A framework for estimating the applicability of GAs for real-world optimization problems

Hsin-yi Jiang
Iowa State University

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A framework for estimating the applicability of GAs for real-world optimization problems

by

Hsin-yi Jiang

A dissertation submitted to the graduate faculty
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Program of Study Committee:
Carl K. Chang, Co-major Professor
Andrew S. Miner, Co-major Professor
Samik Basu
Daniel Tauritz
Johnny S. Wong
Dan Zhu

Iowa State University
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I would like to dedicate this thesis to my grand parents, parents, and uncle Ming. Without their support, I would not have been able to complete this work. I would also like to thank my friends for their kind help during the writing of this work.
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Genetic Algorithms (GAs) have been gradually identified as an optimization-problem solver for certain classes of real-world applications. As GAs are increasingly utilized, a foundational study on how well GAs can perform with respect to varying problem domains becomes crucial. Yet, none of the prevalent theoretical studies are built upon the linkage between the theory and application of GAs. This dissertation introduces a methodology for estimating the applicability of a GA configuration for an arbitrary optimization problem based on run-time data. More specifically, this work analyzes the convergence behavior within a finite number of generations for each GA run through the estimation of the trace of the transition matrix of the corresponding Markov chain from run-time data. The analytical and empirical results show that the methodology is helpful for evaluating the applicability of GAs to optimization problems. Through the methodology, the number of generations needed for empirical convergence with respect to a fitness function (or a problem) can be estimated. The proposed methodology entails an evaluation metric and connects theory to application of GAs, for estimating the applicability of a GA to a problem. The methodology is demonstrated through a case study on evolutionary testing.
CHAPTER 1. INTRODUCTION

1.1 Overview of this Work

This dissertation develops a framework for estimating the applicability of a particular Genetic Algorithm (GA) configuration for an arbitrary optimization problem based on runtime data. GAs are increasingly employed to solve complex real-world optimization problems featuring ill-behaved search spaces (e.g., non-continuous, non-convex, non-differentiable) for which traditional algorithms fail. The quality of the optimal solution (i.e., the fitness value of the global optimum) is typically unknown in a real-world problem, making it hard to assess the absolute performance of an algorithm that is being applied to that problem. In other words, with a solution provided by a GA run, a method or theory to measure the quality of the solution is generally lacking. Although many researchers applying GAs have provided experimental results showing their successful applications, those are merely averaged-out, ad hoc results. They cannot represent nor guarantee the usability of the best solutions obtained from a single GA run, since the solutions can be very different for each run. Therefore, it is desirable to provide a formalized measurement to estimate the applicability of GAs to real-world problems.

1.2 Problem Statement and Motivation of this Work

In many real-world optimization problem domains, researchers have gradually found that GAs possess the properties suitable for certain classes of applications. Many researchers have reported success in applying GAs to real-world problems, but have failed to provide a theoretical foundation to explore or explain why GAs were appropriate for the specific problems. As GAs are increasingly utilized, a foundational study on how well GAs can perform for each of
the various problem domains becomes crucial. Note that many theoretical studies have investigated the behaviors of GAs using Markov chains [Eiben, A. E. and Aarts, E. H. L. and Hee, K. M. V. (1991); Nix, A. E. and Vose, M. D. (1992); Ding, L. and Yu, J. (2005); Jiang, H. and Chang, C. K. and Zhu, D. and Cheng, S. (2007); Fogel, D. B. (1995); Rudolph, G. (1994); Suzuki, J. (1995, 1998); Vose, M. D. and Liepins, G. E. (1991); Rudolph, G. (1996); Davis, T. E. and Principe, J. C. (1993)]. Yet, no existing theoretical studies are built upon the linkage between the theory and application of GAs. Through existing analyses, the convergence of a canonical form of Genetic Algorithm termed CGA with best solutions maintained has been proven [Rudolph, G. (1994)], the expected value of the first hitting time of GAs has been calculated [Ding, L. and Yu, J. (2005)], and the convergence rate of GAs has been predicted by the second largest eigenvalue of the transition matrix [Suzuki, J. (1995); Jiang, H. and Chang, C. K. and Zhu, D. and Cheng, S. (2007)]. Other methods, such as the analysis on Walsh transformation [Bethke, A. D. (1980); Forrest, S. and Mitchell, M. (1993)] or Fourier transformation of fitness functions of GAs [Kosters, W. A. and Kok, J. N. and Leiden, P. F. (1999)], have also been adopted by some researchers. Although many papers have proposed various approaches to analyzing the behaviors of GAs, most existing GA theories lack concern for practicality [Schoenauer, M. et al. (2007); Jiang, H. and Chang, C. K. (2008); Jiang, H. and Chang, C. K. and Zhu, D. and Cheng, S. (2007)]. For instance, the convergence of GAs studied by Rudolph is only meant as a theoretical study, since time is assumed to go to infinity [Rudolph, G. (1994)]. In reality, it is impossible for any application to wait for an infinite amount of time to obtain the optimal solution. Moreover, the computation time for deriving transition matrices of GAs with respect to real-world problems is much larger than calculating fitness values of the entire search space (i.e., the state space). It is not practical because researchers will not waste more time to obtain weaker solutions. In general, “theoretical studies of GAs are criticized for rarely being applicable to the real-world [Schoenauer, M. et al. (2007)],” and applications of GAs to real-world problems are frequently studied without foundational support [Jiang, H. and Chang, C. K. (2008); Jiang, H. and Chang, C. K. and Zhu, D. and Cheng, S. (2007)]. In application domains of GAs, a more practical and
functionally equivalent approach to evaluate the applicability of GAs is desired in view of the current state of the art.

