fails when applying backward algorithm. In fact, when tracing back, the approach does not take into consideration the control dependencies of the last definition inserted into the events, thus omitting the case where a problem node exists in a dependent condition.

```
1    public int Calc (int x, int y, int z) {
2            int result = -1;
3            bool Fail = false;
4            if (x < 0 || y < 0 || z < 0 )
5                    Fail = true ; //illegal parameter value
6            else
7                    Fail = false;
8            if (not Fail) {
9                    x = y //overwrite x by a new value
10                   result = 0;
11           }
```

Figure 2.11: Calc method with data and control dependencies needed

In *Figure 2.11*, following the extended chain approach, “result” data dependencies is included in the fitness evaluation. However, “result” definition at Calc line 10 is controlled by the “if” at line 8; much in the same way, “Fail” definitions (lines 5 and line 7) are controlled by the “if” at line 4. Because the approach does not take into consideration the control dependencies of the last definitions of the problem nodes, control node 8 and 4 are not considered in the event sequences. As a result, we have a lack of information regarding how to make the flag “Fail” false and the whole evolutionary search will stagnate and degrades again into a random search.

For this reason, in our work, we will extend the chaining approach to incorporate control nodes such as nodes 8 and 4 into the approach level fitness.

The second disadvantage of McMinn’s approach is the high number of fitness evaluations needed to achieve the test coverage. The example codes tested required a minimum of 55,000 and a maximum of 300,000 fitness evaluations because the approach works sequentially; it starts with one event sequence, and if test data is not found, a new event sequence is generated and the search starts all over. To overcome this time consuming drawback, we propose to generate all possible data dependencies sequences, and run them in parallel, each in its own execution thread.

Chapter 3: SBST and Meta-heuristic algorithms

We present in this chapter the general concepts in Search Based Software Testing. Detailed implementation will be explained in next chapters.

3.1. Search Based Software Testing

Search based software engineering (SBSE) aims at solving software problems by applying search techniques to explore large search spaces, guided by a fitness function that captures properties of the acceptable software artefacts we seek.

We are mostly interested in the application of SBSE in testing, more precisely the automation of test data generation. The generation of input data can be modeled as a search problem in a large search space that we aim to optimize. Thus, we can easily apply the SBSE techniques to our problem. We use the term Search Based Software Testing (SBST) throughout our work to indicate the application of SBSE to the testing problem.

The meta-heuristic search techniques used in SBST are high-level frameworks which utilise heuristics in order to find solutions to combinatorial problems at a reasonable computational cost. For each problem, there are usually two main decisions of implementation, the first one being the encoding of the solution, i.e. how many variables a solution has, their types, etc, and the second main decision is the transformation of the test criteria into an fitness function.

3.1.1. Solution

In SBST, a solution is a test input data generated in order to achieve a testing goal. In MC/DC unit testing, one method is tested at a time. The input data is the set of the method's parameters, and the objective is to achieve with these input parameters one MC/DC test case at a time for each decision in the code. If we want to generate test data for the Calc method in *Figure 2.3*, for example, the method's parameters are three integers x, y and z. Thus, an input data is a triplet of integers, forming a solution drawn from a 3-dimensional search space.

3.1.2. Fitness Function

The fitness function of a meta-heuristic algorithm aims at guiding the search effectively into a promising neighbourhood of the search space, seeking the optimum solution. For the testing problem, the testing criterion objective is translated into a fitness function. The fitness function formulas are generated offline, before the actual search for the data is started. When the search starts by the mean of a meta-heuristic algorithm, the fitness is calculated for each solution generated and its value is used to compare and contrast the solutions with respect to the overall search goal.

In SBST, the test objectives need to be defined numerically and transformed into a fitness function. The search space is the system under test input domain and the fitness is computed by monitoring program execution results.

In this chapter, we apply the genetic algorithm as an example of evolutionary techniques and the hill climbing as an example of local search techniques to automate the test data generation. The rest of the sections of this chapter will detail the specifications of each algorithm, its implementation and its application to our search problem.

3.2. Evolutionary Testing Techniques

The evolutionary technique is a meta-heuristic family that consists mainly of evolving a whole population of possible solutions, instead of just one a time, such as in the case of local search meta-heuristic algorithms. There are three types of evolutionary algorithms, the evolutionary strategies, the evolutionary programming and the genetic algorithms, the latest type being the most used technique today. The first genetic algorithm was introduced in 1975 by Holland and Goldberg and it was inspired by the Darwin theory of species' evolution.

3.2.1. Evolutionary Algorithms Overview

An evolutionary algorithm starts with a population of μ solutions. Between the μ individuals of the current population, the algorithm chooses λ individuals that are called parents. These parents will reproduce to generate a new population of descendents. The new generated population has the same number of individuals as the initial one. In general, two main operations are performed on the pairs of chosen parents. The first operation is crossover, it is a technique used to combine parts of the two parents into a child and thus the resulting one or two children are a recombination of their parents. The second operation is mutation; it consists of slightly modifying part of the generated child. There are several types of crossover and mutation; we will describe in details our implementation of the two operators in the following sections. Once the new population replaces the old one, a fitness evaluation is performed on each of the newly generated individuals in the new population. *Figure 3.1* summarizes the steps of an evolutionary algorithm.

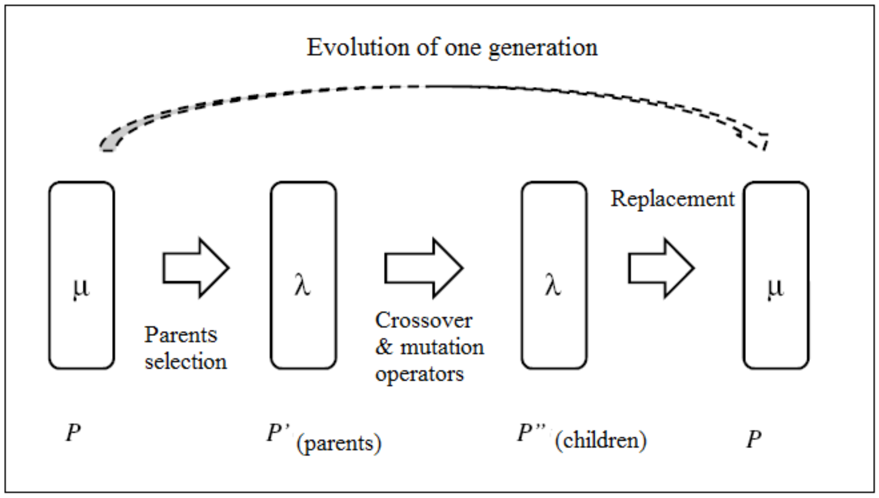


Figure 3.1: An evolutionary algorithm generation

The evolutionary techniques consist of evolving its population by keeping at each new generated population the fittest individuals only.

The technique of selection of the fittest individuals can differ largely with the different types of evolutionary algorithms. Most of the techniques however consist of selecting the fittest parents, hoping they would generate the fittest offspring. While this assumption may not work all the time, and bad offspring may be generated, it is in the nature of the evolutionary techniques to diversify the solutions generated, to better explore the search space.

3.2.1.1. Selection of the Fittest Parents

The main characteristic of the fittest selection technique is the number λ of parents selected for reproduction and the criteria of selection. For instance, in some algorithms, λ is less than μ, and the λ individuals are selected based on the quality of their fitness function. In this case, either the remaining (μ - λ) individuals are copied without reproduction in the new population, or the λ parents are reproduced in different pairs several times, and thus the overall reproduction generates μ new solutions.

3.2.1.2. Stopping Criteria

Evolutionary algorithms evolve their population in iterations, and when used to solve an optimisation problem, they usually converge after a certain number of iterations to the optimal solution they found. In such cases, the search converges to a small area in the search space and the new individuals formed tend to resemble a lot to their parents. This can constitute a stopping criterion for the algorithm. In constraint solving problem, the algorithm stops whenever a solution verifies all the constraints. However, in some cases, the search fails to converge and no solution to the studied problem is found. Thus, a maximum number of iterations or a maximum execution time should be set as a stopping criterion, so that the algorithm does not run indefinitely.

3.2.1.3. Evolutionary Algorithms Applied to the Testing Problem

Evolutionary algorithms were used as a search technique for testing problems, called Evolutionary Testing. ET has proved its effectiveness in searching for test data (Wegener, Baresel, & Sthamer, 2001). The population of individuals in an ET is a population of input test data. The objective function of the ET for a specific target in the program under test is the fitness function generated for each test case. Thus, applying ET to the MC/DC data generation problem, the algorithm evolves a population of test input data as possible solutions. The evaluation of the individuals consists of the evaluation of the fitness function of the MC/DC test cases at the target decision in the code.

In this case however, the testing problem is not a pure optimization problem where the algorithm can stop when it converges to an optimal solution. Of course the goal is to minimize the fitness function, but the stopping criterion in this case is either the fitness function of an individual is found equal to zero (the test data achieved the test case) or a maximum allowed number of iterations is reached.

The genetic algorithm being the most used evolutionary testing technique, we will present in details its implementation in the following section and how we customised it to fit our problem.

3.2.2. Genetic Algorithm

The Genetic algorithm (GA) is the most used ET technique in SBST. It is mostly useful when the search space is large and no mathematical analysis is available for the problem.

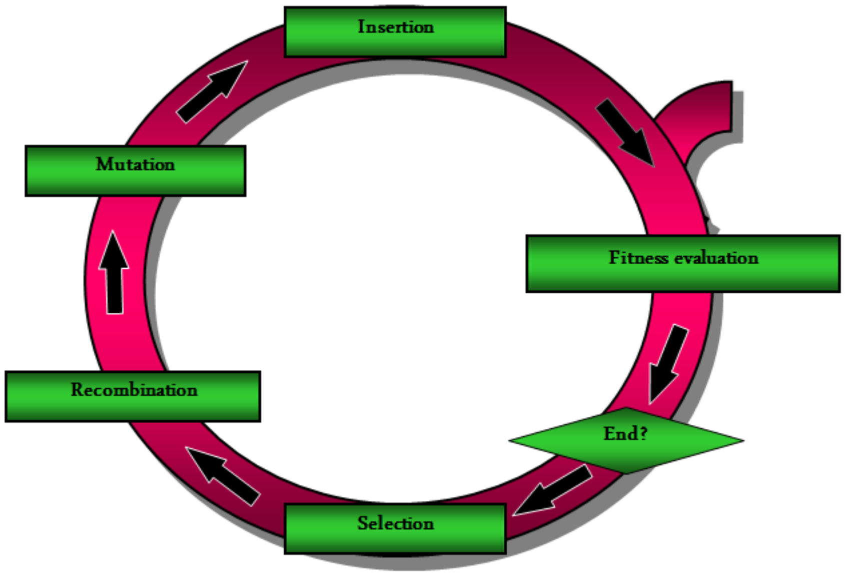


Figure 3.2: Search evolution in GA (Harman, ICSE FoSE talk, May 2007)

Figure 3.2 presents the steps performed in each GA iteration. Applying GA to a testing problem, the main customisation needed is in the fitness evaluation. In the MC/DC testing, and generally in most of the testing techniques, a set of test goals is available and the search is required to generate test data to cover all the members of the set. Since each test goal has a mapped fitness function, then the search should iterate for each test goal. The customised GA is presented in *Figure 3.3* (Wegener, Sthamer, Jones, & Eyres, 1997).

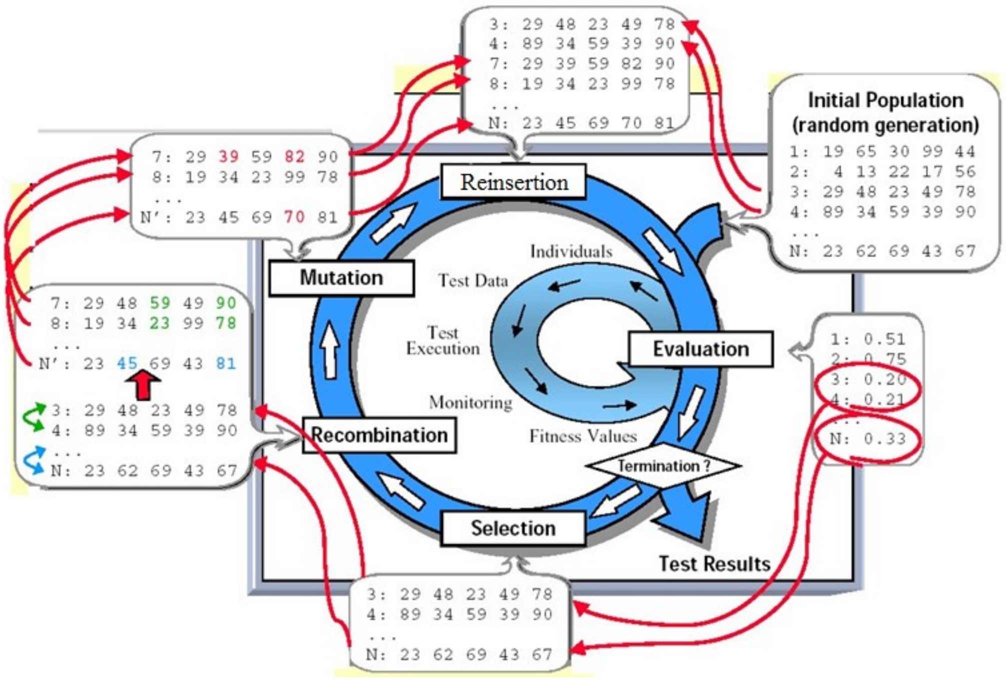


Figure 3.3: Search evolution in GA applied to testing problems (Wegener, 97)

GA starts with the first test case as a test goal, and it iterates the same way as previously. However, in the fitness evaluation phase, the algorithm performs test executions by executing each individual in the population on the program under test. The collected information contains the nodes executed as well as the values of the variables at the target decision and is then fed into the evaluation module of GA. Then, the algorithm evaluates the fitness function of the current individual for the selected test goal with the collected information.

For each test goal, the algorithm iterates until either it finds a test data achieving the currently selected test goal (in this case the fitness function of an individual is zero), or the maximum number of iterations is reached. In either case, the algorithm shouldn't stop the search, rather a second test goal is selected and the search either restarts the iterations with a new initial random population or continues with the current population with a new objective. In our implementation of GA, we restart the search with the same current population. We believe that this technique can speed up the search considering that the search might be at this point in a better space area than a randomly selected one. It is mostly because for the same target decision, the search to reach the target for different test cases is the same and thus we can take advantage of the previous iterations. At the same time, if the current population is not a good starting point, the newly evaluated individuals would have very bad fitness function and the algorithm will redirect the search in a new search area. In this case, we do not have the possibility to get stuck in a local optimum; for a new goal, the entire fitness landscape is modified and local optima are redefined for the new test goal.

3.2.2.1. Pseudo-Code of GA

Table 3.1: Pseudo-code of implemented GA

```
GA_evolve(max_number_of_evaluations, CrossoverProb,MutationProb) {
Initialize randomly population P[0];
Fitness_evaluation=0;
generation = 0;
Test_acheived =false;
for each test_case in MC/DC test set
    while(Fitness_evaluation < max_number_of_evaluations)
        generation = generation + 1;
        Test_acheived  = Evaluate (P[generation-1],test_case);
        If (Test_acheived)
            Break;
        Crossover (P[generation]);
        Mutate (P[generation]);
    end while
    Fitness_evaluation=0;
    Generation = 0;
    Reinitialise(P[generation]); //set fitness to not evaluated
end for
}
```

```
Evaluate (P[generation],test_case) {
        For each test_data in P[generation]
                If ( NotEvaluated(test_data) )   //a parent copied without modification
                {
                        RunProgram (test_data)
                        [Test_data.AF,   Test_data.BF]   =   EvaluateFitness   (test_case,
        decisions_executed, variables_values)
                        if (Test_data.AF== 0 && Test_data.BF == 0)
                                return true;
                        Fitness_evaluation++;
                }
        End for
        NormaliseBranchFitness(P[generation]);
        For each test_data in P[generation]
                Test_data.fitness = Test_data .AF + normalized(Test_data.BF) ;
        End for
        Return false;
}

EvaluateFitness (test_case, decisions_executed, variables_values) {
        [ApproachLevelFitness,diverged_decision]=ApproachLevel(target,
decisions_executed);
        If (ApproachLevelFitness == 0)
                BranchFitness(target,test_case, variables_values);
        Else
                BranchFitness(diverged_decision, variables_values);
        Return [ApproachLevelFitness , BranchFitness];
}

Crossover (P[generation]) {
        Rank(P[generation]); //rank individuals in their reverse order of fitness function
        P'.Add(fittestIndividual);   //1-point elitism
        iCnt ++;
        do
                [parent1,parent2] = Select2Parents();
                If (random(1.0) < CrossoverProb)
                {
                        [Offspring1,offspring2] = Perform Crossover(parent1,parent2);
                        P'.Add(offspring1,offspring2)
                }
                Else   //no crossover performed, copy the parents to the new population
                        P'.Add(parent1,parent2);

                iCnt  = iCnt + 2;
        While iCnt < generation_dimension
        P = P';
}

Mutate (P[generation]) {
        For each individual in P[generation]
                If (Not isTheFittest(individual) )
                        If (random(1.0) < MutationProb || isWorst(individual) )
                                doRandom Mutation(individual);
        End for
}

Select2Parents(){
        While (not found1) {
                Individual = getRandom(populationDim);
                if (individual.fitnessRank > getRandom(populationDim)) {
                                parent1 = individual;
                                found1 = true;
                }
        }
        While (notfound2) {
                Individual = getRandom(populationDim);
                if (individual.fitnessRank > getRandom(populationDim) && individual !=
        parent1) {
                                parent2 = individual;
                                found2 = true;
                }
        }
        Return [parent1, parent2];
}
```

3.2.2.2. Selection of Fittest

In our implemented algorithm, we select all the individuals as parents, thus $\mu = \lambda$. However, in the crossover step, we perform the crossover only on a portion of the parents, following a crossover probability, and the rest of the parents are copied as they are to the next generation. As well, in the mutation step, the mutation is performed on each offspring following the mutation probability. In general, the mutation probability is very low, about 5%, to lower the effect of randomness in the search. Thus, a small number of offspring are affected by the mutation.

The selection of the pairs of parents for the crossover is done based on a fittest selection criterion. In fact, we rank the population in a decreasing order of fitness value, the last individual being the fittest. Then, the selection is done using a caster skews, with a probability proportional to the rank of the individual. Thus, the greater the rank of an individual, the higher its probability of being selected to reproduce. This technique, called ranking, is useful when the fitness function values of several individuals are too close to each other; it reduces the effect of the fitness variance on the selection. In this case, it is the rank of the individual that affects the probability of its selection and not the value of the fitness itself.

3.2.2.3. Elitism

An evolutionary algorithm is called elitist if it guaranties the survival of the fittest individual from one generation to the next one. Elitism is thus the technique guaranteeing the survival; an n-point elitism guaranties that the n best individuals are transferred to the next generation. In our algorithm, we used 1-point elitism where only the best individual, with the lowest fitness function, is copied to the next generation with no modification. Thus, in the crossover step, we first copy the best individual directly in the next generation, before any crossover is performed. The fittest individual is not removed from the current population, thus it can be selected again for crossover. As well, the best individual will not be mutated in the mutation step, guaranteeing thus that it is copied intact to the next generation.

3.2.2.4. Fitness Evaluation

The fitness evaluation is performed for each individual in the population. Details on the evaluation will be presented in the next chapter. Since some individuals might end up travelling from one generation to another without being affected by the crossover or the mutation, it is a waste of time to re-evaluate their fitness function for the same test goal; the fitness evaluation including test execution on the code, information collecting and mathematical calculations. Thus, for each individual, we verify if it already has a fitness calculated, thus it is a travelling parent and we skip to the next individual. However, when the algorithm restarts the iterations for a new test goal, all the fitness functions of the current population are reinitialised, because for a new test goal, a new objective, the fitness values differ (*Reinitialise(P[generation])* method).

3.2.2.5. Crossover Operator

There exist several types of crossover operators: 1-point, n-point, uniform, whole arithmetic, etc.

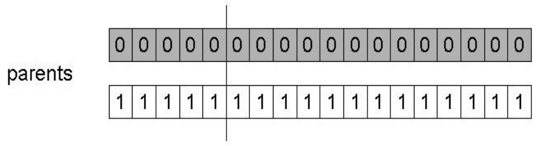


Figure 3.4: 1-point crossover

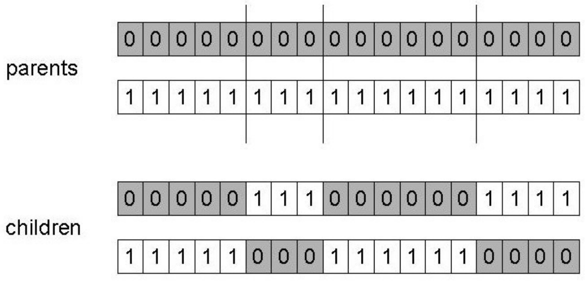


Figure 3.5: n-point crossover

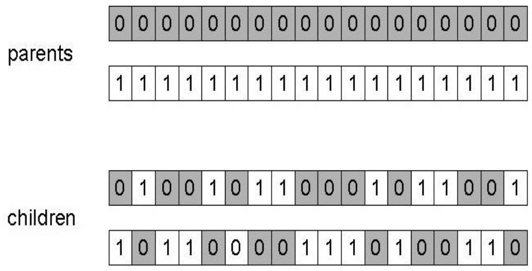


Figure 3.6: Uniform crossover

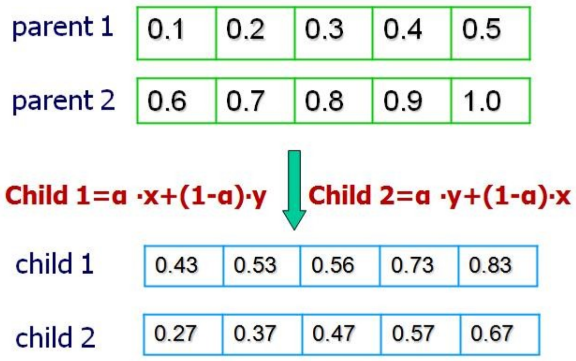


Figure 3.7: Whole arithmetic crossover, α= 0.2

The 1-point crossover, illustrated in *Figure 3.4*, consists of choosing a random point on the two parents, split the parents at this crossover point, and then create children by exchanging tails.

The n-point crossover, illustrated in *Figure 3.5*, is a generalisation of the 1-point crossover. It consists of choosing n random crossover points, split along those points and glue parts, alternating between parents.

The uniform crossover, illustrated in *Figure 3.6*, assigns 'heads' to one parent, 'tails' to the other, flips a coin for each gene of the first child to decide which gene parent it will inherit, and makes an inverse copy of the inherited gene for the second child.

For real valued individuals, a more suitable crossover operator applies arithmetic operations on the parents as illustrated in *Figure 3.7*. The arithmetic recombination exploits the idea of creating children "between" parents. The acting formula is: $z = \alpha x + (1-\alpha) y$; where x and y are the parents, z is the child, $0 < \alpha < 1$. When α is fixed, it is called a uniform arithmetical crossover, otherwise α is randomly picked between 0 and 1 every time.

The arithmetic crossover can be either a single arithmetic crossover where the formula is applied only on one part of the individual or a whole arithmetic crossover where the formula is applied on the entire individual.

We will use non-uniform whole arithmetic recombination on the test data solutions because we use GA to test programs with real-valued parameters.

3.2.2.6. Mutation Operator

The mutation operation consists of altering each gene of the individual independently with a probability p_m as illustrated in *Figure 3.8*. Typically, p_m is small, around 5%, to lower the effect on randomness on the search.

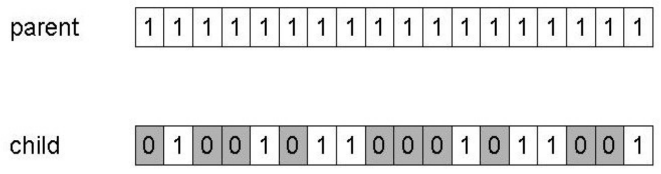


Figure 3.8: Mutation operator

When the crossover is performed, offspring are created and replace their parents in the population. The mutation is then performed on each individual in the population with the probability p_m.

There are also several types of mutation. The uniform mutation consists of drawing a random number with a uniform distribution between two boundaries. For instance, for bit mutation, the random number can be either 0 or 1. For an integer representing the days of the week, the boundaries would be 1 and 7.

The non-uniform mutation, mostly used for floating points, consists of drawing a random number with a Gaussian distribution, and then modifies it a bit for each gene separately.

In the program tested in our work, we perform uniform mutation; starting from restrain input boundaries and then we expand them to the entire parameter space, for example the integer space.

3.3. Local Search Techniques

Local search is a family of meta-heuristic algorithms based on the concept of neighbourhood of the current configuration (solution). There are mainly two types of local search, the descent techniques and more advanced techniques such as simulated annealing and taboo. The main idea of local search is to start with one initial solution and modify it iteratively.

3.3.1. Local Search Algorithms Overview

Local search algorithms rely on the neighbourhood of the current solution. To solve an optimisation problem using local search algorithms, we need first to define the solution space ***S***, i.e., the search space of possible solutions, and the objective function f that evaluates a real value in R for each solution s ∈ ***S*** such that:

$$f : \boldsymbol{S} \rightarrow R$$

Moreover, the definition of a neighbourhood is very crucial for any local search algorithm; a function N is usually defined that associates a subset N(S) of all possible solutions P(S) as neighbours of the current solution S such that:

$$\mathrm{N} : \boldsymbol{S} \rightarrow \mathrm{P}(\boldsymbol{S})$$

Each iteration, the algorithm defines the set of neighbours of the current solution, selects one of the neighbours and makes it the new current solution.

We call a local minimum in the solution neighbourhood N(S), a solution S such that:

$$\forall S' \epsilon N(S), f(S) \leq f(S')$$

Alternatively, we call a local maximum in the solution neighbourhood N(S), a solution S such that:

$$\forall S' \epsilon N(S), f(S) \geq f(S')$$

A typical schema of a local search algorithm is shown in *Table 3.2*.

Table 3.2: Local search schema

```
1 Build initial configuration S
2 Best_S = S
3 Iterate
4       Select S' from N(S)
5       S = S' //not obligatory
6       If (S > Best_S)
7             Best_S = S
8 Return Best_S
```

There are different strategies for the choice of a neighbour solution S' from the possible neighbours N(S) of S at line 4 in *Table 3.2*. Each local search meta-heuristic algorithm applies a different neighbour selection strategy.

The affectation of the current solution by the neighbour solution at line 5 in *Table 3.2* is not mandatory. In fact, in some local search algorithms, such as the descent algorithm, the neighbour solution becomes the current solution only if its fitness is better than the current solution. The disadvantage is that the algorithm can converge quickly to a local optimum and the search is stopped when the search space is similar to *Figure 3.9*.

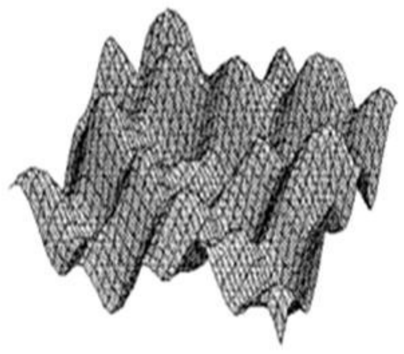


Figure 3.9: Local optima problem in local search

To solve this problem, several solutions were proposed. One technique consists of performing a random restart when an optimum is reached. The algorithm restarts the search several times, each time with a new randomly generated initial solution. This approach allows exploring different regions of the search space, however its inconvenience relies in the fact that the algorithm does not benefit from the knowledge acquired during the previous search. A second approach is to add a bit of randomness in the local search, thus, the algorithm can accept some of the degrading solutions on the short term, which might lead to a better optimum on the long run. An example of such algorithms is the simulated annealing. A third approach is to memorize the solutions already visited and ban them in the future, so that the algorithm is forced to try unexplored neighbours, this is the case of the taboo search.

3.3.1.1. Local Search Applied to the Testing Problem

The first strategy used to automate the test data generation for structural testing was local search used by Miller and Spooner in 1976. A solution in a testing problem is an input test data. The objective function for a specific target in the program under test is the fitness function generated for each test case. Thus, applying local search to the MC/DC data generation problem, the algorithm evolves one test input data as a possible solution, improving it in iterations, aiming to reach a test data that would achieve the MC/DC test goal selected.

3.3.1.2. Stopping Criteria

The goal of the local search being to minimize the fitness function, the first stopping criterion is the fitness function of an individual found equal to zero; in this case the test data achieved the test goal. The algorithm selects another test goal and restarts the search, until all MC/DC test goals for the target are reached. If after a maximum allowed number of iterations, the algorithm fails to find a test data with a zero fitness function, the search is forced to stop so that it does not loop forever. In this case, it is either that the test goal is impossible to achieve or that the algorithm just failed in its search. Either way, the test goal is reported as failed.

The hill climbing being a well known local search technique, we will present in details its implementation in the following section and how we customised it to fit our problem.

3.3.2. Hill Climbing Algorithm

Hill climbing (HC) is a well known and simple to implement local search algorithm. It starts with a random solution and tries to improve it. At each iteration, the neighbouring of the current solution is investigated and if a better solution is found, it replaces the current solution. In a “steepest ascent" climbing strategy, all neighbours are evaluated, with the neighbour offering the greatest improvement chosen to replace the current solution. In a “random ascent" strategy (sometimes referred to as “first ascent"), neighbours are examined at random and the first neighbour to offer an improvement is chosen (McMinn, 2004).

In our implementation of HC, we chose the random ascent strategy, where neighbours are generated based on a step λ drawn from a uniform distribution N $[0, \sigma]$, the variance being a parameter to the algorithm. The fitness function of the generated neighbour is evaluated, if it improves the fitness function, the neighbour becomes the new current solution, otherwise a new neighbour is generated with a new step λ.

3.3.2.1. HC Restart Algorithm

HC being a strict local search algorithm, it has the problem of convergence to local optimum. *Figure 3.10* shows a possible solution space for a search problem, where the x-axis represents the possible solutions, and the y-axis represents the fitness function for each solution.

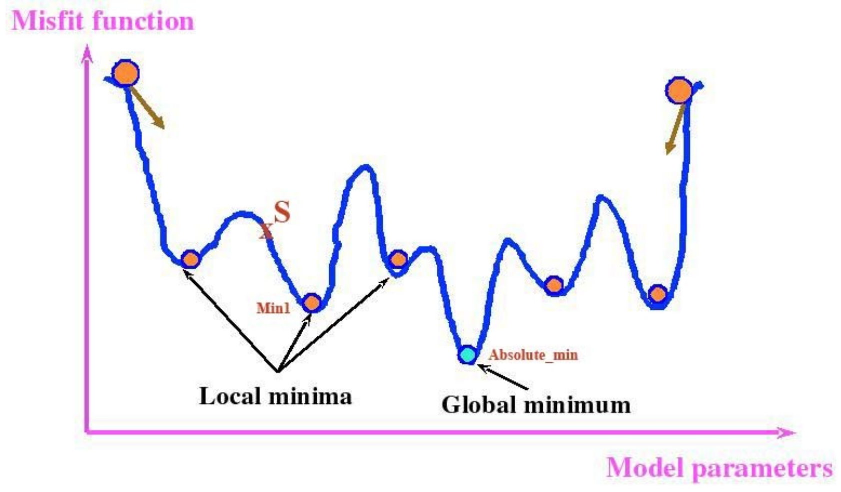


Figure 3.10: Local minimum illustration

Assume that the global minimum in the figure has a fitness value equal to zero, and the local minima have a low fitness value slightly higher than zero. The current solution being at S, HC selects a solution S’ in the neighbourhood of S, such that the fitness of S’ is less than the fitness of S. HC is thus most likely driving the search towards Min1, a local minima. When S is equal to Min1, no neighbour solution will have a fitness value lower than S and the search is stuck, not able to reach the zero-fitness solution. In the case where the neighbourhood selection is set to be wide enough, the search might find an S’ with a lower fitness, however this is unlikely because the idea of local search is to explore thoroughly the close neighbourhood of a solution and thus improving the fitness by small steps at a time.

To solve the problem, we perform random restarts of the algorithm after a maximum number of iterations. Since we already know that the optimal value to reach is zero, when a local optimum is reached being different from zero, the algorithm restarts from a totally random solution. We set a maximum number of restarts, if the algorithm fails to find a zero-fitness solution after all the restarts; the test goal is reported as failed. However, if the local optimum reached is in fact zero, a test case is achieved and the search stops for this test case. Another test case is selected and the search is launched again with a new starting initial solution.

3.3.2.2. Pseudo-Code of HC

Table 3.3: Pseudo-code of HC

```
HC_evolve(Fitness_eval_max, max_restart_allowed) {
Test_acheived =false;
for each test_case in MC/DC test set
        Fitness_evaluation_per_param =(Fitness_eval_max / max_restart_allowed) /nb_param;
        while restart < {
                Initialize randomly Solution S;
                Best_ S = S;
                Fitness_evaluation_per_param=0;
                for each parameter in S
                        while(Fitness_evaluation_per_param < max_ evaluation_per_param)
{
                                S' = Neighbour(S,parameter);
                                Test_acheived  = Evaluate (S',test_case);
                                If (Test_acheived)
                                        Return S';
                                If(S' > Best_S) {
                                        Best_S = S';
                                         S = S';
                                }
                                Else If(S' > S) {
                                        S = S';
                                }
                        end while;
```

```
                    Fitness_evaluation_per_param=0;
                End for;
                restart ++ ;
        End while;
        Test_acheived = false;
End for
}

Neighbour(S,param){
        S' = S.copy();
        eps = random.nextGaussin() * v ; //v = standard dev, parameter of the algo
        S'.param = S.param + eps;
        return S';
}
Evaluate (S,test_case) {
        RunProgram (S)
        [S.AF, S.BF] = EvaluateFitness (test_case, decisions_executed, variables_values)
        if (S.AF== 0 && S.BF == 0)
                return true;
        Fitness_evaluation_per_param++;
        Return false;
}

EvaluateFitness (test_case, decisions_executed, variables_values) {
        [ApproachLevelFitness,diverged_decision]=ApproachLevel(target,
decisions_executed);
        If (ApproachLevelFitness == 0)
                BranchFitness(target,test_case, variables_values);
        Else
                BranchFitness(diverged_decision, variables_values);
        Return [ApproachLevelFitness , BranchFitness];
}
```

3.3.2.3. Neighbour Selection

A uniformly generated Є is drawn from a Gaussian distribution with 0 mean and σ standard deviation. σ is a parameter for the algorithm, thus for different solution space, the value of σ can differ. A solution can be made of several method parameters; thus its neighbourhood space can be multi-dimensional. Our neighbour selection technique would modify one parameter at a time, keeping the others fixed. This way, we make sure the neighbourhood of each dimension is explored. Thus, we pass the parameter index *param* to the Neighbour method, a neighbour S' is created as a copy of the current S solution, then the value of *param* is modified by Є and updated in S'.

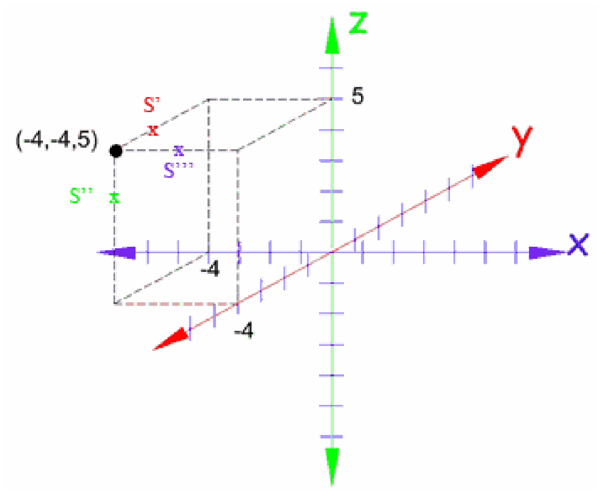


Figure 3.11: Mutli-dimentional solution

3.3.2.4. Fitness Evaluation

HC evaluates the fitness function for each generated neighbour. Details on the calculations will be presented in the next chapter. The fitness function of each neighbour is compared to the fitness of the current solution. If it improved, than the neighbour replaces the current solution, otherwise the neighbour is dropped and another neighbour is selected.

3.3.2.5. Iterations per Parameter

The search can run up to a maximum number of iterations, after which the search for the test case is reported as failed if no test datum is found to zero the fitness function.

For a multi-dimensional solution, we explore the neighbourhood of the solution per parameter at a time. The algorithm is fed with two parameters:

- A maximum number *fitness_eval_max* of allowed fitness evaluation per test case.
- A maximum number of restarts *max_restart_allowed*

Thus, *fitness_eval_max* is divided by *max_restart_allowed* to know how many fitness evaluations can be done in one search iterations before a restart is done. Since we are searching the neighbourhood of the solution by parameter, then we divide again this number by the number of the solution's parameters to get the maximum allowed fitness evaluation per parameter *Fitness_evaluation_per_param*, in other words the maximum allowed neighbour selection for the current solution.

Chapter 4: Our MC/DC Test Automation Approach

4.1. MC/DC Criterion

The MC/DC criterion was developed to provide many of the benefits of exhaustive testing of Boolean expressions without requiring exhaustive testing (Hayhurst, 2001).

4.1.1. Definitions

For sake of completeness we report in the following the basic definitions needed to understand MC/DC and MC/DC test data generation.

- A condition is “A Boolean expression containing no Boolean operators”, for example (a < b).
- A decision is “A Boolean expression composed of conditions connected by Boolean operators. A decision without a Boolean operator is a condition. If a condition appears more than once in a decision, each occurrence is a distinct condition” (Hayhurst, 2001). For example, (a < b && a < c) is a decision composed of two conditions. “&&” is the Boolean operator AND.

Each “if” statement in a code is a decision statement and it contains one or more conditions.

Other terms that need to be defined are a predicate, major clause and minor clause. A predicate is a synonym used for condition. Major clause is the condition the test aims to prove that it affects correctly the outcome of the decision, while the minor clauses are all other conditions in the decision.

4.1.2. Goal

MC/DC is intended to assure, with a high degree of confidence, that requirements-based testing has demonstrated that each condition in each decision in the source code has the proper effect on the outcome of the decision (Hayhurst, 2001). The goal of MC/DC criterion is thus to prove that:

- every decision in the program under test has taken all possible outcomes at least once,
- every condition in a decision has taken all possible outcomes at least once,
- more importantly that each condition in a decision affects independently and correctly the outcome of this decision.

A side effect is also that the tester is able to locate where exactly the error is in a decision, if any.

4.1.3. MC/DC Test Cases

There are two MC/DC variants. In the first one, also referred to as the unique cause MC/DC, minor clauses must hold the same Boolean value for the two values of the major clause. The second interpretation of MC/DC, a weaker criterion known as the masking MC/DC, allows minor clauses to be different (Ammann, Offutt, & Huang, 2003). In this work, we will consider the strongest interpretation, the unique cause MC/DC, as it is the criterion required by the standard DO-178B.

In order to generate the test suite to cover the MC/DC criterion for one decision, the major clause value should vary while the minor clauses outcomes are fixed, to show the effects of the major clause on the entire decision.

Boolean conditions such as $a < b$ are denoted by capital letters representing the condition outcome (A ,B, C, etc.) and the Boolean outcomes are denoted true (T) or false (F).

To help understanding a decision such as (A and B), logical operators (or, and, etc.) are presented schematically by logical gates, and a truth table is built for the entire logical circuit. This truth table represents the truth table for the decision under test.

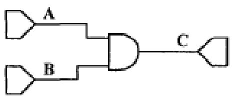
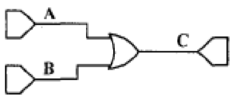
Schematic Representation	Truth Table
input	
output	
 C := A *and* B;	A B C *T T T* *T F F* *F T F* *F F F*
 C := A *or* B;	A B C *T T T* *T F T* *F T T* *F F F*

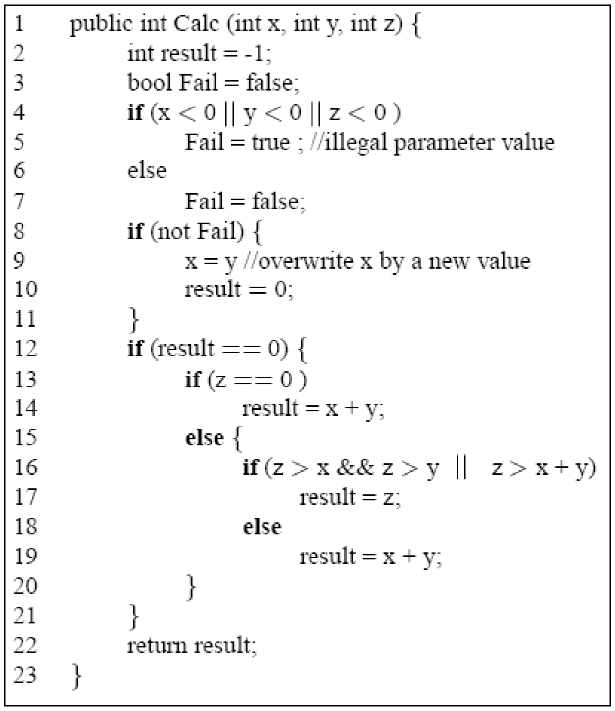
Figure 4.1: Representations for Elementary Logical Gates (Hayhurst, 2001)

Figure 4.1 illustrates the logical "and" and "or" Boolean operators represented by logical gates. It also provides the truth table for these gates. Each row in the truth table presents a possible test case, thus in the truth table of the "and" gate for example, we have four possible test cases for the decision "A and B". However, when developing test sets, we want also to minimize the number of test cases required to cover the MC/DC criterion. Thus, for each major clause, we search for a pair of rows where the condition outcome varies, the minor clauses outcomes are fixed and the outcome of the entire decision varies. For the "A and B" truth table, the pairs of rows for each major clause are:

- A: {(TT→T),(FT→F)}
- B: {(TT→T),(TF→F)}

Thus the final test set is {(TT), (FT), (TF)}.