1.3 The Goal of this Work

This work aims to develop a practical support for researchers and practitioners to evaluate the applicability of GAs to their problem domains. We have proven that the convergence rate of Markov transition matrices with respect to encodings of optimization problems is related to the second largest eigenvalue of the transition matrices in absolute value with its physical meaning explained. The second largest eigenvalue can bound the expected value of the first hitting time of the optimal solutions corresponding to those optimization problems [Ding, L. and Yu, J. (2005); Jiang, H. and Chang, C. K. and Zhu, D. and Cheng, S. (2007)]; however, the computation time of constructing the transition matrix with respect to an optimization problem takes more than the computation time of calculating all the feasible solutions [Jiang, H. and Chang, C. K. (2008)]. Relying on the second largest eigenvalue of the transition matrix with respect to a problem to acquire convergence degrees of GAs is impractical due to the long computation time. With a concern for practicality, we propose a novel method, an important approach for real-world applications, to derive the applicability of a GA to a problem based on the approximate sum of eigenvalues. Mathematically, the sum of eigenvalues of a matrix is equal to the sum of the diagonal elements (which is called “trace”) of the matrix. According to that property, our methodology is developed to estimate the trace of the corresponding transition matrix. Through this method, a degree of convergence can be determined for each GA run. Being aware of the degree of convergence, researchers and practitioners will be able to obtain certain information about the applicability of GAs and know how good the solutions generated by GAs are, so that correct decisions can be made. Moreover, a possible approach for estimating the number of generations needed for global convergence is also proposed. The general methodology is illustrated in Figure 1.1. In summary, this dissertation makes the following contributions to theory and application of GAs:

- a problem statement for the current state of the art;
Figure 1.1 General Methodology for Estimating the Applicability of GA $G$ for Optimization Problem $P$

- a novel and possible approach to build a linkage between theory and application of GAs;
- the verification of the proposed approach.

The rest of this dissertation is organized as follows. Chapter 2 provides the literature review of this work. Chapter 3 reviews the basic operators of GAs, Markov chains, and how to model the operators of GAs using Markov chains. Research assumptions and definitions are also presented in this chapter. Chapter 4 proves that the convergence rate of a CGA (see Section 3.3.3.2) with best solution maintained over time depends on the second largest eigenvalue of the corresponding transition matrix, and explains the relationship between the second largest eigenvalue of the transition matrix, and the first hitting time (i.e., expected waiting time) of the optimal solution of a GA. Chapter 5 explores an evaluation matrix to evaluate the applicability of GAs to real world optimization problems. In Chapter 6, a case study about an evolutionary algorithm (EA) used in software testing (also called evolutionary testing) is provided. Chapter
7 proposes a possible approach for estimating the number of generations needed for the global convergence. Chapter 8 proves that the proposed metric can be generalized to support certain classes of EAs. Chapter 9 concludes the dissertation and outlines future research work.
CHAPTER 2. REVIEW OF LITERATURE

2.1 Real-World Optimization Problems

Generally, if a problem has more than one feasible solution, the problem can be considered as an optimization problem. Theoretically, the optimization problem is defined as the problem which can be solved by more than one feasible solution and has at least one criterion to evaluate solutions, with the goal being the search for the best solution within the domain of all the feasible solutions.

In the real-world, there are many optimization problems in which GAs are applicable. Among many fields of study, such as combinatorial optimization problem domains, machine learning, information retrieval, and data mining, project management and software engineering are two heavily studied fields that provide ample opportunities to apply GAs for performance improvement.

I have research interests in both Project Management (PM) and Software Engineering (SE). Some problems in those two domains are listed below.

2.1.1 Problem Domain 1 - Project Management Problems

In PM, optimal scheduling is one of the typical optimization problems [Chang, C. K. and Christensen, M. J. (1999); Chang, C. K. and Christensen, M. J. and Zhang, T. (2001); Chao, C. (1995); Ge, Y. (2004)]. One branch in PM research explores ways to intelligently match employees to tasks with respect to the factors gathered during early project development. Typical factors include salaries of employees (costs), capabilities of employees, learning curves of employees, and potential hazard levels of assignments [Xu, R. and Qian, L. and Jing, X. (2003)]. Researchers may expand or narrow this list of factors depending upon their research
goals.

2.1.2 Problem Domain 2 - Software Engineering Problems

Software Testing Problems - In SE, the traditional waterfall model regards testing as a key component of verification and validation (V&V) activities [Pressman, R. S. (2005)]. Verification is to inspect whether specific functions are built correctly in the software, and validation is to examine whether the software meets customer requirements. To conduct testing on a piece of software, various strategies have been proposed. Some strategies are formulated as optimization problems [Berndt, D. and Fisher, J. and Johnson, L. and Pinglikar, J. and Watkins, A. (2003); Berndt, D. J. and Watkins, A. (2004); Briand, L. C. and Labiche, Y. and Shousha, M. (2004, 2005); Clark, J. and Dolado, J. J. and Harman, M. and Hierons, R. M. and Jones, B. and Lumkin, M. and Mitchell, B. and Mancoridis, S. and Rees, K. and Roper, M. and Shepperd, M. (2003); Vieira, F. E. and Menezes, R. and Braga, M. (2006)]. For instance, with regard to branch testing in a structural testing problem [Clark, J. and Dolado, J. J. and Harman, M. and Hierons, R. M. and Jones, B. and Lumkin, M. and Mitchell, B. and Mancoridis, S. and Rees, K. and Roper, M. and Shepperd, M. (2003)], the condition statements of the test-aim branch are formulated into a fitness function, which guides the search of input data to satisfy all the conditions of the test-aim branch. That is, researchers measure the “distance” between the test-aim branch and the branch caused by a set of input data. GAs minimize the distance so that the input data (called test cases) of a test aim can be generated.

Software Module Clustering Problems - Owing to the rapid development of computer technologies, industrial applications are increasingly equipped with highly complex software systems, which often consist of a large number of components. To streamline the design phase, a large-scale system can be designed hierarchically. Instead of directly integrating all of the components into a system, a set of congruent components are first grouped into a subsystem. How to cluster the original set of components into several subsystems has attracted the attention of researchers for many years [Chang, C. K. and Cleland-Haung, J. and Hua, S.
and Kuntzmann-Combelles, A. (2001)]. Oftentimes, they try to maximize cohesion inside a component and minimize coupling among components. This kind of problem also represents a class of optimization problems in SE [Mitchell, B. S. and Mancoridis, S. (2002)].