As a general rule, a set of n+l test cases is needed to provide coverage for an n-input decision.



```
1     public int Calc (int x, int y, int z) {
2             int result = -1;
3             bool Fail = false;
4             if (x < 0 || y < 0 || z < 0 )
5                     Fail = true ; //illegal parameter value
6             else
7                     Fail = false;
8             if (not Fail) {
9                     x = y //overwrite x by a new value
10                    result = 0;
11            }
12            if (result == 0) {
13                    if (z == 0 )
14                            result = x + y;
15                    else {
16                            if (z > x && z > y  ||  z > x + y)
17                                    result = z;
18                            else
19                                    result = x + y;
20                    }
21            }
22            return result;
23    }
```

Figure 4.2: Calc method

Consider the Java code in *Figure 4.2*; suppose we are interested in generating input data to satisfy the MC/DC for the decision at line 16 (z > x && z > y || z > x + y). We denote the conditions (z > x) by Z1, (z > y) by Z2 and (z > x + y) by Z3, thus the decision is denoted as (Z1 && Z2 || Z3). We build the truth table of the correspondent logical circuit.

Table 4.1: Truth table of decision at line 16 of the Calc method

#	**Z1**	**Z2**	**Z3**	
0	F	F	F	F
1	F	F	T	T
2	F	T	F	F
3	F	T	T	T
4	T	F	F	F
5	T	F	T	T
6	T	T	F	T
7	T	T	T	T

Searching the truth table for the pairs of rows for each major clause, we obtain:

- Z1: (2,6)
- Z2: (4,6)
- Z3: (0,1), (2,3), (4,5)

To save space test cases were represented by a decimal coding thus for example the number 3 stands for FTTT in the truth table. We have two minimal sets to cover the MC/DC criterion: {2,6,4,3} and {2,6,4,5}. We can choose any one of the two sets.

4.2. The Approach Steps

Results of a 1999 survey of the aviation software industry showed that more than 75% of the survey respondents stated that meeting the MC/DC requirement in DO- 178B was difficult, and 74% of the respondents said the cost was either substantial or nearly prohibitive (Hayhurst & Veerhusen, 2001). In fact, the main challenge when trying to achieve the MC/DC coverage is to overcome the complexity of the code under test; it is not sufficient to generate test data for a program's decisions isolated, rather test data should be appropriately chosen in order to reach the targeted decisions and to achieve the relative test cases.

The most common approach to analyse the structure of the code under test is to extract its control flow graph (CFG). In fact, most of the structural testing approaches rely on the CFG to measure coverage and guide the search for the test input data. We can cite as examples the work of Korel in 1990 on branch coverage, the work of Baresel in 2002 on structural testing using evolutionary testing relying on the CFG to build the fitness function and the work of McMinn in 2004 also using the CFG to build the fitness function for branch testing.

4.2.1. Control Flow Graph

A CFG is a graph representing the program structure. The CFG nodes represent computations. While in some CFG forms, a node represents one statement of code, in other CFG forms, a node can represent a code segment depending on the convention used; a segment being one or more lexically contiguous statements with no conditionally executed statements in it (Binder, 2000). Nodes can be named or numbered by any useful convention.

The edges (also called branches) represent the flow of control, which is usually a conditional transfer of control between a node and another one. An edge connects two nodes, representing the entry into and the exit from the statement.

The entry point of a program is represented by an entry node with no incoming edges. The exit point of a program on the other hand is represented by the exit node with no outbound edges (Binder, 2000).

The CFG is a essential for the MC/DC testing because the flow of control is directed by the conditional nodes in the CFG; these nodes being predicate expressions such as an “if”, “while”, do until”, etc. The CFG of a program is the fundamental structure required to guide the input data into the correct path to reach a targeted decision.

```
1   public int Calc (int x, int y, int z) {
2           int result = -1;
3           bool Fail = false;
4           if (x < 0 || y < 0 || z < 0 )
5                   Fail = true ; //illegal parameter value
6           else
7                   Fail = false;
8           if (not Fail) {
9                   x = y //overwrite x by a new value
10                  result = 0;
11          }
12          if (result == 0) {
13                  if (z == 0 )
14                          result = x + y;
15                  else {
16                          if (z > x && z > y  ||  z > x + y)
17                                  result = z;
18                          else
19                                  result = x + y;
20                  }
21          }
22          return result;
23  }
```

Figure 4.3: Calc method

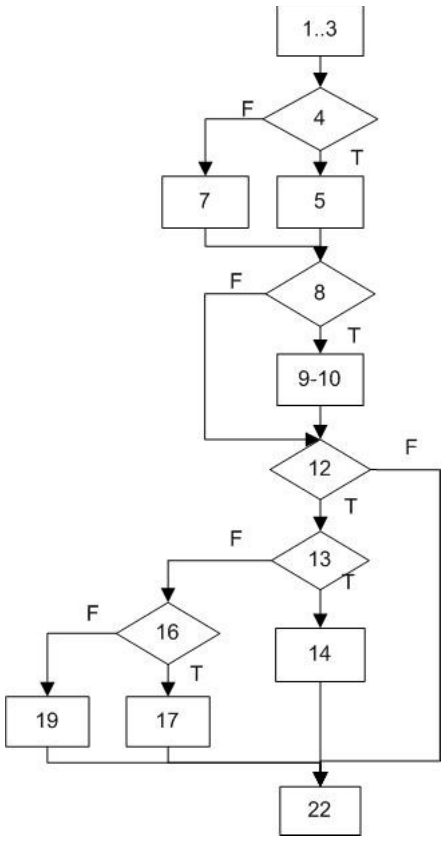


Figure 4.4: CFG for the Calc method

The CFG of the Calc() method is shown in *Figure4.4*. To reach the node 14 for example, nodes 1 to 3 are traversed, then either the true edge or the false edge of both decisions nodes 4 and 8 can be traversed. However, the true edges of nodes 12 and 13 must be traversed to reach 14.

4.2.2. Decision Coverage and MC/DC Coverage

Decision coverage, also known as branch coverage, is achieved when each edge in a CFG is covered, and thus every edge from a decision node is traversed at least once. Ensuring that all decisions in the CFG are tested at least once implies the necessity to reach the decisions first. Let us assume that we want to test the decision at line 16 in the Calc method in *Figure 4.4*. At a first look at the CFG, we can deduce that the input data generated must traverse the true branch of the decision at line 12 and the else branch of the decision at line 13 to reach the target decision. We can deduce that our target decision at line 16 is dependent on the flow of control through the decisions 12 and 13. We call such dependencies control dependencies. Moreover, a test data diverging away from the target at line 13 would be closer to the target from a test data diverging at line 12. In general, to automate the search for test data reaching a target statement, we need a cost function that determines which test data is closer to reach the target node. The cost function verifies for each test data how many controlling nodes were traversed in the required manner. The more traversed controlling nodes the better the cost function. This cost function is the Control Dependencies fitness function.

The problem with the search relying solely on the control dependencies between nodes is that it ignores prior statements that need to be executed first to make the path feasible to reach the target. Going back to our targeted decision at line 16, even though this decision does not appear to depend on decisions at lines 4 and 8, following the CFG, the outcome of these decisions play a decisive role in reaching our target. In fact, the variable "result" used at line 12 depends on the true branch of the decision at line 8. In turn, the decision at line 8 depends on the variable "Fail", which is modified in the else branch of the decision at line 4. In general, we say that our target decision has data dependencies on prior nodes in the program, and thus a cost function for the data dependencies should also be defined. Such a cost function is called Data Dependencies fitness function.

As proposed by (McMinn & Holcombe, 2006) for branch coverage, we will integrate both cost functions for MC/DC coverage. The integrated fitness functions form the Approach level.

Assuming now that we reach the target decision with a test data x_i, then we need to verify if x_i achieves one of the MC/DC test goals. Moreover, if two test data x_i and y_i reach the target decision, but none of them achieve an MC/DC condition, a new cost function is needed to measure which of two test data is closer to achieve the test goal at the condition. In this case, the evaluation function relies on the structure of the target decision and the test case at hand. Such an evaluation function is called Branch fitness function.

4.2.3. Steps to Automate the Approach

The rest of the chapter describes the main steps needed to achieve the MC/DC coverage. In the next section, we explain the code analysis, how we extract the decisions and analyse their structure to generate the MC/DC test cases. In the first step, we perform code analysis via code parsing and expression analysis. In the second step, we extract the control and data dependencies between the program nodes. In the following, we discuss in details each step and the three components of our fitness function. In the third step, we present our code instrumentation module. Code instrumentation is a tool used to inject tracing information into the code in a way to trace the flow of control for each input data, as well as collecting variables values at chosen locations in the code. This module helps us evaluate the fitness function at run time with the generated test data. In the last section of this chapter, we apply each step on a real program.

4.3. Code Parsing and Expression Analysis

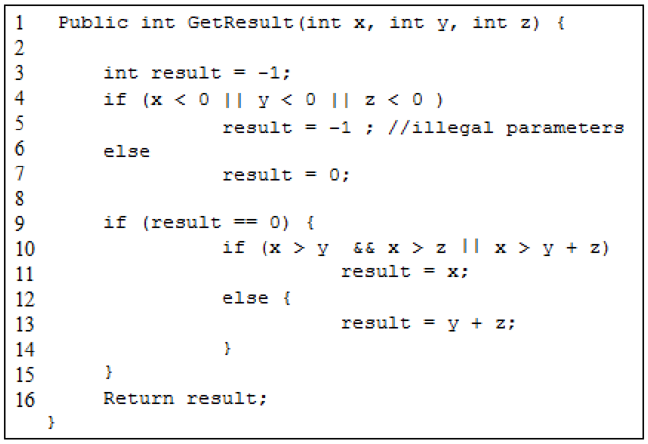
Our code parsing and analysis module assumes code has been developed in Java and implements expression analysis in several steps. First, code is parsed and an Abstract Syntax Tree (AST) is constructed. Second, the AST is revisited and sub-trees of decisions are transformed into a reduced representation, Abstract Decision Tree (ADT). We discuss these steps in details in the following sections.

4.3.1. Building the Parse Tree

In order to generate test cases and test data for the code under test, we need to perform lexical analysis and syntax analysis on the code. Lexical analysis reads the characters in a source program and groups them into a stream of tokens in which each token represents a logically cohesive sequence of characters, such as identifier, a keyword (if, while, etc.), a punctuation character or a multi-character operator like :=. The character sequence forming a token is called the lexeme for the token (Aho, Sethi, & Ullman, 2000). On top of the lexical analysis, syntax analysis involves grouping the tokens formed into grammatical phrases that are used by the compiler to synthesize output (Aho, Sethi, & Ullman, 2000). The syntax structure of the output is presented by a parse tree.

The lexical and syntax analysis is performed in our code parsing module via JavaCC and JJTree on top of Java 1.5 grammar. First, we generate a top-down parser using javacc on top on the Java 1.5 grammar. Second, we construct the parse tree of the code using jjtree. JJTree is a pre-processor for JavaCC that inserts parse tree building actions at various places in the JavaCC source. The output of JJTree is run through JavaCC to generate the parser code (Sun Microsystems, Inc., 2007). Next, the parser is compiled and run on the code to generate the parse tree.

The parse tree is a tree representation of the syntax of the code, where each node in the tree represents a program node. The most basic class within the tree design is the Node class. Each element of the syntax is represented by a node. The basic node class provides a group of constructors and several member functions. Two data members are provided for the Node object: a pointer to a list of nodes, usually the node's children, and a string, which is generally used to hold the name of the derived class, and thus usually considered as the node's type. As a result, in the parse tree, each node is identified by its type and linked to its children.



```
Public int GetResult(int x, int y, int z) {

    int result = -1;
    if (x < 0 || y < 0 || z < 0 )
              result = -1 ; //illegal parameters
    else
              result = 0;

    if (result == 0) {
              if (x > y  && x > z || x > y + z)
                        result = x;
              else {
                        result = y + z;
              }
    }
    Return result;
}
```

Figure 4.5: GetResult method

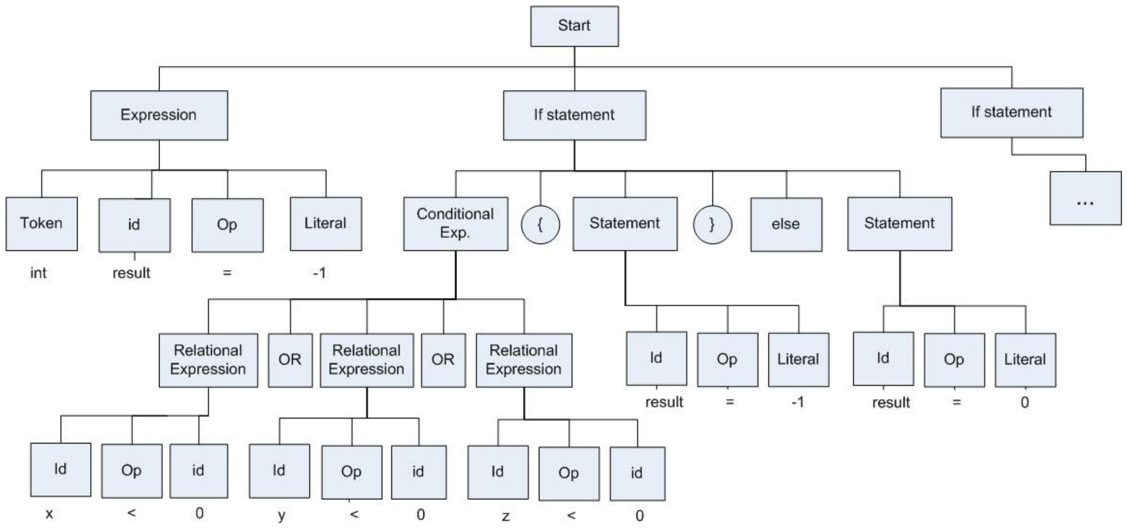


Figure 4.6: AST for the GetResult method

The generic parse tree of the GetResult method (*Figure 4.5*) is represented in *Figure 4.6*. The “if statment” node represents a decision and its block in the code, the “Conditional Expression” represents the conditional part (exemple if (result== 0)), the “Relational Expression” represents the conditions forming the decision and the “Statement” node represents the statement “true” or “else” block of the decision.

4.3.2. Building the Abstract Syntax Tree

The parse tree is a generic tree containing all the nodes of the program, and generated based on the grammar parser. Each node in the tree can have up to n direct children (If statment id: 4) read from left to right. Since the generation of the test cases for MC/DC requires a clear division of the decisions structure, we need to transform the parse tree into a more adequate structure. A useful starting point is a translation into an Abstract Syntax Tree (AST) in which each node represents an operator (i.e., boolean operators) and the children of the nodes represents the operands (i.e., relational expressions). AST differs from parse trees because superficial distinctions of form, unimportant for the problem at hand, do not appear in AST (Aho, Sethi, & Ullman, 2000). An example of the translation is shown in *Figure 4.7*.

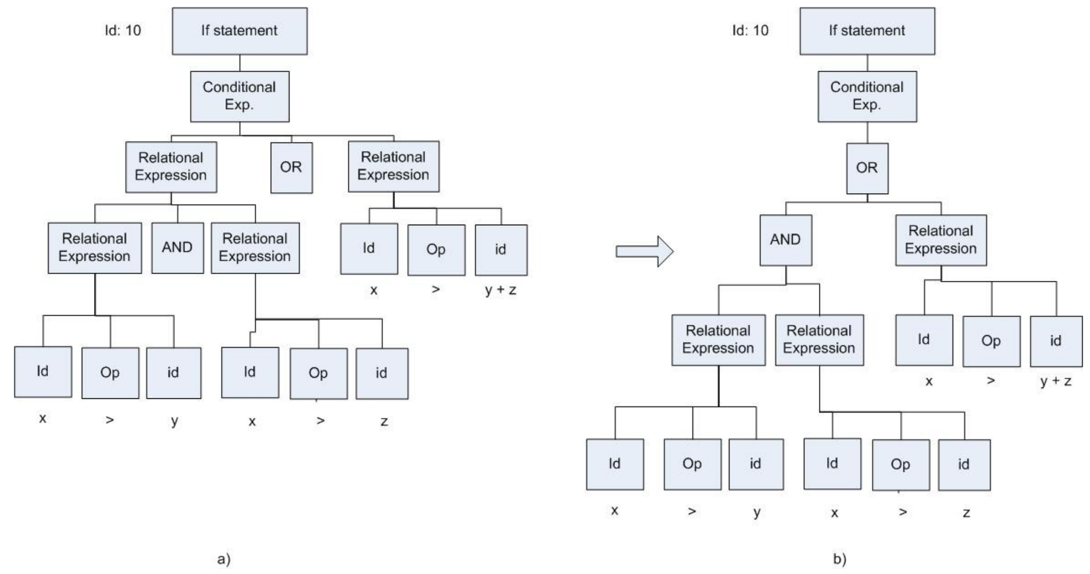


Figure 4.7: a) Parse tree b) AST of statement 10 of the GetResult method

4.3.3. Building the Abstract Decision Tree

The resulting AST still contains all the program nodes of the code under test. However, we are only interested in extracting the decisions logical structure, in fact logical structure is the sole information required to generate MC/DC sets. Thus, we write an AST visitor that collects only the subtrees of the decisions such as “if”, “while, “for”, etc. For example in *Figure 4.6*, the visitor collects the children of the Condtional Exp. nodes of the “if” statement, and drops the subtrees of the Statements nodes. Moreover, Boolean conditions such as x < y are denoted by capital letters representing the condition outcome and the relational expressions nodes are also denoted by capital letters representing their outcome. The new generated subtrees are called Abstract Decision Trees (ADT). Each decision has an ADT representing its logical structure. The ADTs of the GetResult method are shown in *Figure 4.8*.

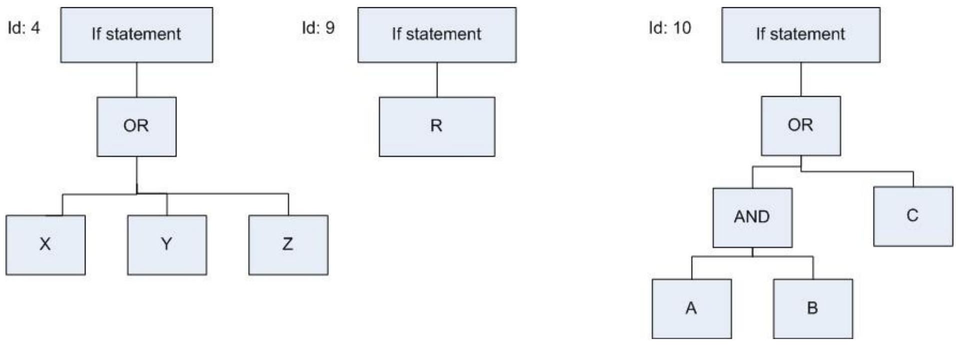


Figure 4.8: ADTs of the GetResult method

4.4. MC/DC Test Cases Generator Module

4.4.1. Pseudo-Algorithm of the MC/DC Test Cases Generator

The ADTs form the input for an MC/DC generator and a grammar is used to analyse the syntax of the trees. Each node in the ADTs is assigned a Boolean value (either 1 or 0) and a Boolean variable Evaluated, to verify if the node value has already been computed. A high level pseudo-code of the algorithm is represented in the following:

- Extract the conditions from the trees. The conditions form the leaves of the ADTs. Let N be the number of extracted variables.
- Construct a truth table (TT) of size (N, 2^N), since for N variables, we have 2^N possible combinations.
- Populate the TT by alternating for each column the True and False values each 2^{column} rows.
- For each TT row:
    - Reset the trees nodes values to 0.
    - Assign the current row values to the leaf variables.
    - Evaluate recursively bottom up the values of the nodes till reaching the top of the tree. This value represents the output of the decision being evaluated.
    - Update the truth table output column with the resulting value.

- At this point, we have the truth table of the decision complete and we can proceed to extract the MC/DC test cases. As discussed in the MC/DC section, for each variable, we need to search for the pairs of rows where the variable is affecting independently the outcome of the decision.

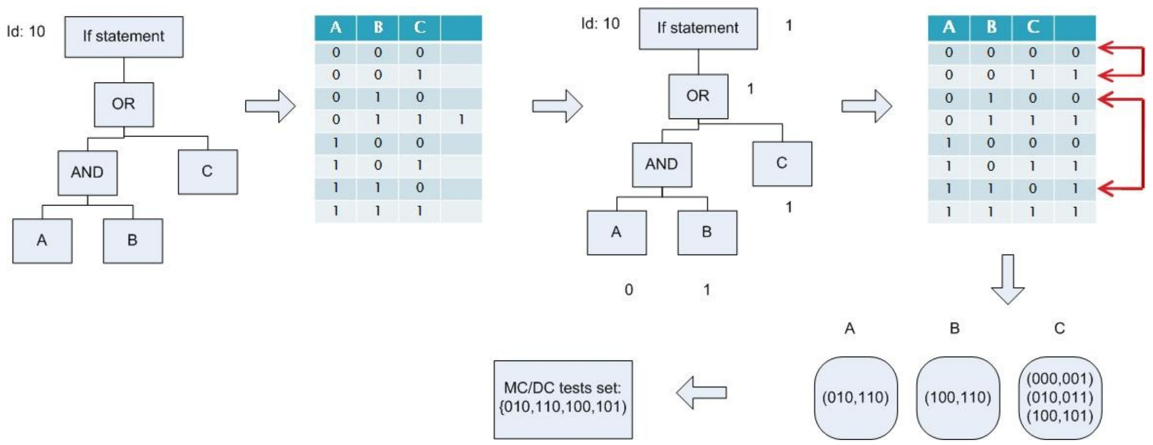
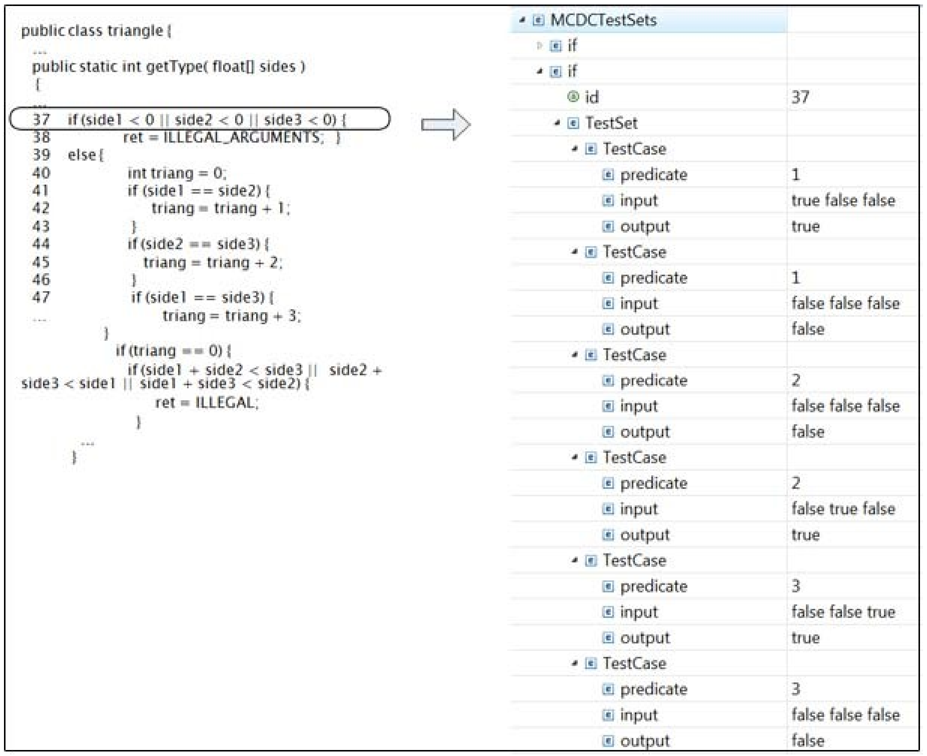


Figure 4.9: Steps of the MC/DC test set generation algorithm

- For each variable:
    - Create an empty set of pairs of test cases.
    - Search for the pairs of rows where the value of this variable varies while the rest of the variables values are fixed.
    - Compare the output of the two rows. If they are different, the test cases are valid as they show the effect of the variable. Add the two rows as a pair into the test cases set.
- Merge the sets of each variable and minimize the number of the resulting MC/DC test cases.

4.4.2. Resulting Set of MC/DC Test Cases

The test cases are stored in an XML format. They are used as an input to the data generator module, where test data is automatically generated for the decisions to satisfy the saved set. *Figure 4.10* shows the generated test cases for the decision at line 37 of a small program. For each condition in an “if”, noted as a predicate, the test set contains all the MC/DC required tests cases.



```
public class triangle {
  ...
  public static int getType( float[] sides )
  {
  ...
  37  if (side1 < 0 || side2 < 0 || side3 < 0) {
  38          ret = ILLEGAL_ARGUMENTS;  }
  39  else {
  40          int triang = 0;
  41          if (side1 == side2) {
  42              triang = triang + 1;
  43          }
  44          if (side2 == side3) {
  45             triang = triang + 2;
  46          }
  47           if (side1 == side3) {
  ...               triang = triang + 3;
          }
         if (triang == 0) {
            if (side1 + side2 < side3 ||  side2 +
side3 < side1 || side1 + side3 < side2) {
                ret = ILLEGAL;
            }
       ...
    }
```

```
MCDCTestSets
  if
  if
    id              37
    TestSet
      TestCase
        predicate   1
        input       true false false
        output      true
      TestCase
        predicate   1
        input       false false false
        output      false
      TestCase
        predicate   2
        input       false false false
        output      false
      TestCase
        predicate   2
        input       false true false
        output      true
      TestCase
        predicate   3
        input       false false true
        output      true
      TestCase
        predicate   3
        input       false false false
        output      false
```

Figure 4.10: Example of an MC/DC test set

4.5. Proposed Fitness Function

4.5.1. Control Dependency Fitness Function

By means of the CFG of a program, we can calculate the set of control dependencies of each decision, i.e., the prior decisions that need to be evaluated in the required way in order to bring the flow of execution to the desired target. For instance, going back to the Calc method in *Figure 4.3,* and its CFG in *Figure 4.4*, the decision at line 16 depends on the evaluation to true of the decision at line 12 and the evaluation to false of the decision at line 13. We can deduce that the target decision at line 16 is dependent on the flow of control through the decisions 12 and 13. These nodes are called critical branches as they determine the flow of control towards or away from the target (Korel, 1990). Consequently the set of control dependencies for the decision at line 16 includes the decisions of line 12 and 13, i.e., these are the branching nodes that must be executed with a specific outcome in order for the target to be reached. We write ControlDep(16) = {12,-13}; where ControlDep is the set of control dependencies for the decision at line 16, and it includes a dependency on the true branch of 12 and a dependency on the false branch of 13.

In general, the term control dependency is used to describe the reliance of a node execution on the outcome at previous branching nodes (Ferrante, Ottenstein, & Warren, 1987). More formally, a node z is post-dominated by a node y in G if and only if every path from y to the exit node e contains z. Node z post-dominates a branch (y, x) if and only if every path from y to the exit node e through (y, x) contains z. The node z is control dependent on y if and only if z post-dominates one of the branches of y, and z does not post-dominate y (McMinn, 2004).

Once the control dependencies set is formed, the search needs to reward test data that execute the greatest number of controlling decisions. For instance, a test data diverging away from the target at line 13 would be closer to the target than a test data diverging at line 12. In general, we need an evaluation function that would evaluate which test data is closer to reach the target. Such an evaluation function is called Control Dependencies fitness function.

The Control Dependencies fitness function is an objective function that considers the branching nodes included in the control dependencies set. Let $dependent_{decisions}$ be the number of nodes in the ControlDep set of our target, and let $executed_{decisions}$ be the number of nodes in the ControlDep set that is actually executed in the required manner with the current input data. Thus, the control dependency fitness function to minimize is defined as:

$$ControlDepFit_{testdata} = dependent_{decision} - executed_{decisions}$$

If the function is zero, the test data reached the target decision. However, if the function is greater than 0, the test data is known to have diverged at a critical branch away from the target, exactly at the node preceding the target by the amount of the fitness function. We will call this node $diverged_{node}$. For instance, in the Calc method, the input diverging at node 12 (nodes 12 and 13 both not executed as required) will have the fitness evaluation to 2 - 0 = 2, however the input diverging at node 13 (node 12 being true as required), will have the fitness equal to 2 - 1 = 1. In this case, the algorithm is able to distinguish different test input data based on their level of approach from the target, and the search is guided into the closer input data.

4.5.2. Data Dependency Fitness Function

Going back to our targeted decision at line 16 in the Calc method, even though this decision does not appear to depend on decisions at lines 4 and 8, according to the CFG, the outcome of these decisions play a decisive role in reaching our target. In fact, the variable “result” used at line 12 depends on the true branch of the decision at line 8 which in turn depends on the flag “Fail” modified in the else branch of the decision at line 4. In this case, the Control Dependency Fitness function provides no guidance at all on how to make the “Fail” flag false and how to make the “result” variable equal to zero; the search landscape is completely flat.

This fact is at the basis of the Korel chaining approach (Korel, 1990) and the McMinn extension (McMinn & Holcombe, 2006). In the later work terminology, line 12 is called a problem node; in a similar way we call “result” a problem variable because the lacking of knowledge on “result” can cause the search to behave as a random search. In such cases, we say that our target decision has data dependencies on prior nodes in the program.

To avoid random search, McMinn and Holcombe in 2004 and 2006 suggest including “result” data dependencies in the fitness evaluation (McMinn & Holcombe, 2006), ignoring however the control dependencies that the data dependency nodes might in turn have. For instance, “result” definition at Calc line 10 is controlled by the decision at line 8; much in the same way, “Fail” definitions (lines 5 and line 7) are controlled by the decision at line 4. Because dependencies determination presented in the work of

McMinn and Holcombe focuses only on data dependencies, control nodes 8 and 4 are not considered. We believe that explicitly incorporating control nodes such as nodes 8 and 4 into the approach level fitness leads to an easier implementation and an improved performance.

3.5.2.1. The Pseudo-Code of the Extended Dependencies Algorithm

Figures 4.11 and *Figure 4.12* report our extension of the algorithm of McMinn. In our approach we aim at collecting control nodes either directly or indirectly (i.e., via data dependencies) affecting the traversal of the problem node.

```
Let pn be the problem node under test
Let $S$ be the set of dependencies
Let $DepSets$ be the set of collected dependencies sets
1    $getDependencies(pn, S)$ {
2        $S = S \cup getControlDep(pn)$
3        $PV = getUsedVariables(pn)$
4        $for\ each\ pv \in PV$ {
5            $lastDefs = getLastDefs(pv)$
6            $for\ each\ ld \in lastDefs$ {
7                $S(ld) = S \cup getControlDep(ld)$
8                $newPV = getUsedVariables(ld)$
9                $for\ each\ cd \in getControlDep(ld)$
10                   $newPV = newPV \cup$
                         $getUsedVariables(ld)$
11               $for\ each\ v \in newPV$
12                   $getDependencies(node(v), S(ld))$
13               if $(empty(newPV))$
14                   $DepSets.add(S(ld))$
             }
         }
     }
```

Figure 4.11: Algorithm to calculate the sets of dependencies given a problem statement

```
Let $DepFit = \{\phi\}$ be the set of fitnesses dependencies sets
Let $DepSets$ be the set of collected dependencies sets

$for\ each\ s_i \in DepSets$ {
    $DepFit.add(s_i)$
    $for\ each\ s_j \in DepSets\ and\ s_j \neq s_i$
        if $(thenElseConflicts(s_i, s_j) == false)$ {
            $S_{i,j} = s_i \cup s_j$
            $DepFit.add(S_{i,j})$
        }
    }
```

Figure 4.12: Algorithm to calculate the sets of dependencies given a problem statement

The functions *getControlDep* and *getUsedVariable* return the set of reverse control dependencies (nodes controlling the current node) and used variables respectively. *S* and *DepSets* are initialized as empty sets. *DepSets* stores the set of dependencies for a given problem node. At algorithm termination, these sets of dependencies are merged by algorithm in *Figure 4.12* to build the sets of dependencies used in defining fitness functions.

There are two main differences with the Chaining approach of (McMinn & Holcombe, 2006). First, our test data generation code is written in Java and thus we can take advantage of Java multi-threading nature: for each last definition of variables involved in the problem node we store its dependencies (line 14 in *Figure 4.11*); the algorithm in *Figure 4.12* merges the sets of dependencies and each merged set leads to a different fitness function run in parallel into its own thread. More conceptual is the difference in computing dependencies. We perform a closure similar to the Chaining approach but we are interested in extending the level approach by interleaving control dependencies and data dependencies to improve the guidance provided by the approach level fitness.

Again in the Calc method, consider for example line 12 (problem node); “result” last definition at line 10 causes line 10 control dependence, line 8, to be added to S. At the algorithm termination, both lines 8 and 4 will be in S.

```
Let errno be a global variable

0  void exit(int b) {
       ...
1      if (b > 0)
2            r1 = true
3      else
4            r1 = false
5      if (r1)
6            error1 = 1
7      if (errno)
8            error2 = 1
9      if (error1&&error2)
10           target
       ...
```

Figure 4.13: Example of multiple flags

More in details consider the part of the program presented in *Figure 4.13*. We assume that global variables such as "errno" are modeled as extra parameters. We will go through the *getDependencies* algorithm (*Figure 4.11*) for this piece of program.

- The function *getControlDep* returns the empty set when the method declaration first line (line 0) is passed. *getUsedVariables* called on the same line also returns the empty set.
- Suppose that line 10 in the program is the target statement; the problem node (line 9) uses flag variables "error1" and "error2".
- When called with parameters 12 and φ, the function *getDependencies*, first identifies used variables ("error1" and "error2" at line 3) and then computes for each used variables the last definition set. For example, for "error1" last definition is line 6.
- Last definition is controlled by the decision at line 5 and thus line 5 is added to S (line 7 in the algorithm).
- The decision at line 5 uses the variable "r1" that is added to *newPV* (new problem variables). "r1" has two definitions points either at line 2 (then branch) or line 4 (else branch).

- *getDependencis* recursion called over node 5 and S = {5} generates a last definition set for "r1" of {2, 4}.
- The cycle at line 6 in the algorithm iterates over {2, 4}.
- Suppose that line 2 (then branch) is selected (line 6 in the algorithm) then line 7 adds line 1 to S.
- Notice that in the case of an else branch (e.g., last definition at line 4 in the program), *getControlDep* returns minus the control node number; negative values encode last definitions in the else branch. In essence, we encode with positive numbers the control flows going into then branches while negative values stand for else branches.
- Recursion of *getDependencis* with parameters 1, {5, 1}, will check "b" last definition leading to line zero, method definition first line. Line zero in our model has no control dependencies and uses no variables.
- Both *newPV* and *getControlDeps(0)* are the empty sets and set {5, 1} is added to *DepSets*, line 14 in the algorithm.
- The same way, the set {5,−1} is added to *DepSets*.
- Finally, when *getDependencies* computes "errno" induced dependencies, the set {7} is added to *DepSets.*
- Overall, the call to the function *getControlDeps(9, φ)* generate the sets: {{5, 1}, {5,−1}, {7}}.

At this point, *DepSets* is now the input to the algorithm in *Figure 4.12* that generates the actual new set of dependencies for fitness definition. The function *thenElseConflicts(si, sj)* returns true if a set contains both the then and the else branch of the same decision. Therefore when the algorithm is executed over the set {{5, 1}, {5,−1}, {7}} it generates the sets of dependencies: {φ, {5, 1}, {5,−1}, {7}, {5, 1, 7}, {5,−1, 7}}. Overall, six fitness functions one for each set in *DepFit* are defined and six threads will be started probing various combination of control flow to cover line 9 MC/DC. For example, the set {5,−1, 7} is interpreted as: we need to enter the "else" branch of line 1, and the "then" branch of line 5 and line 7.

We believe that this extending of the approach level, which includes the data dependencies, improves the guidance of the search towards more promising search area for test data. The new extended approach is intended to overcome the problem of lack of guidance and flat search when flag variables are used at predicates or when strong data dependencies exist between the predicates of the code.

4.5.3. Branch Fitness Function

Once the test data reaches the target, it needs to satisfy one of the MC/DC test cases. However, for individuals not satisfying any of the MC/DC test cases, no guidance is given as to how to descend down the landscape to solutions that are closer to achieving one of the test cases (McMinn P. , 2004). Along these horizontal planes, the search becomes random. Thus, we need another measurement to verify if the test data satisfied a test case, and if not, how close it is from satisfying it. The value obtained is called "branch distance".

For a given program, every test data diverging away from the target at node x receives the same approach level value. However, a branch distance calculation is performed at the diverging node, to evaluate which of the test data is closer to satisfy it (make it true or false according to the control dependency set). If every test data reaches the target decision but none achieves one of the MC/DC test cases, every test data will have a zero approach level. However, a branch distance calculation is performed at the target decision to evaluate which of the test data is closer to satisfy one of the test cases at this node. Of course, if a test data reaches the target and achieves one of the MC/DC test cases, then its branch fitness as well as its approach fitness would evaluate to zero.

Table 4.2: Conventional cost functions for relational predicates (Bottaci, 2001)

Expression	Cost
$a = b$	0 when $a = b$ else $min(abs(a - b), L)$
$a < b$	0 when $a < b$ else $min(a - b + P, L)$
$a \leq b$	0 when $a \leq b$ else $min(a - b, L)$
$a > b$	0 when $a > b$ else $min(b - a + P, L)$
$a \geq b$	0 when $a \geq b$ else $min(b - a, L)$

Table 4.3: Modified relational predicate cost functions (Bottacci, 2003)

Predicate expression	Cost of predicate expression
$a \leq b$	$a - b + R - \epsilon, \quad a > b$ $a - b - R, \quad a \leq b$
$a < b$	$a - b + R, \quad a \geq b$ $a - b - R + \epsilon, \quad a < b$
$a = b$	$abs(a - b) + R - \epsilon, \quad a \neq b$ $-R, \quad a = b$

Table 4.4: Our extended branch fitness

Expression	Then Branch	Else Branch
$a == b$	$abs(a - b)$	$a == b?k : 0$
$a \neq b$	$a! = b?k : 0$	$a\ ! = b?abs(a - b) : 0$
$a < b$	$a < b?0 : a - b + k$	$a < b?a - b + k : 0$
$a <= b$	$a <= b?0 : a - b$	$a <= b?a - b : 0$
$a > b$	$a > b?0 : a - b + k$	$a > b?a - b + k : 0$
$a >= b$	$a >= b?0 : a - b$	$a >= b?a - b : 0$
$a\|\|b$	$min[fit(a), fit(b)]$	$fit(a) + fit(b)$
$a\&\&b$	$fit(a) + fit(b)$	$min[fit(a), fit(b)]$

The branch distance at a decision is calculated based on the structure of this decision. A work done by Bottacci in 2001 provides fitness formula for all possible logical operations in a decision. In *Table 4.2* (P small positive number and L very large positive number), the initial functions are only applicable for the true branch of a decision. In 2003, Bottacci extended these formulas to cover the else branch as well. The extension used an arbitrary value R, being a minimum absolute cost for any predicate, to differentiate the "then" and the "else" branch, R is added to the value of the fitness for the "then" branch, and subtracted from the value of the fitness for the "else" branch, shown in *Table 4.3* (Bottacci, 2003). We believe that a ternary operator representing the conditional expressions would better extend the initial functions as no arbitrary values are added. The extended branch fitness formulas are shown in *Table 4.4*.

Branch fitness is always a positive value. When trying to achieve a test case, we compare the closeness of the test data to achieve the test case, rather than the value of the test data itself. Thus, a negative value of the fitness function would not add any valuable information to the search. Thus, an absolute value is applied to the value of the branch fitness before it is returned.

4.5.3.1. Example of the Branch Fitness Calculation

Considering the Calc method again in *Figure 4.2*, suppose our goal is to generate test cases to satisfy MC/DC for line 16: if (z > x && z > y || z > x + y). Suppose also that we want to satisfy the test case (TFF), which means the condition z > x should be true, and the two conditions z > y and z > x + y should be false. Numbers 0 and 1 are used to represent false and true; they are interpreted as real values simplifying fitness evaluation i.e., distance from the sought value assignments. If two different test cases reach line 16, we need to decide which one of them is the most promising one to obtain (100). Thus, we need to evaluate the branch fitness for each test data, using the "then" branch fitness for z > x and the "else" branch fitness for z > y and z > x + y, the formulas being presented in *Table 4.5*. The overall branch fitness function is then computed based on the addition of the branch fitness functions of each condition in the decision. We show in the last section in this chapter a detailed calculation for real test data.

Table 4.5: Calc line 16 branch fitness computation

Expression	**Then branch**	**Else branch**
fit(z > x)	abs(z > x?0 : z − x + k)	abs(z > x?z − x + k : 0)
fit(z > y)	abs(z > y?0 : z − y + k)	abs(z > y?z − y + k : 0)
fit(z > x + y)	abs(z > x + y?0 : z − x − y + k)	abs(z > x + y?z − x − y + k : 0)

4.6. Code Instrumentation Module

The code instrumentation module is a parsing tool used to instrument the code under test and extract relevant information. In the reverse engineering terms, code instrumentation relies on "unparsing" techniques. At a first step, the code is parsed using the parsing technique presented in section 4.3.1 (building the parse tree), preserving all comments and white space. Then, the parse tree generated is annotated with instrumentation; the required nodes to be instrumentation are located in the tree, and the printing of the node is modified to inject tracing information in the code. The instrumented tree is then unparsed and the initial code is regenerated with the new tracing information injected in it.

The Approach Level fitness requires the collection of the executed decisions in the code for each test data. Thus, when the program is executed for an input test data x_i, the instrumentation module should be able to analyse the flow of execution of the program and collect the decisions that were executed. Without this information, it is impossible to evaluate the Approach Level Fitness.

Table 4.6: Instrumentation of a decision

```
If (node.Is(ASTIFStatement) )
        If (node.child.Is(ASTElseBranch) )
                Print (- node.line);
        Else
                Print (node.line);
End if
```

For this reason, in the code unparsing, every time a decision node is encountered, a printout needs to be inserted in the "then" and "else" branch of the decision as shown in *Table 4.6*. If the "then" branch is executed, a number representing the line of the decision is printed and the decision is known to have been executed to true. If the "else" branch is executed; a negative number representing the line of the decision is printed.

This kind of collected information helps building the *ExecutedDecisions* set and thus evaluating the Approach Level.

The branch fitness function needs to be evaluating either at the diverging decision or at the target decision, we call either of the decision *dt*. As discussed above, the branch fitness formula is dependent on the structure of *dt*. Once the fitness formula is built, it needs to be evaluated with the current variables values at *dt*. However, for different test input data, the program might have different flow of execution and thus the variables used at *dt* might be evaluated much differently. The code instrumentation tool provides the technique to extract the values of the variables at run time for each test data executed on the program.