2.2 Analyzing the Behaviors of GAs

2.2.1 Markov Chain Based Approaches

A variety of methods have been employed to analyze the behaviors of GAs [Rudolph, G. (1994); DeJong, K. A. and Spears, W. M. and Gordon, D. F. (1995); Suzuki, J. (1995); He, J. and Kang, L. (1999); He, J. and Yao, X. (2001); Ding, L. and Yu, J. (2005); Coley, D. A. (1999); Mitchell, M. (1996); Goldberg, D. E. (1989); Grefenstette, J. J. (1992); Bethke, A. D. (1980); Forrest, S. and Mitchell, M. (1993); Bridges, C. L. and Goldberg, D. E. (1991); Naudts, B. and Kallel, L. (2000)]. Among them, different approaches are derived and asserted. While each method has its own merits, Markov chain analysis can be most successfully applied to capture the essential spirit of GAs due to the following reasons:

- The initial population of a GA run is based on a probability distribution. Usually, it is a uniform distribution.
- From one generation to another, the GA selects the individuals based on the proportions of the fitness values of the individuals in the current population. In other words, the selection operator selects the individuals from (and only from) the current state where each individual has some probability of being preserved in the next generation. Note that the fitness function of the GA run is considered in the selection operation.
- Regardless of the type of recombination employed to solve the optimization problem, the recombination and mutation operators are both related to probability issues.

and Yao, X. (2001), and Ding [Ding, L. and Yu, J. (2005)], including their methodologies and results, are particularly relevant to my approach.

Rudolph’s main contribution on the behavior of GAs is to prove that the CGA with best solution maintained converges to its global optimal solution [Rudolph, G. (1994)]. Additionally, he mentions that in an ergodic Markov chain, the expected value of the transient time in which an arbitrary state $i$ goes to any other state $j$ is finite. This claim is a well established result in Markov chain theory. The detailed proof can be seen in [Iosifescu, M. (1980) (p. 133)]. This implies that the expected value of the transient time in which the initial state moves to the optimal state is finite, since both the initial state and the optimal state are the states in Markov chain.

Later, De Jong et al. proposed a method to capture the “hardness” of a GA (i.e., the level of difficulty to apply it) by computing the expected waiting time (i.e., the first hitting time) through the use of transition matrices [DeJong, K. A. and Spears, W. M. and Gordon, D. F. (1995)]. To my knowledge, this was the first attempt to use the first hitting time to predict the applicability of GAs. In 2005, the expected first hitting time of the optimal state was investigated and calculated again by Ding et al. [Ding, L. and Yu, J. (2005)]. They proposed an approach to reformulate the transition matrices so that the formula to derive the expected value of the first hitting time became simpler than before. Besides the computation of the expected waiting time, De Jong et al. introduced the concept of predicting the behaviors of GAs within a fixed number of generations based on the derived transition matrices [DeJong, K. A. and Spears, W. M. and Gordon, D. F. (1995)]. This concept provides an insight for the waiting time in practical use, which is similar to Assumption 3 in Chapter 3 of this dissertation.

In Suzuki’s work, the investigation of behaviors of GAs was first linked to the second largest eigenvalue of the transition matrix and convergence rates of Markov chains [Suzuki, J. (1995)]. My preliminary result, which is presented in Chapter 4 and derived from a different approach in Markov chain theory, matches this assertion in some sense. In addition to the eigenvalue-based approach, He and Kang proposed another perspective to bound the convergence rate through the “minorization condition” in Markov chain theory [He, J. and Kang, L. (1999)].
He and Yao devoted their work to calculating the computational time complexity of evolutionary algorithms (EAs) [He, J. and Yao, X. (2001)]. Their work generalized Droste’s work, which provided a rigorous complexity analysis of the (1 + 1) EA (i.e., EA with a population size of 1 and only with mutations), for a class of fitness functions [Droste, S. and Jansen, T. and Wegener, I. (1998)]. With He and Yao’s approach, Droste’s work was extended to general EAs through drift analysis. Several drift conditions were studied for deriving the computational time. Their work began with modeling the evolution of an EA population as a random sequence, e.g., a Markov chain. The general case was considered with three operators (selection, crossover, mutation) and a population with multiple individuals. Then, they analyzed the relationship between the drift of the sequence and the optimal solution of the problem. Various bounds on the first hitting time were derived under different drift conditions. They also asserted that some drift conditions caused the random sequence to drift away from the optimal solution, while others enabled the sequence to drift towards the optimal solution. The conditions used to determine the time complexity of an EA to solve a problem were also investigated and proposed [He, J. and Yao, X. (2001)].

2.2.2 Other Approaches

Starting from the early 1970s, a series of approaches different from Markov chain analysis were proposed to analyze the behaviors of GAs. In 1975, Holland introduced the notion of schemas to formalize the informal notion of “building blocks” [Coley, D. A. (1999) Mitchell, M. (1996)]. His building block hypothesis stated that GAs attempt to find highly fit solutions to a problem through short, low-order, and above-average schemata. However, the schema theory merely demonstrated a rough idea in high level that better performing schemata will receive an increasing number of trials in the next generation. It does not give us much information about the detailed analysis of the behaviors of GAs. In 1987, the term “deception problem” was coined by Goldberg, who said that a problem is deceptive if certain hyperplanes guide the search toward some solutions or genetic building blocks that are not globally competitive [Goldberg, D. E. (1989)]. Comparing Goldberg’s statement with Holland’s building block hypothesis,
the deception problem appears to suggest a contradiction. Hence, deception problems are considered “hard” problems for GAs. Nevertheless, the deception is neither a sufficient nor necessary condition to characterize problems that are hard for GAs [Grefenstette, J. J. (1992)].

Goldberg isolated the deception problems from Bethke’s work [Bethke, A. D. (1980); Forrest, S. and Mitchell, M. (1993)]. Bethke used discrete Walsh functions to analyze the fitness functions of GAs. He developed the Walsh-Schema transform to calculate the average fitness of schema efficiently and used it to characterize functions as easy or hard for GAs to optimize. This method helps to produce ideas for solving a problem; however, it can be difficult to convert functions to Walsh polynomials. This method, a static analysis, examines only a flat population, where every possible string is assumed to be represented in equal proportion [Bridges, C. L. and Goldberg, D. E. (1991)]. Bethke’s method fails to capture the more dynamic aspects found in GAs. To address this issue, Bridges and Goldberg proposed another approach called the Nonuniform Walsh Transform [Bridges, C. L. and Goldberg, D. E. (1991)]. Unfortunately, as in the case of Walsh transformations, it is difficult to convert fitness functions into such forms.

In 2000, Naudts and Kallel studied two widely-known predictive measures of problem difficulty in GAs (with both the GA-easy and GA-hard functions): epistasis variance and fitness distance correlation [Naudts, B. and Kallel, L. (2000)]. They found that the values of the measures can be completely unreliable and entirely uncorrelated to the convergence quality and speed of GAs.

In general, the GA theory developed thus far shows that it is difficult to fully capture the behaviors of GAs, especially in finite time with different types of fitness functions. The missing link is the bridge between the theory and its applicability to practical problems [Jiang, H. and Chang, C. K. (2008)]. This observation coincides well with the recent claims stated in the front pages of the journal [Schoenauer, M. et al. (2007)] concerning the difficulty in directly linking GA theory to real-world applications. In this study, the objective is to develop the necessary support theory to effectively bridge the gap between evolutionary computation and real-world applications.
CHAPTER 3. BACKGROUND OF GENETIC ALGORITHMS

This chapter reviews and presents the background information for GAs, Markov chains, how to model GAs using Markov chains, existing theorems, and research assumptions of my work.

3.1 Optimization Problems and Fitness Functions of GAs

As mentioned before, an optimization problem is defined as the problem which can be solved by more than one feasible solution, has at least one criterion to evaluate solutions, with the goal of the problem being the search for the best solution within the domain of all the feasible solutions. The (feasible) solutions of GAs are encoded into strings, usually called chromosomes or individuals. With a GA being chosen as the optimization method, the criteria to evaluate solutions are formulated as a fitness function for the GA.

3.2 The Canonical Genetic Algorithm and Its Operators

The CGA (also called a simple GA) can be sketched as follows [Rudolph, G. (1994)].

Choose an initial population (i.e., a list of a fixed number of individuals)
Compute the fitness of each individual
Perform selection
Repeat
Perform crossover
Perform mutation
Compute the fitness of each individual
Perform selection
Until stopping criterion is satisfied

In other words, it is composed of three operators:

- Selection (also called Reproduction)
- Crossover
- Mutation

Selection is a process in which individuals are copied according to their fitness values. Usually, the individuals with higher fitness values have higher probabilities to be selected into the next generation. Therefore, a typical fitness function for a selection operator should be the function to be maximized. This operator is actually an artificial version of natural selection, the Darwinian theory of “survival of the fittest” [Goldberg, D. E. (1989)]. Various selection methods, such as roulette wheel selection (proportional selection), tournament selection, and \((\mu, \lambda)\) selection, etc., are proposed. Among them, roulette wheel selection is commonly adopted in the literature. It selects individuals based on their proportions of the fitness values among the individuals in the current population (generation). For demonstration purposes, this dissertation mainly discusses roulette wheel selection. In Chapter 8, the selection operator is generalized to any type of selection methods.

Crossover, including one point crossover, two point crossover, and uniform crossover, etc., mimics the mating of creatures. It swaps some bits of two chosen individuals. The resulting individuals are passed into the next generation.

The mutation operator simulates biological mutation, maintaining genetic diversity from one generation to another. A simple and common way to implement it is to sweep each individual bit of strings within a population once, and each bit has a fixed probability to be flipped to another number.

3.3 An Overview of Markov Chain

Markov chains are named after Prof. Andrei A. Markov (1856-1922) who first published his result in 1906 [Ching, W. K. and Ng, M. K. (2006)]. His research work on Markov
chains launched the study of stochastic processes, which was followed by a large variety of applications. In this work, the discrete homogeneous finite state Markov chain is applied. Specifically, a Markov chain is a sequence of random variables $X_1, X_2, X_3, \ldots$ with the Markov property [Iosifescu, M. (1980)]. The Markov property is the property that:

$$Pr(X_{n+1} = x|X_n = x_n, \ldots, X_1 = x_1) = Pr(X_{n+1} = x|X_n = x_n), \forall n \in N. \quad (3.1)$$

The future state is only dependent on the current state and independent of the past states.

A Markov chain is called *time-homogeneous* if:

$$Pr(X_{n+1} = x|X_n = y) = Pr(X_n = x|X_{n-1} = y), \forall n \in N. \quad (3.2)$$

To form a Markov chain, three basic components should be considered: a state space, an initial distribution, and a transition matrix.

Consider a *random walker* in a small town. Within the town, there are a finite number of places to go. Suppose that at time $t, t \in N$, the random walker stands in a place in the town. At time $t+1$, he walks to any place in the town with a certain probability, dependent only upon the place he was in at time $t$ (i.e., time is a non-factor). If each place in the town is assigned a distinct number (as an index), say, $1, 2, \ldots, k \ (k \in N)$, and at each time $t$, $X_t$ is a random variable denoting the index of the random walker’s location, $(X_0, X_1, \ldots)$ is a random process taking values in $\{1, 2, \ldots, k\}$. Such a random process can be treated as a discrete homogeneous finite state Markov chain. Figure 3.1 illustrates the transition matrix of a Markov chain for the random walker in the small town. In Figure 3.1, places are considered as states of the Markov chain. If the current time is $t$, ‘*‘ represents the probability of transitioning from state $i$ to state $j \ (i, j \in \{1, \ldots, k\})$ at time $t + 1$.

### 3.3.1 Definitions and Theorems in GA, Markov Chain Theory, and Linear Algebra

**Definition 1.** A nonnegative square matrix $A$ is said to be stochastic if and only if the sum of the entries in any row of $A$ is 1.
Figure 3.1  The Transition Matrix of the Random Walker in the Small Town

**Definition 2.** A square matrix $A_{r \times r}$ is called positive (i.e., $A > 0$) if and only if $a_{ij} > 0$ \( \forall i, j \in \{1, 2, \ldots, r\} \).

**Definition 3.** A stochastic matrix $A$ is said to be regular if and only if there exists a natural number $r$ such that $A^r$ is positive (i.e., $A^r > 0$).