Table 4.7: Instrumentation of variables at decision nodes

```
If (node.Is(ASTVar) )
        If (node.parent.Is(ASTIFstatment) )
                Print (getValue(node.name, node.data , node.line) );
End if

If(node.Is(ASTClassOrInterfaceBodyDeclaration) )
        Print (“getValue(node_name, node_value, node_line) {
                        Print (<decision id: node_line>
                                <variable name:node_name>node_value</variable>
                                </decision> )
End if
```

Table 4.7 shows the pseudo-code for the instrumentation. If a variable in a decision is encountered during the parsing, it is reprinted with an injected *getValue*() method. The *getValue*() method is also inserted in the body of the program, it prints the name of the variable, the decision line in which it occurred and more importantly the value of the variable at run time.

4.7. Overall Fitness Function Evaluation

To evaluate the fitness function for a test input data, the instrumented program under test is executed with the test data. The information collected for each execution is the set of *decisionExecuted* and the set of *variablesValues* at the target decision or at the diverged node. These two sets are fed into an evaluation method that will start by calculating the *ApproachLevelFitness* function. If the *ApproachLevelFitness* is zero, then the test data reached the target and thus the *BranchFitness* is calculated at the target decision with the set of *variablesvalues*. If the *ApproachLevelFitness* is greater than zero, then the test data did not reach the target and the *BranchFitness* is calculated at the diverging node. If the *ApproachLevelFitness* and the *BranchFitness* are both zero, then the test data achieved an MC/DC test goal. Otherwise, the fitness function of the test data will be equal to *ApproachLevelFitness + normalized(BranchFitness)*, normalization of *BranchFitness* to make it between 0 and 1.

We present in the following an example of fitness function calculations for the Calc method in *figure 4.2*. We assume that our target decision is at line 16.

4.7.1. Preliminary Phase Activities

- The control depedency set of this decision is: {12,-13}.
- The sets of data dependencies for this decision are: {φ,{2},{2,3,4,8},{2,3,-4,8}}.
- The sets of dependencies are thus: {φ,{2,12,-13},{2,3,4,8,12,-13},{2,3,-4,8,12,-13}}. The fitness function for each set runs in parallel threads. In this example, we consider the thread of the dependency set {2,3,-4,8,12,-13}.
- The MC/DC test cases extracted from the MC/DC test cases generator in section 4.1.3 for the target decision at line 16 in the Calc method were: {(010,110,100,011}. In this example, we will aim to achieve the test case (010).
- The target decision is: **if** (z > x && z > y || z > x + y).

4.7.2. Calculations on the Fly

Assume now that at run time the test data generator outputs two test data (12,-2,3) and (1,2,0) for the parameters x, y and z of the Calc method. The approach needs to evaluate the fitness function for these two test data in order to verify if one of them satisfies or is close to satisfy the MC/DC test case (010).

- Test input data T1=(12,-2,3):

$$\mathrm{ApparoachLevelFitness}(T1,16) = \mathrm{Count}(\{2,3,-4,8,12,-13\} - \{2,3,4\}) = \mathrm{Count}(\{-4,8,12,-13\}) = 4$$

$$\mathrm{BranchFitness}(T1,-4) = \big(\mathrm{Fit}(x>0) + \mathrm{Fit}(y>0) + \mathrm{Fit}(z>0)\big)T1 = 0 + 2 + 0 = 2$$

Because the goal is to traverse to the else branch of the decision at line 4, we applied the else branch formulas to the branch distance. Also, the branch fitness is always positive.

- Test input data T2 = (1,2,0):

$$\mathrm{ApparoachLevelFitness}(T2,16) = \mathrm{Count}(\{2,3,-4,8,12,-13\} - \{2,3,-4,8,12,13\}) = \mathrm{Count}(\{-13\}) = 1$$

$$\mathrm{BranchFitness}(T2,-13) = \mathrm{Fit}(z == 0)\,T2 = k = 0.1$$

Because the goal is to traverse to the else branch of the decision at line 13, we applied the else branch formula for the equality. We choose k =0.1 in this case.

- Normalisation of the branch fitness

$$BranchFitness(T1)_{normalised} = \frac{BranchFitness(T1)}{BranchFitness(T1) + BranchFitness(T2)} = \frac{2}{2.1} = 0.9$$

$$BranchFitness(T2)_{normalised} = \frac{BranchFitness(T2)}{BranchFitness(T1) + BranchFitness(T2)} = \frac{0.1}{2.1} = 0.045$$

- *Comparison of the test data*

$$Fitness(T,d) = ApproachLevelFitness(T,d) + BranchFitness(T)_{normalised}$$

$$Fitness(T1,16) = 4 + 0.9 = 4.9$$

$$Fitness(T2,16) = 1 + 0.045 = 1.045$$

→ T2 is closer to reach the decision target.

Assume now that the data generator outputs the test data (4,7,3) alone.

- Test input data T3 = (4,7,3)

$$\mathrm{ApparoachLevelFitness(T3,16)} = \mathrm{Count}(\{2,3,-4,8,12,-13\} - \{2,3,-4,8,12,-13\}) = \mathrm{Count}(\{\varphi\}) = 0$$

$$\mathrm{BranchFitness(T3,16)} = (\mathrm{Fit}(z > x)_F + \mathrm{Fit}(z > y)_T + \mathrm{Fit}(z > x + y)_F)_{T3} = 0 + 4 + 0 = 4$$

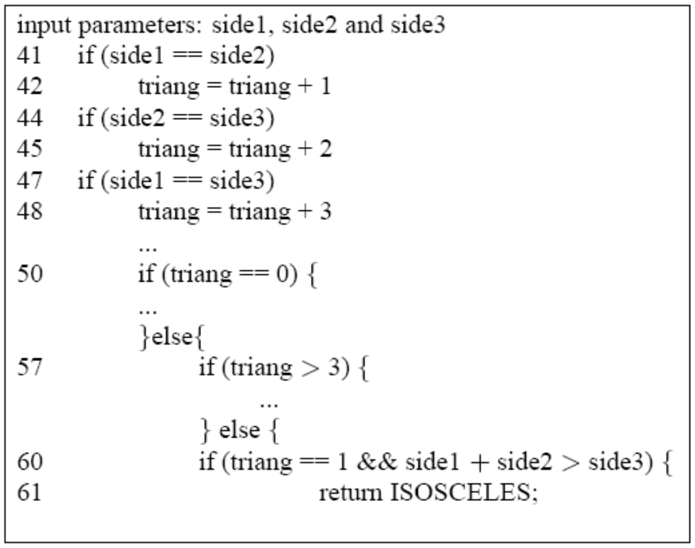
The ApproachLevelFitness is zero; the test data reached the target. Since there is only one test data, that there is no need to normalize the BranchFitness. The test case to achieve is 010, thus we want (z < x) to be false, (z > y) to be true and (z > x+y) to be false.

Chapter 5: Experimental Study and Results

In this chapter, we report results from a preliminary experimental study carried out to evaluate the performance of our approach for MC/DC automatic test input data generation using GA. The GA based approach is compared to two other searching strategies: random search (RND) and HC. In the next subsections, we briefly describe two Java programs used as test beds, the hypotheses, and the main experimental steps, details about the algorithmic settings, and finally, we present results and their interpretation.

5.1. Subject Programs

The first program is a triangle classification program (Triangle) which is a well-known problem used as a benchmark in many testing works.



```
input parameters: side1, side2 and side3
41    if (side1 == side2)
42            triang = triang + 1
44    if (side2 == side3)
45            triang = triang + 2
47    if (side1 == side3)
48            triang = triang + 3
              ...
50            if (triang == 0) {
              ...
              }else{
57                    if (triang > 3) {
                              ...
                      } else {
60                    if (triang == 1 && side1 + side2 > side3) {
61                                    return ISOSCELES;
```

Figure 5.1: Fragment of the Triangle program

This program takes three real inputs representing the lengths of triangle sides and decides whether the triangle is irregular, scalene, isosceles or equilateral. It counts 80 lines of code; the complete program code is presented in the Annexe of the thesis.

The second tested program, NextDate, takes a date as input, validates it and determines the date of the next day. The input date is entered as three integers, a day, a month and a year. First, the program verifies if the entered date is legal; the year is between 2,000 and 3,000, the month is between 1 and 12 and the day is between 1 and 28, 29, 30 or 31, depending on the entered month and year. If the date verification is passed, the program returns the next date. The complete code of the program is available in the Annexe; it counts 88 lines of code.

5.1. The Approach Steps

The automation of the testing approach is divided mainly into five steps illustrated in *Figure 5.2*.

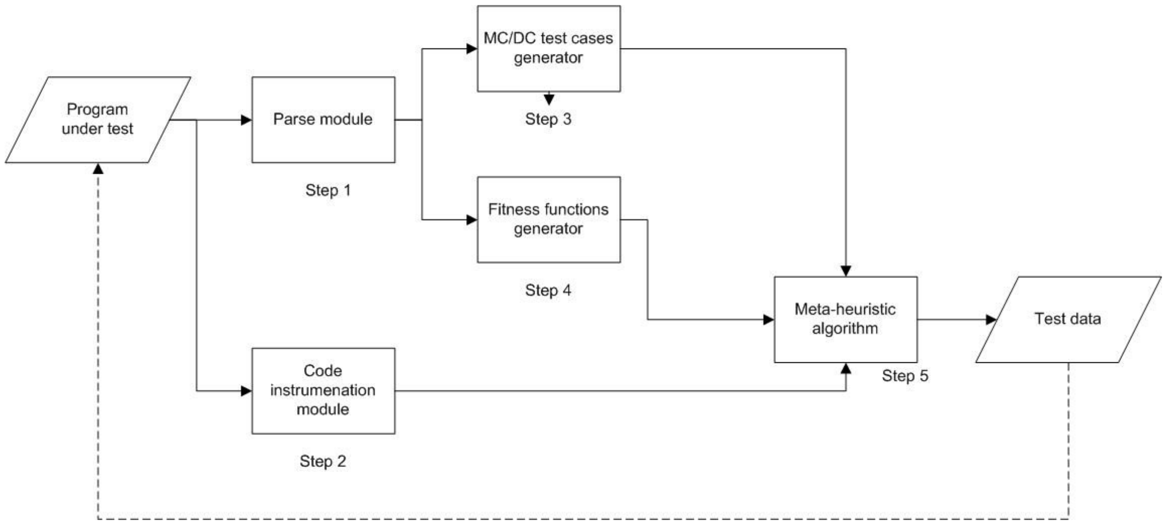


Figure 5.2: Approach steps

The program under test is first fed into the parsing module and the code instrumentation module. The parsing module output is then used as input to the MC/DC test suite generator and to the fitness functions generator. The output of code instrumentation is an instrumented program that is used by the search algorithm to evaluate the fitness values. The fifth step is the meta-heuristic algorithm. Having available the MC/DC test goals, the fitness formulas and the instrumented code, the algorithm starts its search for the test data to achieve the set of test cases for each goal and each decision in the tested code.

5.2. Algorithmic Settings

We present in the following sections the algorithmic settings for each of the GA, HC, and the RND algorithms. The first section presents the common settings of the three algorithms and the following sections detail the specific sections of each algorithm.

5.3.1. Common Settings

5.3.1.1. Stopping Criterion

The sole common parameter between RND, HC and GA is the termination criterion MaxNbrEvaluation. Based on several runs, we observed that 5,000 fitness evaluations were usually sufficient to decide if the MC/DC coverage was attainable given the predicate and the algorithm initialization (single point for HC, initial population for GA). However, we were also interested to see the effect of the fitness evaluations on the coverage attained for each algorithm. Thus, MaxNbrEvaluation was set to 5,000 fitness evaluation per test case for a first experiment, and then it was increased to 10,000 maximum fitness evaluations for a second experiment.

5.3.1.2. A Solution

For both tested programs, a solution is a three integer input data. Thus the three algorithms, GA, HC, and RND, generate a triplet of integers as evolving solutions each iteration. This is a special case, however the three algorithms supports integers and floats.

5.3.2. Genetic Algorithm

For GA, the elitist strategy was used; each iteration the entire population was replaced, except for the fittest individual (i.e., test data). The number of individuals in a generation is set to 100. We set an overall maximum number of GA generations of 400;

this is to say that either the computation is halted after the maximum allowed number of fitness evaluations or after 400 generations per test case.

The values of pc (crossover probability) and pm (mutation probability) are set to 0.70 and 0.05 respectively. We use a whole-arithmetic crossover technique with an α uniformly drawn from a normal distribution with zero mean and standard deviation equal to 1. The mutation technique used is a uniform mutation.

5.3.3. Hill Climbing

To select a neighbour, a parameter is incremented and decremented by a step uniformly drawn from a Gaussian distribution with zero mean and standard deviation σ.

We set 100 total iterations for HC. For the fitness evaluation limit of 5,000, each iteration, 100 neighbours of each parameter are explored. For the fitness evaluation limit of 10,000, 200 neighbours of each parameter are explored. This allows us to perform 16 random restarts of the search in no input data is found to achieve the test goal.

The standard deviation σ is changed for different input domain. For the triangle program, it is set to 400 for the entire integer domain. For the NextDate program, σ is set to 5 for the days, 10 for the month and 50 for the years, since the domain space for days, months and years is set to 50, 500 and 4,000 respectively. The domain space in this case is bigger than the acceptable input domain (12 month, 30 days and 2000 years); however, we wanted to test the program with non acceptable parameters to verify its behaviour.

5.3.4. Random Generator

We compare our results to the most trivial data generator, the random generator RND. It randomly generates a triplet of integers and evaluates the fitness value for this triplet using the same set of test cases and fitness functions. If the fitness value is zero, the generated data achieved a test goal, it is returned and a new test goal is selected. If the fitness value is not zero, the algorithm does not use this value to guide its search; rather it just generates randomly a new triplet. The maximum number of iterations is set to the same used for HC and GA.

5.4. Results for the Triangle Program

For each of the two exemplary programs, each algorithm computation was repeated 30 times using the traditional fitness function (without integrating data dependencies into the fitness function) and using the proposed fitness function (with integrating data dependencies into the fitness function) for GA and HC. The goal is to show the MC/DC coverage for the two programs under test for both fitness functions.

5.4.1. Results Without Integrating Data Dependencies

Several experiments were conducted on the MC/DC coverage for the Triangle program. First, we studied the impact of the parameters domain space on the automation of the search for the test data. Then, we studied the impact of the number of search iterations on the data generation as well. The data generation measurement is reported by the percentage of MC/DC test cases that were achieved by the generated test data.

5.4.1.1. Impact of the Parameters' Domain Space

The fitness evaluation is set to a maximum to 5,000 evaluation per test case for this experiment.

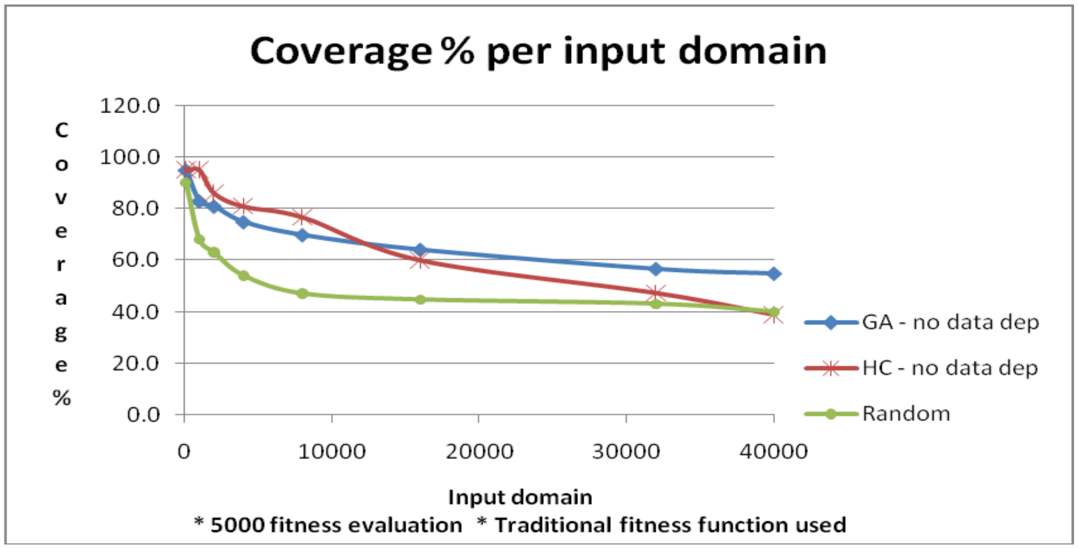


Figure 5.3: Results for Triangle program without integrating data dependencies in the fitness function (maximum of 5,000 fitness evaluation)

Table 5.1: Results for Triangle program without integrating data dependencies in the fitness function (maximum of 5,000 fitness evaluation)

Input domain	GA (%)	HC (%)	RND (%)
-100,+100	95.0	95.0	90.0
-1000,+1000	83.0	95.0	68.0
-2000,+2000	81.0	86.0	63.0
-4000,+4000	75.0	80.9	54.0
-8000,+8000	69.9	76.7	47.1
-16000,+16000	64.2	60.1	44.7
-32000,+32000	56.8	47.4	43.1
Integer domain	54.7	39.0	40.0

Figure 5.3 reports the performance of RND, HC and GA for various dimension of the search space. Triangle takes three integers and decides the kind of corresponding triangle. The results show that the larger the input parameter domains the lower the attained average MC/DC coverage. As shown in *Table 5.1*, when the parameters range between plus or minus 100, even a simple random search attains an average of 90 % of MC/DC coverage. The reason is that the number of fitness evaluation is high (i.e., 5,000 per test case) and the entire search space is explored.

However, as the dimension of the search space increases (up to the integer range), the coverage for the three searching strategies decreases. For example, GA drops to 55 % and HC to 39%, performing as a random search. RND drops quickly to 68% for an input domain of -1000 to 1000, and gets as low as 40% for the integer domain. HC performs better for small input domain, attaining a better coverage percentage than GA for input domain lower than |8,000|, but then degrades to perform as a random search for higher inputs.

Table 5.2: Coverage per program decision for the entire integer domain (maximum of 5,000 fitness evaluation)

Decision	GA (%)	HC (%)	RND (%)
37	100.0	96.6	100.0
41	100.0	53.5	50.0
44	98.3	53.5	50.0
47	98.3	55.7	50.0
50	50.0	53.5	50.0
51	100.0	72.4	100.0
57	0.0	0.0	0.0
60	0.0	0.0	0.0
63	0.0	0.0	0.0
66	0.0	0.0	0.0
Total	54.7	38.5	40.0

The reason for such performance degradation is in the equilateral and isosceles triangle types. First and foremost, equilaterals and isosceles triangles imposes hard constraint and, sampling out of the entire integer space, the probability to obtain the same number repeated two or three time is very low.

A second reason is related to the structure of control and data dependencies of the Triangle program. *Table 5.2* reports the details of average MC/DC coverage for the decisions in the Triangle program shown in the excerpt of *Figure 5.1* for the entire integer input domain. The traditional fitness function has zero coverage for the critical nodes at lines 50, 51, 57, 60, 63 and 66. As shown in the Triangle code excerpt, the decision at line 57 has a reverse control dependency from the “if” at line 50, and both have data dependencies on lines 42, 45 and 48. These lines in turn are controlled by the “if” at lines 41, 44 and 47 respectively. In other words, a fitness function based on the standard approach level and branch distance has no guidance to reach the line 57 and thus the three “if” controlled by line 57, for example, the “if” at line 60. Thus the code section deciding if the triangle is equilateral or isosceles is extremely difficult to reach if the search space is large and not entirely explored by the search algorithm. Indeed, these three “if” are not reached by RND, HC or GA within 5,000 fitness generations searching into the 32 bits integer range. This is the reason why in *Figure 5.3* we observe the drop in MC/DC coverage.