Note that the product of stochastic matrices is a stochastic matrix.

**Definition 4.** A state in a Markov transition matrix is called transient if there is a non-zero probability that once the chain leaves that state, it will never return.

**Definition 5.** A state in a Markov transition matrix is called absorbing if once the chain enters that state, it never leaves.

**Definition 6.** The trace of a square matrix $A_{r \times r}$ is defined to be the sum of the elements on the main diagonal of $A$, i.e.,

$$\text{Trace}(A) = a_{11} + a_{22} + \cdots + a_{rr}.$$ 

**Definition 7.** [Burden, R. L. and Faires, J. D. (2005)] [Convergence Rate] Suppose \( \{\beta_n\}_{n=1}^{\infty} \)
is a sequence known to converge to zero, and \( \{\alpha_n\}_{n=1}^{\infty} \) converges to a number \( \alpha \). Then it is called that \( \{\alpha_n\}_{n=1}^{\infty} \) converges to \( \alpha \) with convergence rate (or rate of convergence) \( O(\beta_n) \) if there exist a constant \( K \) and a number \( M' > 0 \) such that
\[
|\alpha_n - \alpha| \leq K|\beta_n|, \text{ for all } n \geq M'. \tag{3.3}
\]
In addition, Inequality (3.3) indicates that \( \alpha_n = \alpha + O(\beta_n) \) for large \( n \).

**Definition 8. [Empirical Convergence]** Let \( P \) be a square matrix of order \( r \) and \( \{P^n\}_{n \in \mathbb{N}} \) converges to \( P^* \) as \( n \to \infty \). In other words, for all \( \epsilon > 0 \), there exists a constant \( n_1(\epsilon) \) such that
\[
\left( \sum_{i,j=1}^{r} |p_{ij}^{(n)} - p_{ij}^*|^2 \right)^{1/2} < \epsilon, \forall n \geq n_1(\epsilon),
\]
where \( p_{ij}^{(n)} \) is the element in the \( i^{th} \) row and \( j^{th} \) column of \( P^n \), and \( p_{ij}^* \) is the element in the \( i^{th} \) row and \( j^{th} \) column of \( P^* \). Then \( \{P^n\}_{n \in \mathbb{N}} \) is called to empirically converge to \( P^* \) with respect to a given \( \epsilon > 0 \) at \( n = k \) if \( k \geq n_1(\epsilon) \).

**Theorem 1** [Rudolph, G. (1994)] The transition matrix of the CGA with mutation probability \( p_m \in (0, 1) \), crossover probability \( p_c \in [0, 1] \) and fitness proportional survivor selection is regular.

Theorem 1, formulated by Rudolph, is used to prove the convergence of CGA, with best solution maintained, to its global optimal solution [Rudolph, G. (1994)].

**Theorem 2** [Iosifescu, M. (1980)] If \( P \) is a \( r \times r \) regular stochastic matrix, then \( P^n \) converges as \( n \to \infty \) to a positive stable stochastic matrix \( \prod = ev^T \), where \( e = (1, 1, \ldots, 1)^T \) is a \( r \times 1 \) column vector in which all elements are of the value 1, and \( v^T = (v_1, v_2, \ldots, v_r) \) is a \( 1 \times r \) probability row vector with non-null entries. Moreover, there exists a constant \( a > 0 \) such that
\[
|p_{ij}^{(n)} - v_j| \leq an^{m_2-1} |\lambda_{2,P}|^n, \tag{3.4}
\]
where \( p_{ij}^{(n)} \) is the \( i^{th} \) row and \( j^{th} \) column of \( P^n \), \( \lambda_{2,P} \) is the second largest eigenvalue of \( P \) in absolute value, and \( m_2 \) is the (algebraic) multiplicity of \( \lambda_{2,P} \).
Theorem 3 [Iosifescu, M. (1980)] Let the transition matrix $P$ be

$$P = \begin{pmatrix} P_1 & 0 \\ R & A \end{pmatrix},$$

where $P_1$ is regular, $R \neq 0$. Then

$$P^n = \begin{pmatrix} P_1^n & 0 \\ \sum_{i=0}^{n-1} A^{n-1-i}RP_1^i & A^n \end{pmatrix}.$$ (3.5)

As $n \to \infty$, $P^n$ converges to

$$\lim_{n \to \infty} P^n = \begin{pmatrix} e_1 v^T & 0 \\ e_2 v^T & 0 \end{pmatrix},$$ (3.6)

where $v^T = (v_1, v_2, \ldots, v_r)$ is a $1 \times r_1$ probability row vector with non-null entries, $e_1 = (1, 1, \ldots, 1)^T$ is a $r_1 \times 1$ column vector if $r_1$ is the number of rows in $P_1$, and $e_2 = (1, 1, \ldots, 1)^T$ is a $r_2 \times 1$ column vector if $r_2$ is the number of rows in $R$.

Note that $A^n$ converges to 0 as $n \to \infty$. Moreover, $\lim_{n \to \infty} P^n$ has the property that each of the columns has the same entry value. This is insightful for the proof that the initial state will not impact the final state if time goes to infinity.

Theorem 4 [Iosifescu, M. (1980)] [Perron’s Formula] If $A$ is a square matrix of order $r$, $\lambda_1, \lambda_2, \ldots, \lambda_q$, $q \leq r$, are the eigenvalues of $A$, and $m_1, m_2, \ldots, m_q$ are the (algebraic) multiplicities of the eigenvalues, respectively, $m_1 + m_2 + \cdots + m_q = r$, then

$$a_{ij}^{(n)} = \sum_{k=1}^{q} \frac{1}{(m_k - 1)!} \left( \frac{d^{m_k-1}}{d\lambda^{m_k-1}} \left( \lambda^n A_{ij}(\lambda) \prod_{i \neq k} (\lambda - \lambda_i)^{m_i} \right) \right)_{\lambda = \lambda_k},$$

where $a_{ij}^{(n)}$ is the element in the $i^{th}$ row and $j^{th}$ column of $A^n$, and $A_{ij}(\lambda)$ is the element in the $i^{th}$ row and $j^{th}$ column of the adjoint of the matrix $(\lambda I_r - A)$; that is, $A_{ij}(\lambda)$ is equal to the product of $(-1)^{i+j}$ and determinant of the minor of $(\lambda I_r - A)_{ji}$. Note that the minor of $(\lambda I_r - A)_{ji}$ is derived by deleting the $j^{th}$ row and $i^{th}$ column from the matrix $(\lambda I_r - A)$, and $I_r$ is the identity matrix of order $r$.

Theorem 5 [Iosifescu, M. (1980)] If $A$ is a regular matrix, then there exists a real eigenvalue $\lambda_1 > 0$ which is simple (i.e., of algebraic multiplicity 1) and which exceeds the absolute values of all other eigenvalues of $A$. 
Lemma 1 [Iosifescu, M. (1980)] If $A$ is a stochastic matrix (i.e., $A$ is nonnegative and the sum of the elements in any row of $A$ is 1), then the eigenvalues of $A$ are in absolute value at most equal to 1. Moreover, 1 is an eigenvalue of $A$.

Theorem 6 [Horn, R. A. and Johnson, C. R. (1985)] [Schur] If $A$ is a square matrix of order $r$ with eigenvalues $\lambda_1, \lambda_2, \ldots, \lambda_r$ in any prescribed order, there exists a unitary matrix $S$ (square matrix) of order $r$ such that

$$S^* AS = T = [t_{ij}]$$

is upper triangular, with diagonal entries $t_{ii} = \lambda_i, i = 1, 2, \ldots, r$. That is, every square matrix $A$ is unitarily equivalent to a triangular matrix whose diagonal entries are the eigenvalues of $A$ in a prescribed order.

Theorem 2, 3, 4, 5, 6, and Lemma 1 are directly from Markov chain theory and linear algebra. Theorem 4, 5, 6, and Lemma 1 are utilized to deduce my preliminary result [Jiang, H. and Chang, C. K. and Zhu, D. and Cheng, S. (2007)].

3.3.2 Research Assumptions

The first two assumptions adopted in this research are based on Rudolph’s work [Rudolph, G. (1994)].

Assumption 1 [Problem Definition] The problems $\max \{f(b) | b \in IB^l\}$, where $0 < f(b) < \infty$ for all $b \in IB^l = \{0, 1\}^l$, and $l$ is the length of the binary strings which represent feasible solutions, are the subjects for discussion.

Assumption 2 [Choice of Solution Method] The CGA, which only has selection, crossover, and mutation operators, with the best solution maintained, is the algorithm to be analyzed. (More specifically, roulette wheel selection, any crossover operation, and bit mutation are considered before Chapter 8 in this dissertation.)

The last assumption pertains to the concerns for practicality and applicability.
**Assumption 3** The number of generations of GAs is a reasonably large number, and it is fixed.

### 3.3.3 Markov Chain Analysis for GAs

#### 3.3.3.1 State Representations

Two types of state representations for the finite state homogeneous Markov transition matrices are commonly adopted in Markov chain analysis. Michael D. Vose, Joe Suzuki, et al. applied the transition matrix with the states representing the occurrences of the individuals [Suzuki, J. (1995, 1998); Vose, M. D. and Liepins, G. E. (1991)]. The cardinality of different populations (i.e., the dimension of the state space), becomes [Suzuki, J. (1995)]

\[ |S| = \binom{m + 2^l - 1}{m}, \]

where \( S \) is the state set, \( m \) is the size of a population, and \( l \) is the length of the binary strings.

Günter Rudolph and David B. Fogel [Fogel, D. B. (1995); Rudolph, G. (1994)] proposed the transition matrix in which the states are defined by every possible configuration of an entire population of bit strings. Therefore, there are \( 2^{ml} \) states, where \( m \) is the size of a population, and \( l \) is the length of the binary strings.

Although the approaches of both Vose and Rudolph possess similar concepts and functionalities, and they can be converted to each other (see Theorem 11), the representations are different. Each approach has its advantages. While fewer states and the distributions of the individuals can be obtained in Vose’s approach, the analysis of this approach is not as intuitive as Rudolph’s approach. For instance, if there are four individuals (3-digit binary strings) within a generation, say “101, 111, 011, 111”, this generation is represented by the state “101111011111” in Rudolph’s approach. For Vose’s approach, one has to list the sorted state space “000, 001, 010, 011, 100, 101, 110, 111” first, and obtain the state “11101101100”.

Since my research goal is to seek an evaluation metric to estimate the applicability of GAs for real-world applications and Markov chain analysis is not so practical (discussed in Section VI), either approach can be chosen as the transient analyzing method. Due to the fact
that Rudolph’s approach is more intuitive than Vose’s, my work uses Rudolph’s approach to transform the encodings of optimization problems to Markov chains [Rudolph, G. (1994)]. Rudolph’s work studies the convergence of CGAs with the best solution maintained. The transition matrices of his Markov chains are described below.

### 3.3.3.2 Transition Matrices

A CGA is a canonical GA which consists of an $m$-tuple of binary strings $b_i$, $i \in \{1, 2, \ldots, m\}$, of length $l$. The bits of each string are considered to be the genes of an individual chromosome. The $m$-tuple of individual chromosomes is said to be a population of a generation. From one generation to another, CGA applies three operators on the population. The operators include selection, crossover, and mutation operators.

The selection operator, in which the roulette wheel selection (proportional selection) is assumed, forms a transition matrix $S$. As mentioned before, there are $m$ (an even number) individuals for each generation. By Assumption 1, $S$ is a $2^{ml} \times 2^{ml}$ matrix with the element

$$s_{ij} = \frac{\prod_{k=1}^{m} O_k \cdot f(\pi_k(j))}{(\sum_{k=1}^{m} f(\pi_k(i)))^m}$$

if \(\{\pi_1(j), \pi_2(j), \ldots, \pi_m(j)\} \subseteq \{\pi_1(i), \pi_2(i), \ldots, \pi_m(i)\}\), where $\pi_k(i), k \in \{1, \ldots, m\}$ are the $k^{th}$ segment of length $l$ from the state $i$, $O_k$ is the number of occurrences of $\pi_k(j)$ in state $i$, and $f(\cdot)$ is the fitness function. Otherwise, $s_{ij} = 0$.