5.4.1.2. Impact of the number of Search Iterations

The same experiment is conducted again with a maximum number of allowed fitness evaluations of 10,000. Again, the data dependencies are not included in the fitness function. The results of the experiment are shown in *Figure 5.4*. The performance of the three algorithms GA, HC, and RND is then compared with the results of the first experiments in *Figure 5.5, 5.6,* and *5.7.*

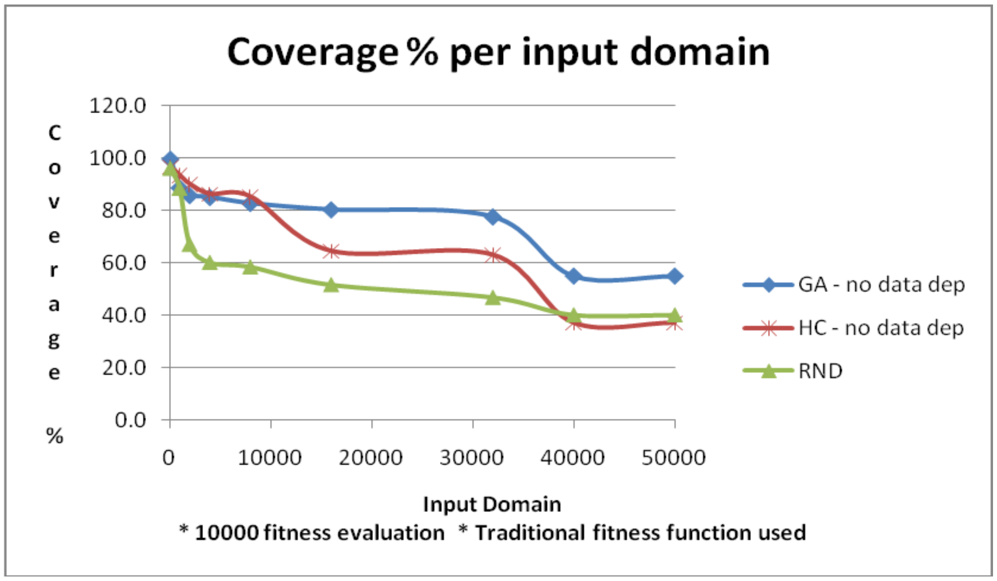


Figure 5.4: Results for Triangle program without integrating data dependencies in the fitness function (maximum of 10,000 fitness evaluation)

Table 5.3: Results for Triangle program without integrating data dependencies in the fitness function (maximum of 10,000 fitness evaluation)

Input domain	GA (%)	HC (%)	RND (%)
-100,+100	99.7	96.7	96.0
-1000,+1000	88.7	93.4	88.4
-2000,+2000	85.8	90.1	67.0
-4000,+4000	85.1	86.3	60.1
-8000,+8000	82.8	85.4	58.4
-16000,+16000	80.4	64.6	51.6
-32000,+32000	77.6	63.2	46.7
Integer domain	54.9	37.3	40.0

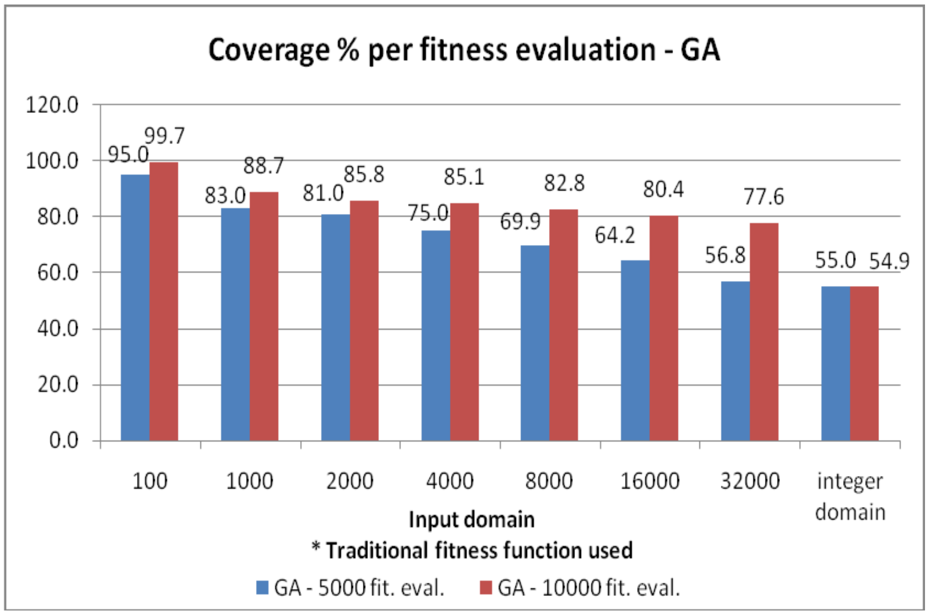


Figure 5.5: Impact of fitness evaluation on GA - without data dependency

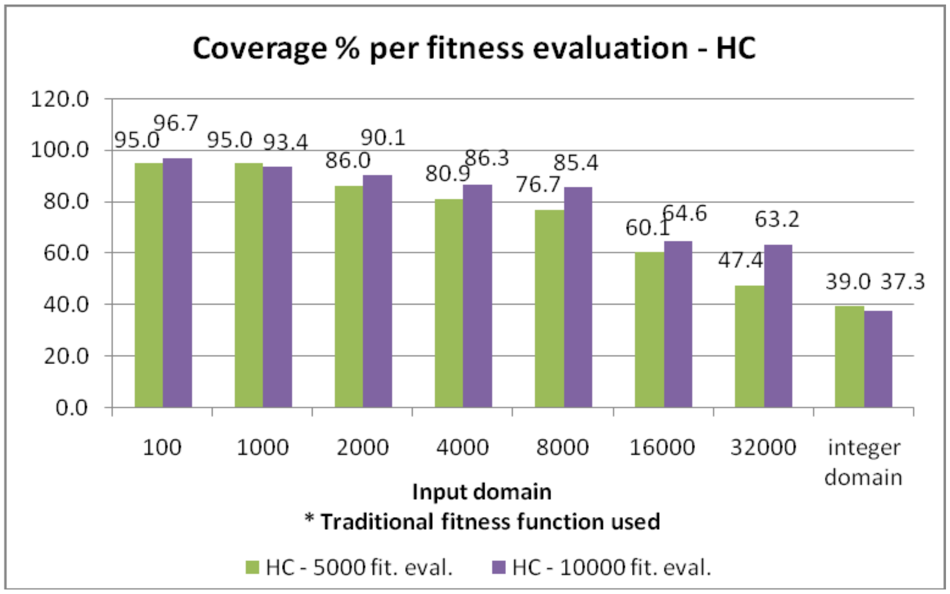


Figure 5.6: Impact of fitness evaluation on HC - without data dependency

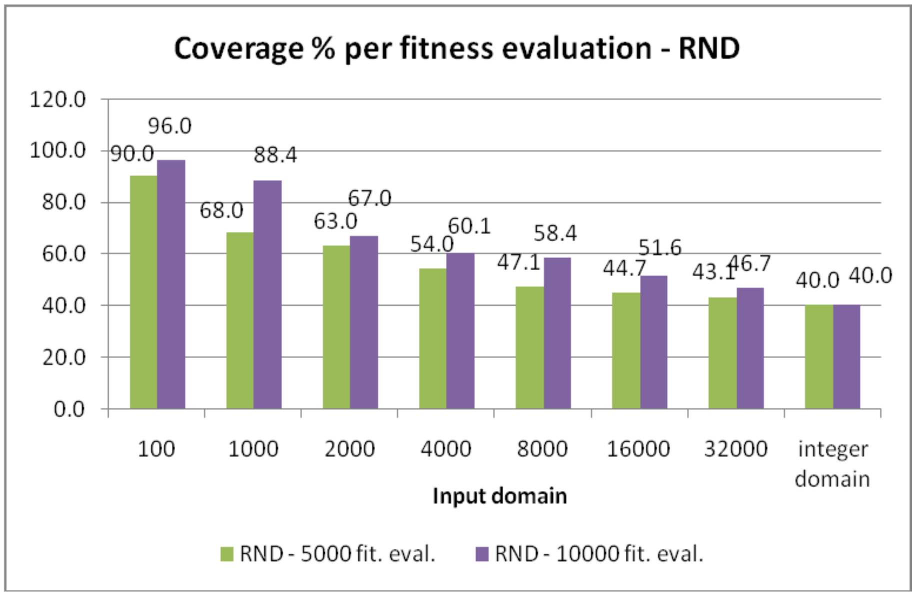


Figure 5.7: Impact of fitness evaluation on RND

Results in *Figure 5.5, 5.6* and *5.7* show that for small input domain, the three algorithms perform better with a higher number of fitness evaluations. Moreover, with higher input domain, the impact of the evaluations becomes bigger in the case of GA and HC. For example, GA covers 77% vs. 57% for an input domain of 32,000; for the same domain, HC covers 63.2 % vs. 47.4%. Still, we can see that when the input domain becomes the entire integer space, even with a fitness evaluation of 10,000, the search degrades to the coverage of a random search; GA covers 54.9%, HC covers 37.3% and RND covers 40%.

5.4.2. Results with Integrating Data Dependencies

We run again both experiments with maximum fitness evaluation 5,000 then 10,000, however this time using our new fitness function having the data dependencies integrated in it. We present first the results of the first experiment and we compare its results with the previous results without data dependencies.

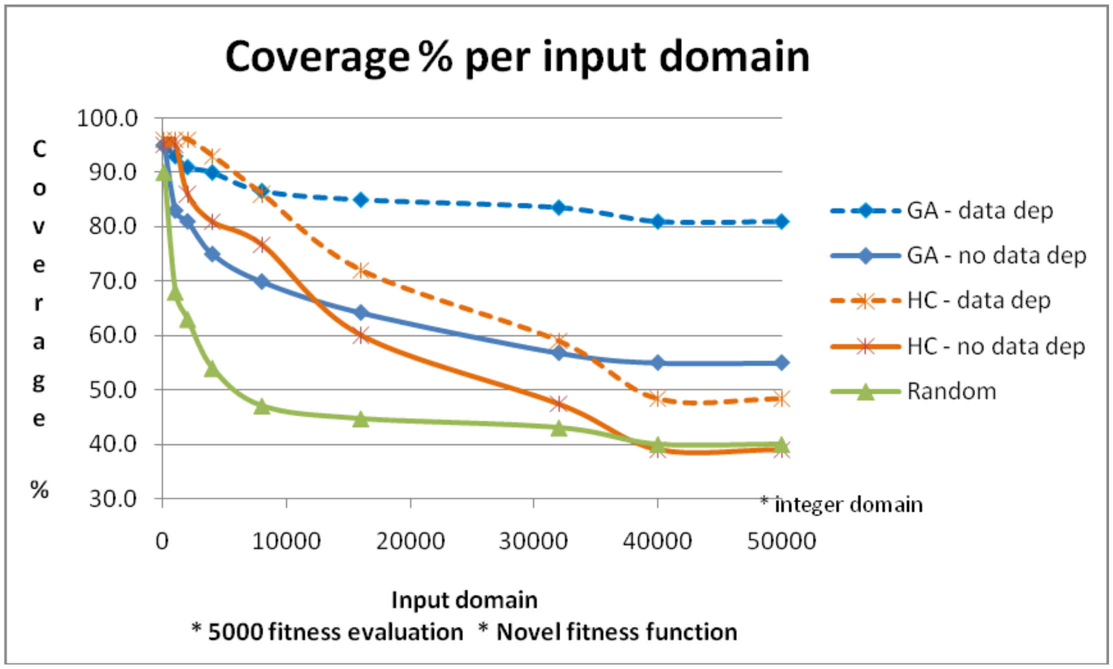


Figure 5.8: Results for Triangle program with data dependencies in the fitness function (maximum of 5,000 fitness evaluation)

Table 5.4: Results for Triangle program with data dependencies integrated in the fitness function (maximum of 5,000 fitness evaluation)

Input domain	GA (%)	HC (%)	RND (%)
-100,+100	95.0	96.0	90.0
-1000,+1000	93.0	96.0	68.0
-2000,+2000	91.0	96.0	63.0
-4000,+4000	90.0	93.0	54.0
-8000,+8000	86.6	86.0	47.1
-16000,+16000	85.0	72.0	44.7
-32000,+32000	83.6	59.0	43.1
Integer domain	81.0	48.4	40.0

Figure 5.8 summarizes the results obtained for the Triangle program with the new fitness function including data dependencies for a maximum fitness evaluation of 5000. Though HC performs best for small input domain, GA largely outperforms HC for larger domains; this is likely due to the neighbourhood definition that needs to be improved to cope with large search spaces. Overall, data dependencies have a lower impact on HC attained coverage.

Table 5.5: a) Input domain -16000 to 16000

Decision	GA (%)	Old GA (%)	HC (%)	Old HC (%)	RND (%)
37	100.0	100.0	100.0	100.0	100.0
41	100.0	100.0	91.4	82.8	51.7
44	100.0	100.0	87.9	89.7	50.0
47	100.0	100.0	89.7	91.4	51.7
50	86.2	86.2	55.2	60.3	56.9
51	100.0	100.0	100.0	100.0	100.0
57	82.8	46.6	27.6	15.5	10.3
60	79.3	51.7	59.8	24.1	11.5

b) Entire integer domain

Decision	GA (%)	Old GA (%)	HC (%)	Old HC (%)	RND (%)
37	96.6	100.0	94.0	96.6	100.0
41	100.0	100.0	53.0	53.5	50.0
44	94.8	98.3	53.5	53.5	50.0
47	100.0	98.3	55.5	55.7	50.0
50	60.3	50.0	55.0	53.5	50.0
51	100.0	100.0	73.3	72.4	100.0
57	86.2	0.0	100.0	0.0	0.0
60	57.7	0.0	0.0	0.0	0.0

63	85.1	49.4	52.9	21.8	5.7
66	66.7	33.3	57.5	14.9	9.2
Total	90.0	76.7	72.2	60.1	44.7

63	56.3	0.0	0.0	0.0	0.0
66	55.2	0.0	0.0	0.0	0.0
Total	81.0	54.7	48.4	38.5	40.0

On the other hand, GA with integrated data dependencies performs substantially better than approach level and branch distance alone. In fact, GA covers 81% vs. 54% for the entire integer domain, which is a 30% gain, obtained due to data dependencies. Indeed, the new fitness outperforms the old one in the code region controlled by the statement 57 as shown in *Table 5.5 a) and b)*. *Table 5.5 a)* shows a comparison in the results of the three algorithms with the old and new fitness function for an input domain of -16,000 to 16,000, while *Table 5.5 b)* shows the results for the entire integer input domain. *Table 5* shows the improvement in the coverage for both GA and HC with the new fitness function. In *Table 5.5 b)* however, the impact of the new function is lower for HC on the decisions in lines 60, 63, and 66, while the new coverage percentage of the decision at line 57 is 100% vs. 0% for the traditional function. An analysis of the evolution of the solutions in HC show that for large search space as the entire integer domain, the neighbourhood step is too small and the hill climbing is stuck at local minima. An increase of the neighbourhood step or a more sophisticated neighbourhood selection should be explored in future work. Overall, on Triangle and the entire 32 bits range, the new fitness with GA attains an 81 % MC/DC coverage substantially increasing the coverage obtained with the previous fitness function relying solely on approach level and branch distance.

5.4.2.1. Impact of the Number of Search Iterations

Again, the same experiment is conducted, this time with 10,000 as maximum number of fitness evaluations.

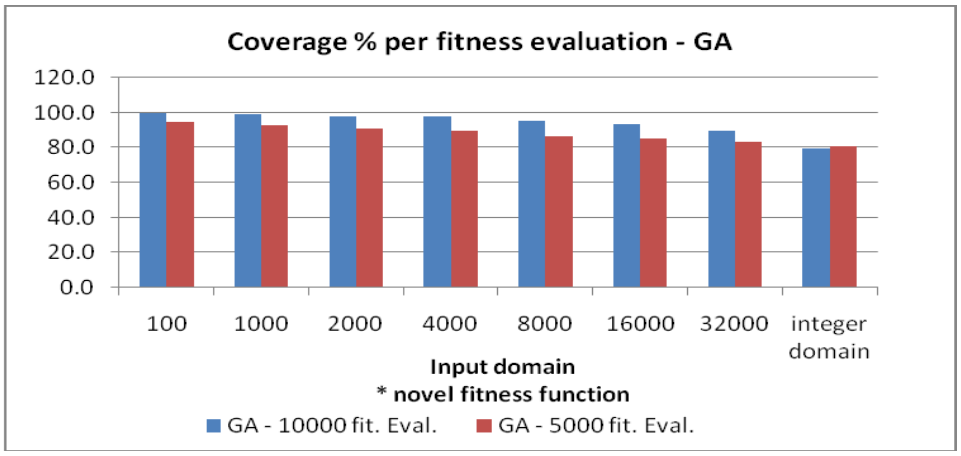


Figure 5.9: Impact of fitness evaluations on GA - with data dependency

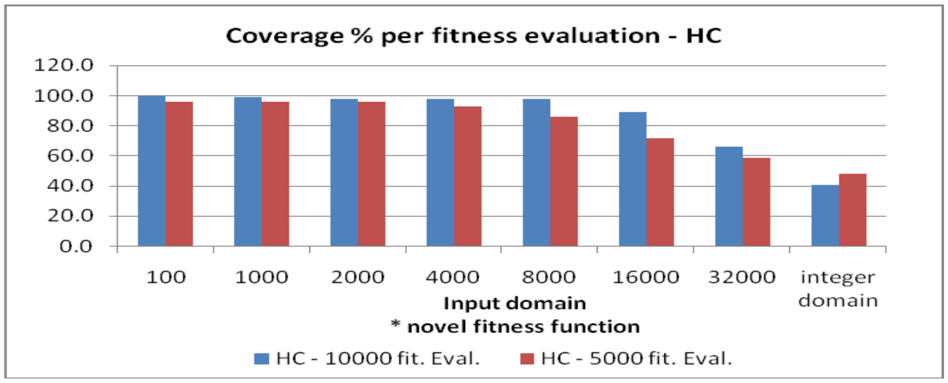


Figure 5.10: Impact of fitness evaluations on HC - with data dependency

Figure 5.9 and 5.10 shows that while a higher number of fitness evaluations can increase the coverage percentage for small input domains, it has no impact on large domains.

5.5. Results for the NextDate Program

The test data generation for NextDate were tried for several fitness evaluations limits. We recorded the coverage percentage for each limit; the results are reported in *Figure 5.11*.

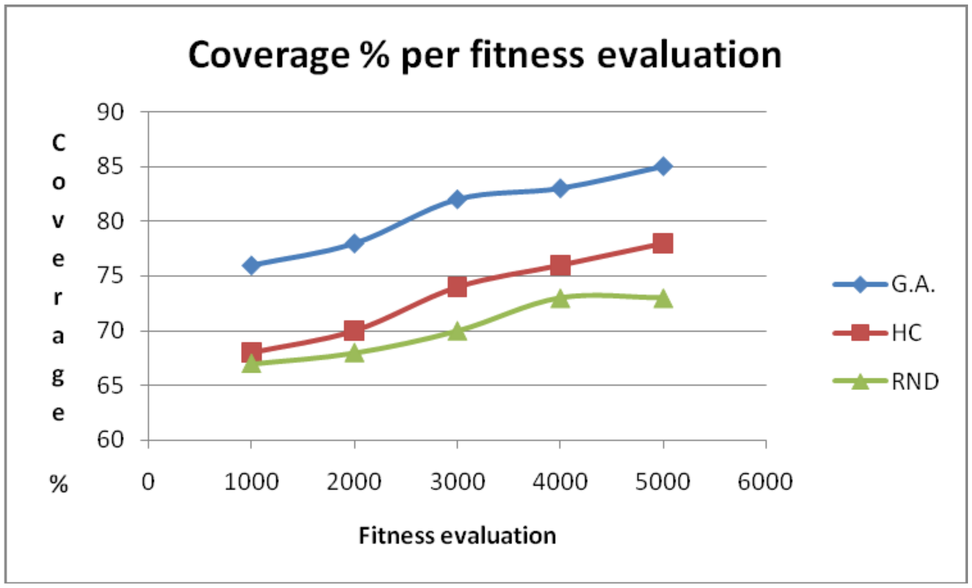


Figure 5.11: Results for the NextDate program

Table 5.6:Coverage % per fitness evaluations for NextDate program

Maximum allowed fitness computation	GA (%)	HC (%)	RND (%)
1000	76	68	67
2000	78	70	68
3000	82	74	70
4000	83	76	73
5000	85	78	73

As shown in the figure, the higher the fitness evaluation limit, the higher the coverage achieved. GA outperforms the other two algorithms. The program tested does not have interaction between data dependencies and control dependencies as the Triangle program; in fact it has no data dependencies between the decisions of the program, thus there was no need to repeat the experiments using the different fitness functions. Indeed, since no data dependencies exist in the code affecting the MC/DC coverage, the search was able to obtain very good results. This validates our new fitness function, since it has no negative effects on data dependency-free programs. Again for this program, GA outperformed HC and RND, even if by smaller percentages of MC/DC coverage.

5.6. Results Discussion

Our preliminary results prove the superiority of the new proposed fitness function. In the case of the first test program, Triangle, the coverage attained with integrated data dependencies is greater than the one attained with the traditional fitness function for both algorithms GA and HC. The impact is mostly shown in GA, as the new coverage outperforms the old one by 30%. The impact on the results of HC is less significant though on the entire input range, which we believe is a result of a poor neighbourhood selection criterion for large input search space. The same observation can be shown when the limit of the fitness evaluations is pushed to 10,000. Introducing the data dependencies in the fitness function doubled the coverage for GA, even with 5,000 fitness evaluations.

Overall, we were able to obtain a MC/DC coverage percentage of 81% using the novel fitness function in GA with 5,000 fitness evaluations and on the entire integer domain, between -2^{32} and 2^{32} and a 85% coverage for 5,000 fitness evaluations and a domain space -15,000 to 15,000.

The Chaining approach presented by McMinn presents a coverage percentage of 99% for the branch coverage criterion on input domain -15,000 to 15,000. However, the MC/DC criterion is a more complex and sophisticated structural criteria to cover than the branch coverage. Moreover, we were able to achieve 85% coverage for the same domain space with a 5,000 fitness evaluation limit, while the Chaining approach requires between 20,000 and 290,000 fitness evaluations. However, we do not have the subject programs tested by this approach; thus we can not know the structural complexity of the code.

Chapter 6: Conclusion

Testing is a widely adopted quality assurance practice; in regulated domains, such as in aerospace, or in safety critical applications testing activities must comply with standard and regulations. In this work, we have presented a new approach and a novel fitness function to generate test input data for the MC/DC coverage criterion. MC/DC is a mandatory testing practice for the aerospace industry according to DO-178B. Software that fails to be tested by this criterion is denied the approval of the Federal Avionic Administration and thus cannot be used in avionic systems.