By the same token, the crossover transition matrix $C$ is also a $2^{ml} \times 2^{ml}$ matrix. After the crossover method is determined, $I_i$ is defined to be the index set in which each element is a binary string with length $ml$ representing a possible mating method for the individuals of state $i$. For each $r \in I_i$, let $p_r$ be the probability of $r$ being selected as a mating method. If $p_c$ is the crossover probability, then

$$c_{ij} = (1 - p_c)\delta_{ij} + p_c \cdot \left(\sum_{r \in I_i} p_r \cdot \prod_{k=1}^{m} Pr\{Cr(\pi_{2k-1}(r), \pi_{2k}(r)) = (\pi_{2k-1}(j), \pi_{2k}(j))\}\right), \quad (3.7)$$

where

$$\delta_{ij} = \begin{cases} 1 & \text{if } i = j \\ 0 & \text{if } i \neq j \end{cases}$$
Cr(·, ·) is the result of the crossover operation, and \( Pr \{ \cdot \} \) is the probability of the event. In (3.7),

\[
Pr\{Cr(\pi_{2k-1}(r), \pi_{2k}(r)) = (\pi_{2k-1}(j), \pi_{2k}(j))\}
\]
depends on the crossover method applied.

Bit mutation is designed to serve as a background operator to ensure that all possible alleles can occur in the population [Fogel, D. B. (1995)]. Once the population of chromosomes reaches a configuration such that crossover no longer produces offspring outperforming their parents, it is the only operator which leads the population to leap out of the homogeneous populations. The mutation transition matrix is denoted as \( M \), which is a \( 2^{ml} \times 2^{ml} \) matrix. Let \( p_m \in (0,1) \) be the probability of flipping each individual bit, then

\[
m_{ij} = \prod_{k=1}^{m} p_m^{H(\pi_k(i), \pi_k(j))} (1 - p_m)^{l-H(\pi_k(i), \pi_k(j))},
\]

where \( H(\cdot, \cdot) \) is the Hamming distance of the strings (chromosomes). The matrix \( CMS \), the product of \( C \), \( M \), and \( S \), forms a transition matrix for CGA.

In order to show that the CGA with the best solution maintained converges to its global optimum, the state space is extended from \( 2^{ml} \) to \( 2^{(m+1)l} \). That is, for each state \( (m \) individuals), there is a referenced individual (assumed to be the leftmost individual) with it. The referenced individual is for the calculation with respect to the presence of the best solution. Since there are \( 2^l \) distinct referenced individuals, the new state space is \( 2^{ml} \cdot 2^l = 2^{(m+1)l} \). The new transition matrix \( P \) is

\[
P = \begin{pmatrix}
CMS \\
CMS \\
\vdots \\
CMS
\end{pmatrix},
\]

where each of the diagonal squares \( CMS \)'s is corresponding to a referenced individual. The referenced individuals are sorted by fitness values in descending order. That is, the first diagonal square represents the highest fitness value, and the second square represents the second highest fitness value, and so on.
The upgrade matrix $U$ is also for maintaining the best solution. If a state in the $i^{th}$ diagonal square has a best fitness value higher than the fitness value of the referenced individual corresponding to the $i^{th}$ diagonal square, this state is upgraded to the $j^{th}$, $j < i$, diagonal square in which the fitness value is equal to the best fitness value of the state. The structure of $U$ is

\[
U = \begin{pmatrix}
U_{11} & & \\
U_{21} & U_{22} & \\
& \vdots & \ddots \\
U_{2l,1} & U_{2l,2} & \cdots & U_{2l,2l}
\end{pmatrix},
\]

which is a lower triangular matrix. Moreover, since it is assumed that there is a unique optimal solution for the optimization problem in Rudolph’s work [Rudolph, G. (1994)], $U_{11}$ is the only $2^{m_l} \times 2^{m_l}$ identity matrix. That is, none of the states in the first diagonal square need to be upgraded.

Figure 3.2 shows an example of the structure of $PU$ with the dashes representing nonzero entries of $PU$, where $m = 1$ and $l = 3$. In fact, the figure can be generalized to any value of $m$ and $l$.

### 3.3.3.3 The Proof of Convergence of CGA

Rudolph’s proof on the convergence of CGA, with best solution maintained to its global optimal solution, is quite unique [Rudolph, G. (1994)]. The concept and method will be briefly reviewed in this subsection.

From Equation (3.8) and (3.9) in the previous subsection, we have

\[
PU = \begin{pmatrix}
CMSU_{11} & 0 \\
R & A
\end{pmatrix},
\]

where $R$ and $A$ are corresponding sub-matrices. Since $U_{11}$ is a $2^{m_l} \times 2^{m_l}$ identity matrix, the block matrix $CMSU_{11}$ in Equation (3.10) can be simplified as $CMS$.

According to Theorem 1, $CMS$ is regular. Theorem 3 shows that the matrix $PU$ converges (i.e., CGA with best solution maintained converges). In addition, based on Equation (3.5) and
Equation (3.6), the first $2^m$ states are absorbing states. That is, regardless of the initial population (state), the populations (states) of CGA with best solution maintained will eventually be restricted within a subset of all the populations (states). According to the design of upgrade matrix $U$ in the previous subsection, all the populations in the subset are under the condition that the global optimal solution is found. Their referenced individuals have the highest fitness value. Hence, we can conclude that CGA with best solution maintained converges to its global optimal solution.
CHAPTER 4. CONVERGENCE RATE AND THE FIRST HITTING TIME

Rudolph’s proof shows that a CGA with the best solution maintained over time will eventually converge to its global optimal solution; however, how long it takes to converge is not specified. To address this problem, a study was conducted to investigate and analyze the convergence rate of a CGA with the best solution maintained over time.