The MC/DC criterion is a structural test that aims to prove that every condition in a decision affects correctly the outcome of the decision. Even though some automation tools exist for structural testing such as the branch coverage, no tool is known of today to automatically generate the test data for the MC/DC coverage. Thus, in our work, we built a tool that automatically analyses the code under test, detects its decisions structure, and generates the test cases and the test data for this criterion with our new proposed fitness function.

The search for the test data is an exhaustive search in large search space. A search optimization technique is therefore useful to automate the search. We used the search based software engineering applied to testing to solve our testing search problem. SBST uses meta-heuristic techniques to optimise the search in large search domains. The testing criterion is thus transformed into an objective function that was used to guide the search. We used in our work one evolutionary technique, the genetic algorithm, and one local search technique, the hill climbing, to search for the test data. We applied these techniques to our testing problem, by formulating the MC/DC criterion test cases as test goals for the search, and we build the solutions from the parameters of the program under test.

The traditional fitness function used in literature for structural testing relies on branch distance and control dependencies between the program nodes. This function has a limitation when flag variables exist in decisions in the code, or when used variables in decisions have data dependencies on prior nodes in the program. In these two scenarios, the landscape of the fitness function becomes flat, the fitness is unable to guide effectively the search relying solely on control dependencies, and thus the meta-heuristic search will degrades into a random search.

Several approaches were proposed in literature to solve this problem for structural testing, however the proposed approaches either were limited to the flag problem only or they integrated data dependencies in their fitness function but they failed to account for its control dependencies as well, leading to the same problem.

In our proposed fitness function, we fully integrated data and control dependencies together to better guide the search and avoid the plateau caused by problematic nodes. We extended McMinn hybrid approach inspired by Korel chaining dependencies computation. We also adapted the branch coverage fitness function to deal with predicate clauses extending Bottaci rules for branch distance computation.

Preliminary data obtained on two Java programs used as a test bed, Triangle and NextDate, showed that the GA with our novel fitness function integrating data dependencies, control dependencies, and branch distance outperformed random data generation, hill climbing, and GA without the dependencies on large search spaces, i.e., when the Triangle input parameters are selected over the entire integer range. In particular, our novel fitness implementation substantially improved MC/DC coverage on the Triangle program (from 55 % to 81 %).

To extend this work, the neighbourhood for hill climbing should be better defined as the current implementation seems not well suited to take advantage of the data dependencies integration into the fitness function when the Triangle input parameters are selected over the integer range.

Finally, we published our work at the **2009 Genetic and Evolutionary Computation Conference.** The article published is entitled 'MC/DC Automatic Test Input Data Generation', by Zeina Awedikian, Kamel Ayari and Guiliano Antoniol.

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Appendices

Appendix 1: Tested programs

- Triangle.java

```
package triangle;
import java.io.*;

public class triangle {

    static final int ILLEGAL_ARGUMENTS = -2;

    static final int ILLEGAL = -3;

    static final int SCALENE = 1;

    static final int EQUILATERAL = 2;

    static final int ISOCELES = 3;

    // La fonction main joue ici le role d'un driver est ne doit pas
etre sujet à des test
    public static void main( java.lang.String[] args )
    {
        float[] s;
        s = new float[args.length];
        for(int i = 0 ; i< args.length; i++)
        {
            s[i] = new java.lang.Float(args[i]);
        }
        System.out.println( getType( s ) );
    }

    public static int getType( float[] sides )
    {
        int ret = 0;
        float side1  = sides[0];
        float side2  = sides[1];
        float side3  = sides[2];

        if (sides.length != 3) {
            ret = ILLEGAL_ARGUMENTS;
        } else {
            if (side1 < 0 || side2 < 0 || side3 < 0) {
                ret = ILLEGAL_ARGUMENTS;
            } else {
                int triang = 0;
                if (side1 == side2) {
                    triang = triang + 1;
                }
                if (side2 == side3) {
                    triang = triang + 2;
                }
                if (side1 == side3) {
                    triang = triang + 3;
                }
                if (triang == 0) {
                    if (side1 + side2 < side3 || side2 + side3 < side1
|| side1 + side3 < side2) {
                        ret = ILLEGAL;
                    } else {
                        ret = SCALENE;
                    }
                } else {
                    if (triang > 3) {
                        ret = EQUILATERAL;
                    } else {
                        if (triang == 1 && side1 + side2 > side3) {
                            ret = ISOCELES;
                        } else {
                            if (triang == 2 && side2 + side3 > side1) {
                                ret = ISOCELES;
                            } else {
                                if (triang == 3 && side1 + side3 >
side2) {

                                    ret = ISOCELES;
                                } else {
                                    ret = ILLEGAL;
                                }
                            }
                        }
                    }
                }
            }
        }
        return ret;
    }

}
```

- NextDate.java

```
package NextDate;

public class NextDate
{
      final static int ILLEGALYEAR = -3;
      final static int ILLEGALMOUNTH = -2;
      final static int ILLEGALDAY = -1;
      static int daysinmounth=0;

      public static void main(String[] args)
      {
            int day = new Integer(args[0]);
            int month = new Integer(args[1]);
            int year = new Integer(args[2]);
            nexDate(day, month, year);
            System.exit(0);
      }
      public static void nexDate(int day, int month, int year)
      {
            int daysinmonth = 0;
            String message = "";
            if ((year < 2000 || year >= 2999 )||(year >3500))
            {
                  message = "Annee Invalide";
            }
            else
            {
                  if (month < 1 || month > 12)
                  {
                        message = "Mois Invalide";
                  }
                  else
                  {
                        switch (month)
                        {
                              case 1:
                              case 3:
                              case 5:
                              case 7:
                              case 8:
                              case 10:
                              case 12:
                                    daysinmonth = 31;
                                    break;
                              case 2:
                                    {
                                          if (((year % 3 == 0) && (year
% 100 != 0)) || (year % 400 == 0))
                                                daysinmonth = 29;
                                          else
                                                daysinmonth = 28;
                                          break;
                                    }
                              default:
                                    daysinmonth = 30;
                        }
                        if (day < 1 || day > daysinmonth)
                        {
                              message = "Jour Invalide";
                        }
                        else
                        {

                              if (day == daysinmonth)
                              {
```

```
                        day = 1;
                        if (month != 12)
                        {
                            month++;
                        }
                        else
                           {
                            month = 1;
                            year++;
                        }
                    }
                    else
                    {
                        day++;
                    }

                    message = day + "/" + month + "/" + year;
                }
            }
        }
        System.out.println(message);
    }
}
```

Appendix 2: Published Article in GECCO 2009

MC/DC Automatic Test Input Data Generation

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ABSTRACT

In regulated domain such as aerospace and in safety critical domains, software quality assurance is subject to strict regulation such as the RTCA DO-178B standard.

Among other conditions, the DO-178B mandates for the satisfaction of the modified condition/decision coverage (MC/DC) testing criterion for software where failure condition may have catastrophic consequences. MC/DC is a white box testing criterion aiming at proving that all conditions involved in a predicate can influence the predicate value in the desired way.

In this paper, we propose a novel fitness function inspired by chaining test data generation to efficiently generate test input data satisfying the MC/DC criterion.

Preliminary results show the superiority of the novel fitness function that is able to avoid plateau leading to a behavior close to random test of traditional white box fitness functions.

Categories and Subject Descriptors

D [**Software**]: Miscellaneous; D.2.5 [**Software Engineering**]: Testing and Debugging—*Testing tools (e.g., data generators, coverage testing)*

General Terms

Algorithms, Experimentation

Keywords

Test input data generation, Search based testing, MC/DC.

1. INTRODUCTION

Testing has traditionally been one of the main techniques contributing to high software dependability and quality. Testing activity consumes about 50% of software development resources, so any technique aiming at reducing software-testing costs is likely to reduce software development costs. Indeed, exhaustive and thorough testing is often unfeasible because of the possibly infinite execution space or high cost with respect to tight budget limitations.

High dependability computerized systems are often software intensive systems belonging to regulated domains such as aerospace and medical application domain. In such domains, quality assurance and testing activities are enforced by law or required by mandatory standards, such as DO-178B, DO-254, EN-50128, IEEE/EIA 12207, or ISO/IEC i2207. These standards and regulations enforce verification and validation activities and they specify the required testing coverage criteria.

Proposed by NASA in 1994, the Modified Condition/Decision Coverage (MC/DC) criterion is a testing strategy required, among other practices, by the RTCA DO-178B. MC/DC is a white box testing criterion aiming at proving evidence that all clauses (Boolean expression not containing any logical operator such as $z > x + y$) involved in a predicate can influence the predicate value in the required way. It subsumes other well-known coverage criteria such as statement and decision coverage.

This paper goes along the research line of Evolutionary Testing (ET) [9] and explores the way search techniques can be integrated with branch distance, control and data dependencies to generate MC/DC test input data at method level.

Our approach is organized in two steps. First, for any given predicate, we compute the sets of Boolean values that once assigned to clauses satisfy MC/DC. In the second step, we apply metaheuristic search strategies to generate test input data assigning true and false Boolean values to clauses so that one of the MC/DC set computed in step one is obtained.

We ground our proposal on the contributions of other researchers [3, 4, 14, 18, 17, 10, 11]. In particular we draw inspiration from the work of [4, 10, 11] integrating data dependencies in the fitness design and evaluation. We extended the algorithm proposed by McMinn [10, 11] for the branch distance fitness [2, 17] adapting it to MC/DC.

To assess the feasibility of our approach we implemented a prototype tool set for code written in Java and applied it to the well-known 'Triangle' and 'NextDate' programs. We report evidence of the superiority of the new fitness function with respect to the simple adaptation of the branch distance to MC/DC.

The primary contribution of this paper can be summarized as follows:

- we propose a search based approach to generate MC/DC test input data;
- we propose to integrate data dependencies via control dependencies in a new fitness function tailored for MC/DC.

The remainder of the paper is organized as follows. Section 2 discusses the related work on the use of search-based techniques to solve test input data generation problem. Section 3 reports basic information to make the paper self contained. It is followed by

Section 4 describing the proposed search-based MC/DC test input data generation approach. Section 5 presents preliminary results on two programs aimed at evaluating the proposed approach with respect to random search and traditional branch distance adapted to MC/DC. Finally, Section 6 concludes.

2. RELATED WORK

Korel [4] and McMinn [9, 11] were the first to integrate data dependencies in test data generation approaches. The goal was to avoid the degeneration of the approach to a random search when the fitness function doesn't take into account the existence of data dependencies between the target structure and certain program statements that need to be executed first. In particular, McMinn [9, 11] introduced Korel chaining approach [4] in fitness definition for white box testing criteria. Our work applies ET to MC/DC coverage and extends [9, 11] so that the chains created contains also the control dependencies of the data dependencies statements to guide even more the evolutionary search.

Automation of structural coverage criteria and structural testing have been the most widely investigated subjects. Local search was first used by Miller and Spooner [12] with the goal of generating input data to cover particular paths in a program. This work was later extended by Korel [8]. In brief, to cover a particular path, the program is initially executed with some arbitrary input. If an undesired branch is taken, an objective function derived from the predicate of the desired branch is used to guide the search. The objective function value, referred to as *branch distance*, measures how close the predicate is to being true. The idea of minimizing such an objective function was refined and extended by several researchers to satisfy coverage criteria of certain given procedural-program structures like branches, statements, paths, or conditions.

To overcome the limitations associated with local search, Tracey et al. [14] applied simulated annealing and defined a more sophisticated objective function for relational predicates. The genetic algorithm, likely to be the best known evolutionary algorithm that overcomes the problems of local search, was first used by Xanthakis [18] to generate input data satisfying the all branch predicate criterion. Evolutionary approaches where search algorithms, and in particular genetic algorithm, are tailored to automate and support testing activities i.e., to generate test input data such as the contributions [6, 15, 16, 17] are often referred to as evolutionary based software testing or simply Evolutionary Testing (ET). A survey of ET and related techniques is beyond the scope of this paper; the interested reader can refer to the survey published by Phill Mcminn [9].

Most of the research on ET makes use of some form of Control Flow Graph (CFG) as the data structure to be manipulated in order to obtain information guiding test input data generation at the unit level, typically function or method. A recent contribution by Tonella [13] has demonstrated ET applicability to the problem of object-oriented testing, more precisely to unit testing of classes. The applications of ET to black box testing have been studied by Tracey et al. [15] and Jones [7]. Tracey et al. used genetic algorithm and simulated annealing to test the specification conformity of a program written in Pascal. Jones used search-based techniques to generate test data from **Z** specification [7].

3. BACKGROUND NOTIONS

In this section, we summarize the basic notions to make the paper self-contained. In particular, we provide essential information on MC/DC, white box fitness functions, Hill Climbing (HC) and Genetic Algorithm (GA).

```
1   public int Calc (int x, int y, int z) {
2       int result = -1;
3       bool Fail = false;
4       if (x < 0 || y < 0 || z < 0 )
5           Fail = true ; //illegal parameter value
6       else
7           Fail = false;
8       if (not Fail) {
9           x = y //overwrite x by a new value
10          result = 0;
11      }
12      if (result == 0) {
13          if (z == 0 )
14              result = x + y;
15          else {
16              if (z > x && z > y && z > x + y)
17                  result = z;
18              else
19                  result = x + y;
20          }
21      }
22      return result;
23  }
```

Figure 1: Example of code under test

Consider the Java code in Fig. 1; suppose we are interested in generating input data so the statement at line 17 is reached. Further, assume our task is to generate test input data to satisfy MC/DC. Given a clause - called the major clause (see [1] for details), say z > x, the other clauses - minor clauses (z > y and z > x + y) are selected in a way z > x can determine the predicate value (true and false). In our case we must have both z > y and z > x + y true. MC/DC requires the predicate value changes between true and false when the major clause, z > x, changes.

There are two MC/DC variants. In the first one, also referred to as the unique cause MC/DC, minor clauses must hold the same Boolean value for the two values of the major clause. The second interpretation of MC/DC, a weaker criterion known as the masking MC/DC, allows minor clauses to be different [1]. In this paper we will consider the strongest interpretation, the unique cause MC/DC, as it is the criterion required by the standard DO-178B. As pointed out by Ammann et al. [1], physical or logical constraints between variables can make infeasible to attain 100 % MC/DC or may make impossible to realize certain clauses Boolean assignments.

Overall, we need to assign values to integer parameters x, y and z so that the 'if' statement at line 16 is reached and each clause (i.e., $z > x, z > y$ and $z > x+y$) affect the value of the predicate while the other two clauses are kept fixed. Clearly while for predicate at line 16, only one assignment of Boolean value is able to satisfy MC/DC, in general, there may be several sets satisfying MC/DC and thus multiple coverage sets are possible. Consider a predicate like $A\&\&(B\|C)$. For major clause A it is sufficient that either B, or C (or both) will be true in order for A to cause the predicate to change values between true and false. Since, in general, there is no particular reason to prefer one set of assignments satisfying MC/DC over the others all possible sets should be considered.

3.1 Code parsing and expression analysis

To determine MC/DC assignments of major and minor clauses it is first required to parse the source code, identify and analyze predicates, extract predicate structure, and identify clauses. This can be done with standard reverse engineering technologies and tools. Our code parsing and analysis module assumes code has been developed in Java and implements expression analysis in several steps. First, code is parsed and an Abstract Syntax Tree (AST) is constructed. This is done via JavaCC and JJTree [1] on top of Java 1.5 grammar.

The AST is then visited and sub-trees of predicate transformed into a reduced representation, Abstract Decision Tree (ADT); ADTs are stored and used by subsequent phases. ADTs only keep predicates logical structure, in fact logical structure is the sole information required to generate MC/DC sets.

Once ADTs are available, each ADT is in turn fed into a module that explicitly builds predicate truth table and identifies for each major clause the sets of Boolean value satisfying MC/DC coverage. Although the explicit construction of the truth table may be considered highly inefficient, it is only performed off-line and in the preliminary phase before actually searching for the test input data and it is very easy to implement. Furthermore, even if the table size is exponential in the number of clauses, it is uncommon that a predicate contains more than 10 or 20 clauses and thus it can easily fit into memory of any modern personal computer.

3.2 The branch coverage fitness function

ET has proved to be very effective to generate test input data for white box coverage criteria in particular for the decision coverage [9]. Decision coverage consists of generating test cases that would satisfy each decision in the code under test. By satisfying all the decisions, all the branches in a code are ensured to be reached and traversed at least once during the execution of the test cases.

Two ingredients are needed [2, 9, 17]. The first component accounts for control dependencies and it is often referred to as the approach level. For example, in Fig 1, the statement at line 17 depends on the 'if' statements at lines 12, 13 and 16: the 'if' statements at lines 12, 13 and 16 control the execution of line 17. Control flow nodes in the program CFG corresponding to those 'if' statements are also called the critical branches because they can cause the program flow to diverge to unwanted code regions. The approach level for a test input datum is computed subtracting one from the distance in critical branches; the distance is measured as the number of control nodes lying between the target node and the node where the flow diverges away. Going back to the target line 17, if the flow diverges at line 13 (two control nodes in between), the approach level assign a fitness value of one. Thus, approach level measures how close we are to line 16 'if', the last controlling statement.

Once the search generates input data leading to line 16, all critical branches are satisfied and thus the approach level fitness is zero. At this point, the approach level is no longer effective in guiding the search. Suppose for example, that the search generates the input parameter assignments (2, 4, 4) and (2, 4, 5). Both sets lead to line 16; for both the approach level fitness is zero and though (2, 4, 4) is *closer* to satisfy the predicate, the fitness doesn't provide any guidance. To overcome this limitation the second component, called branch distance is incorporated into the fitness to quantify the distance to make the control node predicate true (or false). Branch distance is normalized between zero and one; its computation is based on tabulated relations as equations proposed by Bottaci [3].

Clearly, MC/DC requires more details with respect to branch coverage since there is the need to know the values of variables at the control node of interest as well as details on predicate structure.

[1]https://javacc.dev.java.net/

Expression in predicates are assumed side effect free; furthermore, masking effects due to compiler or interpreter optimization have to be dealt with since there is the need to calculate each clause contribution to make the predicate true (or false).

Recently, a novel approach and more complex fitness function [10, 11] inspired by Korel chaining test data generation [4] have been proposed. The new approach aims at avoiding certain types of plateau via data dependencies. Consider again the target at line 17; the variable x in the predicate at line 16 has a data dependency on the assignments at lines 1 and 9 but these data dependencies are not modeled by approach level or branch distance. If the data dependencies are not considered in a code fragment as in Fig 1 the search may sometime behave as a random search. This severe limitation was addressed recently by McMinn et al in [10, 11]. This problem happens when used variables in a decision (i.e., if, while, switch-case or for) have data dependencies on a previous statement that has no control dependency on the current node. In the Calc method of Fig 1: result is set to zero at line 10, which is in the 'then' branch of line 8 'if'. Unfortunately, line 8 does not hold control dependency on line 12 and thus the search degenerates into a random search. Indeed, as pointed out in [10, 11] to avoid this it is sufficient to model and add data dependencies to the fitness function. Thus, this new fitness will include control dependencies, branch distance and data dependencies (e.g., a dependency on node eight). In [11] a detailed algorithm is provided to compute a family of fitness functions. Briefly, the algorithm [11] builds a family of fitness functions considering the data dependencies of used variables at control node i.e., x, y and z. It takes variable last definitions (line one and nine for x) and computes a closure iterating over variables used the definitions e.g., y at line nine.

3.3 Hill Climbing

Hill Climbing (HC) is the simplest, widely used and probably best-known search based algorithm. To generate MC/DC test input data, our HC implementation works as follows. For a given predicate and a given major clause, a set of clauses assignments satisfying MC/DC is randomly selected. HC then starts by choosing a random test case, a test input data, as an initial solution. The quality of the test case is evaluated by the same fitness function used in GA; details of this function are given in the next section. HC attempts to improve the current test case by moving to better points in a neighborhood of the current solution. This iterative process continues until a termination criterion. There are two termination conditions. First, for the given major clause, HC terminates if test input data satisfying the MC/DC clause assignment at hand are found. On the other hand, if after a fixed number of attempts the algorithm is not able to satisfy the MC/DC major clause constraints, the search is stopped and another set of possible MC/DC assignments is selected. If no further set remains a failure is counted.

HC uses a random ascent strategy. A neighbour is generated by modifying one of the solution variables by a step λ drawn from a uniform distribution N $[0, \sigma]$, the variance being a parameter to the algorithm. If the generated neighbour improves the fitness function, the neighbour becomes the new current solution, otherwise a new neighbour is generated with a new step λ.

3.4 Genetic Algorithm

GA starts by creating an initial population of n test cases, n test input data, chosen randomly from the domain D of the program being tested. Each chromosome represents a test case; genes are values of the input variables. In an iterative process, GA tries to improve the population from one generation to another. Test cases in a generation are selected according to their fitness in order to

$z > x$	$z > y$	$z > x + y$
1	1	1
0	1	1

Table 1: MC/DC truth table for major clause $z > x$

Expression	Then Branch	Else Branch
$a == b$	$abs(a - b)$	$a == b?k : 0$
$a \neq b$	$a! = b?0 : k$	$abs(a! = b?a - b : 0)$
$a < b$	$abs(a < b?0 : a - b + k)$	$abs(a < b?a - b + k : 0)$
$a <= b$	$abs(a <= b?0 : a - b)$	$abs(a <= b?a - b : 0)$
$a > b$	$abs(a > b?0 : a - b + k)$	$abs(a > b?a - b + k : 0)$
$a >= b$	$abs(a >= b?0 : a - b)$	$abs(a >= b?a - b : 0)$
$a \Vert b$	$min[fit(a), fit(b)]$	$fit(a) + fit(b)$
$a\&\&b$	$fit(a) + fit(b)$	$min[fit(a), fit(b)]$

Table 2: MC/DC clause based fitness table

perform reproduction, i.e., crossover and/or mutation. Then, a new generation is constituted by the l fittest test cases of the previous generation and the offspring obtained from crossover and mutation. To keep the population size constant, we keep only the n best test cases in each new generation. The iterative process continues until a stopping criterion is met. As in HC we have two stopping criteria. First, for the given major clause, GA terminates if test input data satisfying the MC/DC clause assignment at hand are found. GA is also stopped when an upper limit in computation is reached. In a way similar to HC, all possible assignments for the given predicate and major clause are considered before declaring search failure.

In our experiment, crossover is chosen to be the whole arithmetic crossover , as it is more suitable for real valued solutions [5]. Offspring, test cases, are generated via an affine transformation of parents' genetic material. The arithmetic crossover exploits the idea of creating children "between" parents. The acting formula is: z = α x + (1- α) y; where x and y are the parents, z is the offspring , and $0 < \alpha < 1$ randomly picked for each input value in the test case.

Then, the mutation is performed on each individual in the new population following a mutation probability. The uniform mutation used consists of modifying one of the input values in the test case by drawing a random number with a uniform distribution between the two boundaries of the input space [5].

4. MC/DC TEST INPUT GENERATION

MC/DC test input data generation requires gathering information similar to branch coverage; however, the goal is substantially different thus the branch coverage fitness function and Bottaci equations [3] have to be adapted and extended. Briefly, there is the need of finer grain details since specific Boolean assignments for major and minor clauses are seek. We need to refine the traditional branch coverage additive fitness function (i.e., the one accounting for the approach level and branch distance) so that it guides the search toward test cases that satisfy specific values (true and false) of major and minor clauses.

The main difference is in the way in which branch distance is computed. For MC/DC we need to know the Boolean value of each clause since the value of the predicate is no longer sufficient to guide the search as in branch distance coverage.

4.1 Extending branch distance computation

Suppose our goal is to generate test cases to satisfy MC/DC for line 16 of Fig. 1; further suppose that selected major clause is the first clause $z > x$. This means we need to generate $Calc$ input values to satisfy the truth Table 1. Numbers 0 and 1 are used to represent false and true; they are interpreted as real values simplifying fitness evaluation i.e., distance from the sought value assignments. Clearly, the first line in Table 1 and the test case leading to those Boolean values will be common to the other two major clauses i.e., $z > y$ and $z > x + y$ respectively. If two different test cases reach line 16, we need to decide which is the most promising one to either obtain (1, 1, 1) or (0, 1, 1). Suppose that actually both test cases lead to (0, 1 , 0), then they are relatively closer to (0, 1, 1) and we need to quantify how far they are to make true $z > x + y$.

Let $errno$ be a global variable

```
$void\ exit(int\ b)$ {
    ...
    if ($b > 0$)
        $r_1 = true$
    else
        $r_1 = false$
    if ($r_1$)
        $error_1 = 1$
    if ($errno$)
        $error_2 = 1$
    if ($error_1 \&\& error_2$)
        target
    ...
```

Figure 2: Example of multiple flags

In general, there is the need to quantify how close a test case is to make a clause true or false and thus to drive the control flow into the then or the else branch. To this aim we propose to explicitly represent the else branch fitness function as shown in Table 2 thus extending [3]. In Table 2, k is a small positive number used to show the inequality of a and b and $fit(a)$ is shorthand for the fitness value of clause a.

Going back to line 16 predicate $z > x \&\& z > y \&\& z > x + y$, assuming the current test input data gives clause values (0, 1 , 0) and further assuming we seek (0, 1, 1) then the first and second clauses do not contribute to line 16 fitness (they are both zero). Fitness value is thus only the result of clause $z > x + y$ and it evaluates to $abs(z > x + y?0 : z - y - x + k)$. Table 3 reports the fitness function components for $Calc$ line 16.

4.2 Adding data dependencies

In certain types of programs, control dependencies and branch distance, can lead to a random search due to data dependencies and the lack of real guidance.

In the program of Fig 1 the line 16 is controlled by the 'if' at line 13 ($z == 0$) and 12 ($result == 0$). If the process starts generating test data to reach line 16 relying only on control dependencies and branch distance, it will have absolutely no guidance on how to generate (x,y,z) to make the variable $result$ equal to zero. This fact is at the basis of the Korel chaining approach [4] and the McMinn extension [10, 11]. In [10, 11] terminology, line 12 is called a problem node; in a similar way we call $result$ a problem variable since the lacking of knowledge on $result$ can cause the search to behave as a random search.

To avoid random search [10, 11], we suggest to include $result$ data dependencies in the fitness evaluation. However, $result$ definition at $Calc$ line 10 is controlled by the 'if' at line 8; much in the same way, $Fail$ definitions (lines 5 and line 7) are controlled by the 'if' at line 4. Dependencies determination presented in [11]

Expression	true	false
$fit(z > x)$	$abs(z > x?0 : z - x + k)$	$abs(z > x?z - x + k : 0)$
$fit(z > y)$	$abs(z > y?0 : z - y + k)$	$abs(z > y?z - y + k : 0)$
$fit(z > x + y)$	$abs(z > x + y?0 : z - x - y + k)$	$abs(z > x + y?z - x - y + k : 0)$
$fit(line_{16})$	$fit(z > x) + fit(z > y) + fit(z > x + y)$	$min[fit(z > x), fit(z > y), fit(z > x + y)]$

Table 3: $Calc$ line 16 fitness computation

```
Let pn be the problem node under test
Let $S$ be the set of dependencies
Let $DepSets$ be the set of collected dependencies sets
1     $getDependencies(pn, S)$ {
2         $S = S \cup getControlDep(pn)$
3         $PV = getUsedVariables(pn)$
4         $for\ each\ pv \in PV$ {
5             $lastDefs = getLastDefs(pv)$
6             $for\ each\ ld \in lastDefs$ {
7                 $S(ld) = S \cup getControlDep(ld)$
8                 $newPV = getUsedVariables(ld)$
9                 $for\ each\ cd \in getControlDep(ld)$
10                    $newPV = newPV \cup$
                          $getUsedVariables(ld)$
11                $for\ each\ v \in newPV$
12                    $getDependencies(node(v), S(ld))$
13                if $(empty(newPV))$
14                    $DepSets.add(S(ld))$
15            }
16        }
17        return $DepSets$
18    }
```

Figure 3: Algorithm to calculate the sets of dependencies given a problem statement (1)

focuses on data dependencies and thus control node 8 and 4 are not considered. We believe that explicitly incorporating control nodes such as nodes 8 and 4 into an approach level fitness leads to an easier implementation and improved performance.

Fig. 3 reports our extension of the algorithm [11]. In our approach we aim at collecting controlling nodes either control or data dependencies, nodes directly or indirectly affecting the traversal of the problem node.

The functions $getControlDep$ and $getUsedVariable$ return the set of reverse control dependencies (nodes controlling the current node) and used variables respectively. S and $DepSets$ are initialized as empty sets. $DepSets$ stores the set of dependencies for a given problem node. At algorithm termination these sets of dependencies are merged by algorithm in Fig. 4 to build the sets of dependencies used in defining fitness functions.

There are two main differences with [11]. First, our test data generation code is written in Java and thus we can take advantage of Java multi-threading nature: for each last definition of variables involved in the problem node we store its dependencies (line 14 in Fig. 3); then the algorithm in Fig. 4 merges the sets of dependencies and each merged set leads to a different fitness function run in parallel into its own thread.

More conceptual is the difference in computing dependencies. We perform a closure similar to [11] but we are interested in control dependencies to actually extend the level approach leaving to branch distance the task to guide the search thus we do not need to redefine fitness as in [10, 11].

```
Let $DepFit = \{\phi\}$ be the set of fitnesses dependencies sets
Let $DepSets$ be the set of collected dependencies sets

1     $for\ each\ s_i \in DepSets$ {
2         $DepFit.add(s_i)$
3         $for\ each\ s_j \in DepSets\ and\ s_j \neq s_i$
4             if $(thenElseConflicts(s_i, s_j) == false)${
5                 $S_{i,j} = s_i \cup s_j$
6                 $DepFit.add(S_{i,j})$
              }
      }
```

Figure 4: Algorithm to calculate the sets of dependencies given a problem statement (2)

Again in the $Calc$ method, consider for example line 12 (problem node); $result$ last definition at line 10 causes line 10 control dependence, line 8, to be added to S. At the algorithm termination, both lines 8 and 4 will be in S.

More in detail, consider the pseudo code in Fig. 2. $errno$ is a global variable. The function $getControlDep$ returns the empty set when the method declaration first line (line 0 of Fig. 2) is passed. $getUsedVariables$ called on the same line also returns the empty set.

Suppose that line 10 in Fig. 2 is the target statement; the problem node (line 9) uses flag variables $error_1$ and $error_2$. When called with parameters $9and\ \phi$, the function $getDependencis$ (Fig. 3), first identifies used variables ($error_1$ and $error_2$ - line 3) and then computes for each used variables the last definition set. For example, for $error_1$ last definition is line 6. Last definition is controlled by the 'if' at line 5 and thus line 5 is added to S - line 7 Fig. 3. The if at line 5 uses the variable r_1 that is added to $newPV$ (new problem variables). r_1 has two definitions points either at line 2 (then branch) or line 4 (else branch). $getDependencis$ recursion called over node 5 and $S = \{5\}$ generates a last definition set for r_1 of $\{2, 4\}$. Cycle at line 6 (Fig. 3) iterates over $\{2, 4\}$.

First, line 2 (then branch) is selected (line 6 - Fig. 3) then line 7 adds line 1 to S. Recursion of $getDependencis$ with parameters $1, \{5, 1\}$, will check b last definition leading to line zero, method definition first line. Line zero in our model has no control dependencies and uses no variables. Therefore, both $newPV$ and $getControlDeps(0)$ are the empty sets and set $\{5, 1\}$ is added to $DepSets$, line 14 Fig. 3. Second, line 4 is selected. Line 4 corresponds to the else branch of the if statement at line 1. Notice that in the case of an else branch, $getControlDep$ returns minus the control node number; negative values encode last definitions in the else branch. We encode with positive numbers the control flows going into then branches while negative values stand for else branches. Following the same steps of the algorithm for this last definition of r1, the set $\{5, -1\}$ is added to $DepSets$. Finally, when $getDependencies$ computes $errno$ induced dependencies, the set $\{7\}$ is added to $DepSets$. Overall, the call to the function

$getDependencies(9, \phi)$ generates the sets:

$$\{\{5, 1\}, \{5, -1\}, \{7\}\}.$$

$DepSets$ is the input to the algorithm in Fig 4 that generates the actual new set of dependencies for fitness definition. The function $thenElseConflicts(s_i, s_j)$ returns true if a set contains both the 'then' and the 'else' branch of the same 'if' statement. Therefore when the algorithm is executed over the set $\{\{5, 1\}, \{5, -1\}, \{7\}\}$ it generates the set of dependencies:

$$\{\phi, \{5, 1\}, \{5, -1\}, \{7\}, \{5, 1, 7\}, \{5, -1, 7\}\}.$$

Overall, six fitness functions one for each set in $DepFit$ are defined and for Fig 2 six threads will be started probing various combination of control flow to cover line 9 MC/DC. For example, the set $\{5, -1, 7\}$ is interpreted as: we need to enter 'else' branch of line 1 'if', and we must go into the 'then' branch of line 5 'if' and line 7 'if'. Each of these control nodes in turn will have associated a branch distance computation as in Table 2.

5. EXPERIMENTAL RESULTS

In this section, we report results from a preliminary experimental study carried out to evaluate the performance of our approach for MC/DC automatic test input data generation. We compare GA to two other searching strategies: random search (RND) and HC. In the next subsections, we briefly describe two Java programs used as a testbed, details about the algorithmic settings, and finally, we present results and their interpretation.

5.1 Experimental Design

Two programs serve as testbeds in our experiment. The first one is a triangle classification program (Triangle); triangle classification is a well-known problem used as a benchmark in many testing works. This program takes three real inputs representing the lengths of triangle sides and decides whether the triangle is irregular, scalene, isosceles or equilateral. The second program, NextDate, takes a date as three integers, validates it and determines the date of the next day. The two programs are written in Java. They count respectively 81 and 88 lines of code.

5.2 Algorithmic Settings

The sole common parameter between RND, HC and GA is the termination criterion $MaxNbrEvaluation$. For the Triangle program and based on several runs, it was observed that 5,000 fitness evaluations per clauses assignements are usually sufficient to decide if the MC/DC coverage are obtainable given the predicate and the algorithm initialization (single point for HC, initial population for GA). Thus $MaxNbrEvaluation$ was set to $5,000$. For the NextDate program, the fitness evaluations number was observed to influence the MC/DC coverage and thus was set as a parameter to the algorithm. Other algorithmic settings pertain only to GA. For GA the elitist strategy is used; in each iteration, the entire population is replaced, except for the fittest individual (i.e., test cases). The number of test cases in a generation is 100. The values of p_c (crossover probability) and p_m (mutation probability) are set to 0.70 and 0.05 respectively based on several trial and error. Typically, p_m is small, in order to lower the effect of randomness on the search. Finally, we set an overall maximum number of GA generation of 400; this is to say that either the computation is halted after 5,000 fitness evaluations or after 400 generations.

For each program, a search space is defined based on the program's parameters acceptable range. For the Triangle program, the parameters are inetgers representing the triangle sides. To evaluate the influence of the largness of the search space on the algorithm's performace, we tested the MC/DC coverage atteined of each algorithm for different bounderies of the parameters values, and thus for different input domain space. For the NextDate program, the parameters are a day, a month and a year and thus the search space is fixed by the allowed values for these parameters.

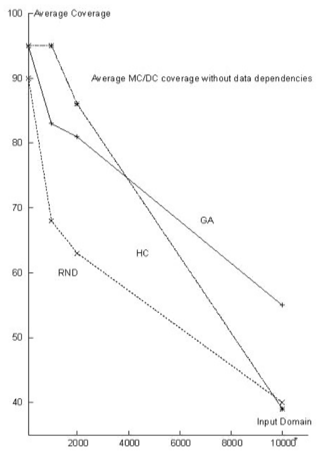

Figure 5: Triangle GA, HC and RND MC/DC coverage at various size of the input domain (10000^* stands for the 32 bits integer input)

For each of the two exemplary programs, each algorithm computation was repeated 30 times with and without integrating data dependencies into the fitness function for GA and HC.

5.3 Results with no data dependencies

Fig. 5 reports the performance of RND, HC and GA for various dimension of the search space. Triangle takes three integers and decides the kind of corresponding triangle. As it can be expected the larger the input parameter domains the lower the attained average MC/DC coverage. When the parameters range between plus or minus 100 even a simple random search attains an average of 90 %, average, MC/DC coverage. The reason is that the number of fitness evaluation is high (i.e., 5,000) and the entire search space is explored. However, as the dimension of the search space increases up to the integer range, the coverage for the three searching strategies decreases. For example, GA drops to 55 %.

The reason for such a performance degradation is in the equilateral and isosceles triangle types. First, equilaterals and isosceles triangles imposes hard constraint and, sampling out of the entire integer space, the probability to obtain the same number repeated two or three time is very low. A second reason is related to the structure of control and data dependencies of the Triangle program. The code is similar (in the dependencies structure) to the code in Fig. 1. If the process starts generating test data to reach line 16 relying only on the control dependencies and branch distance, it will have absolutely no guidance on how to generate (x,y,z) to make the variable $result$ equal to zero. In Triangle, as shown in the Triangle code excerpt of Fig. 6, we have the same situation. The decision

```
input parameters: side1, side2 and side3
41  if (side1 == side2)
42          triang = triang + 1
44  if (side2 == side3)
45          triang = triang + 2
47  if (side1 == side3)
48          triang = triang + 3
            ...
50          if (triang == 0) {
            ...
56          }else{
57                  if (triang > 3) {
                    ...
                    } else {
60                  if (triang == 1 && side1 + side2 > side3) {
61                          return ISOSCELES;
```

Figure 6: Fragment of the Triangle program

at line 57 has a reverse control dependency from the 'if' at line 50, and both have data dependencies on lines 42, 45 and 48. These lines in turn are controlled by the 'if' at lines 41, 44 and 47 respectively. In other words, a fitness based on approach level and branch distance has no guidance to reach the line 57 and thus the three 'if' controlled by line 57, for example, the if at line 60. Thus the code section deciding if the triangle is equilateral or isosceles is extremely difficult to reach if the search space is large and not entirely explored by the search algorithm. Indeed, these three 'if' are not reached by RND, HC or GA within 5,000 fitness generation searching into the 32 bits integer range. This is the reason why in Fig. 5 we observe the drop in MC/DC coverage.

Fig. 5 also provides evidence that HC neighborhood definition needs to be improved to cope with large search spaces. HC is a local search method and for Triangle we resorted on a randomized Gaussian number extraction. We first randomly select one of the three parameters; this parameter is incremented and decremented and if no improvement is found then a Gaussian number is extracted from a Gaussian distribution with zero mean and 300 as standard deviation. The process is repeated of to the fitness computation limit. However, this heuristic may not be the best when the search space is large.

The importance of data dependencies is also supported by the NextDate results reported in Fig. 7. NextDate doesn't have interaction between data dependencies and control dependencies as the Triangle program. In fact, it has no data dependencies between the decisions of the program, thus very good results are obtained. Also, it is observed that the higher the maximum number of fitness evaluations, the higher the MC/DC coverage.

5.4 Results with data dependencies

Fig. 8 summarizes the results obtained for the Triangle program with the new fitness function including data dependencies. GA largely outperforms HC, which is likely due to the neighborhood definition that is not able to escape local sub-optimal solutions. Overall, data dependencies have a lower impact on HC attained coverage.

GA with integrated data dependencies performs substantially better than approach level and branch distance alone, see Fig. 8. In particular, the new fitness outperforms the old one in the code region controlled by the lines 56 ('if' at line 50) and 57 of Fig. 6.

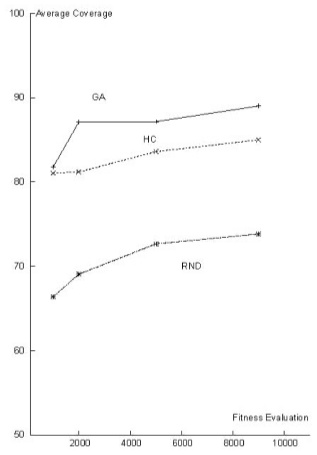

Figure 7: NextDate GA, HC and RND MC/DC coverage for various fitness evaluation limits

Code Line Nb.	Mean. Cov.	Std. Dev	Old. Mean. Cov.
50	60.34	20.61	50
51	100	0	100
57	86.21	22.74	0
60	57.69	15.08	0
63	56.32	15.7	0
66	55.71	16.31	0

Table 4: Triangle modified fitness MC/DC coverage for critical if statements (search space the 32 bits integer range)

Table 4 reports the details of average MC/DC coverage for predicates in critical nodes, the 'if' statements in Triangle at lines 50, 51, 57, 60, 63 and 66. It is worth noticing that the old fitness function has zero coverage for these statements. These statements are also the statements lowering HC performance. Overall, on Triangle and the entire 32 bits range, the new fitness with GA attains an 81 % MC/DC coverage substantially increasing the coverage obtained with the old fitness function relying solely on approach level and branch distance.

6. CONCLUSION

Testing is a widely adopted quality assurance practice; in regulated domains such as in aerospace or in safety critical applications testing activity must comply with standard and regulations. In this paper, we have presented a new approach and a novel fitness function to generate test input data for the MC/DC coverage criterion. MC/DC is a mandatory testing practice for the aerospace industry according to DO-178B.

We adapted the branch coverage fitness function to deal with predicate clauses extending Bottaci rules for branch distance computation. Furthermore, to avoid being trapped by certain types of plateau caused by problematic nodes we also extended McMinn

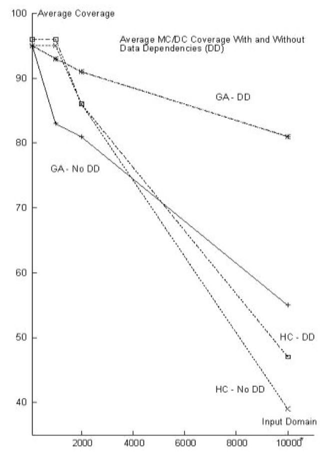

Figure 8: Triangle GA, HC with and without data dependencies MC/DC coverage at various size of the input domain (10000* **stands fro the 32 bits integer input)**

hybrid approach inspired by Korel chaining dependencies computation.

Preliminary data obtained on two Java programs used as a testbed, Triangle and NextDate, show that the GA with our novel fitness function integrating data dependencies, control dependencies and branch distance outperforms random data generation, hill climbing, and GA without the dependencies on large search spaces i.e., when the Triangle input parameters are selected over the entire integer range. In particular our novel fitness implementation substantially improves MC/DC coverage on the Triangle program (from 55 % to 81 %).

Future work will be devoted to better define a neighborhood for hill climbing as the current implementation seems not well suited to take advantage of the data dependencies integration into the fitness function when the Triangle input parameters are selected over the integer range.

7. ACKNOWLEDGMENTS

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