4.1 Convergence Rate

From Theorem 4 [Perron’s Formula], without loss of generality, we can bound \( a^{(n)}_{ij} \) by estimating the term,

\[
\left( \frac{d^{m_k-1}}{d\lambda^{m_k-1}} \left( \frac{\lambda^n A_{ij}(\lambda)}{\prod_{i \neq k} (\lambda - \lambda_i)^{m_i}} \right) \right)_{\lambda = \lambda_k},
\]

where \( k \in \{1, 2, \ldots, q\} \), as follows. Since \( A_{ij}(\lambda) \) is equal to the product of \((-1)^{i+j}\) and determinant of the minor of \((\lambda I_r - A)_{ji}\), it is a polynomial of order \((r - 1)\). Let

\[
f_{ij}(\lambda) = \frac{\lambda^n A_{ij}(\lambda)}{\prod_{i \neq k} (\lambda - \lambda_i)^{m_i}},
\]

then we get the order of the function \( f_{ij}(\lambda) \) is \((n + (r - 1)) - (r - m_k) = n + (m_k - 1)\). Therefore, the order of \((m_k - 1)^{th}\) derivative of \( f_{ij}(\lambda) \) in equation (4.1) is \( n \). Moreover, a multiplier of \( O(n) \) is applied every time during the process in which the derivative is obtained. Hence, it is concluded that if \( A \) is a square matrix of order \( r \), \( \lambda_1, \lambda_2, \ldots, \lambda_q \), \( q \leq r \), are the eigenvalues of \( A \), and \( m_1, m_2, \ldots, m_q \) are the (algebraic) multiplicities of the eigenvalues, respectively, \( m_1 + m_2 + \cdots + m_q = r \), then there exists a positive number \( K \) such that

\[
|a^{(n)}_{ij}| \leq Kn^{m_{\text{max}}-1} |\lambda_{\text{max}}|^n,
\]

(4.3)
where \( a_{ij}^{(n)} \) is the element of \( A^n \) in the \( i^{th} \) row and \( j^{th} \) column, \( m_{max} = max\{m_1, m_2, \ldots, m_q\} \), and \( |\lambda_{max}| = max\{|\lambda_1|, |\lambda_2|, \ldots, |\lambda_q|\} \). This inequality will be exploited to show that the convergence rate is related to one of the eigenvalues of the transition matrix later.

From section 2, the transition matrix of the CGA with the best solution maintained is

\[
PU = \begin{pmatrix}
CMSU_{11} & & \\
CMSU_{21} & CMSU_{22} & \\
& \ddots & \ddots \\
CMSU_{2l,1} & CMSU_{2l,2} & \cdots & CMSU_{2l,2l}
\end{pmatrix},
\]

(4.4)

From the form of \( PU \) in Equation (4.4), we get that the eigenvalues of \( PU \) are the eigenvalues of the diagonal blocks [Suzuki, J. (1995)]. Moreover, in the matrix \((PU)^n\), where \( n \) is the fixed number of generations, the elements of the first \( 2^{ml} \) columns are related to the probabilities of convergence to the global optimum. With the initial distribution \( p_0 \) (a row vector) being known beforehand, to compute the probability of convergence to the global optimum, we have to sum up the first \( 2^{ml} \) elements of \( p_0(\Pi)^n \). Without loss of generality, we can assume that \( p_0 = (p_{0,1}, p_{0,2}, \ldots, p_{0,2^{(m+1)}l}) \). As an alternative, we compute the summation of the elements other than the first \( 2^{ml} \) ones of \( p_0(\Pi)^n \).

In equation (4.4), the matrix \( PU \) can be represented as

\[
PU = \begin{pmatrix}
CMSU_{11} & 0 \\
R & A
\end{pmatrix},
\]

(4.5)

where

\[
R = \begin{pmatrix}
CMSU_{21} \\
\vdots \\
CMSU_{2l,1}
\end{pmatrix},
\]

(4.6)

and

\[
A = \begin{pmatrix}
CMSU_{22} & & \\
CMSU_{32} & CMSU_{22} & \\
& \ddots & \ddots \\
CMSU_{2l,2} & CMSU_{2l,3} & \cdots & CMSU_{2l,2l}
\end{pmatrix},
\]

(4.7)
Then,

$$(PU)^n = \begin{pmatrix} (CMSU_{11})^n & 0 \\ \sum_{i=0}^{n-1} A_i^R(CMSU_{11})^{(n-1)-i} & A^n \end{pmatrix}. \quad (4.8)$$

Let $v(n) = p_0(PU)^n$. Since $A$ is a square matrix, for the element $a_{ij}^{(n)}$ of $A^n$, the inequality (4.3) holds. Hence, we have

$$2^{(m+1)i} \sum_{i=2^{ml+1}}^{2^{(m+1)i-2^{ml}}} v_i(n) = \sum_{i=1}^{2^{(m+1)i-2^{ml}}} p_{0,2^{ml+i}} \sum_{j=1}^{2^{(m+1)i-2^{ml}}} a_{ij}^{(n)} \leq (2^{(m+1)i-2^{ml}})Kn^{m_{max}-1}|\lambda_{max}|^n, \quad (4.9)$$

The following shows $|\lambda_{max}| < 1$. Since the upgrade matrix upgrades some columns of $A$ to the first $2^{ml}$ columns of $PU$, the sum of each row of $A$ is less than 1. Therefore, if $\lambda$ is an eigenvalue of $A = (a_{ij}^{(1)})$ and $u = (u(i))$ is its left eigenvector, we have

$$\lambda u(j) = \sum_{i=1}^{2^{(m+1)i-2^{ml}}} u(i)a_{ij}^{(1)}, \quad j = 1, 2, \ldots, 2^{(m+1)i-2^{ml}}. \quad (4.10)$$

That is,

$$\sum_{j=1}^{2^{(m+1)i-2^{ml}}} |\lambda u(j)| \leq \sum_{i=1}^{2^{(m+1)i-2^{ml}}} |u(i)| \sum_{j=1}^{2^{(m+1)i-2^{ml}}} a_{ij}^{(1)} < \sum_{i=1}^{2^{(m+1)i-2^{ml}}} |u(i)|. \quad (4.11)$$

Hence, $|\lambda| < 1$. Since the eigenvalues of $PU$ are the eigenvalues of the diagonal blocks, we get that the set of eigenvalues of $A$ is contained in the set of eigenvalues of $PU$. Moreover, since $CMSU_{11}$ is a regular (stochastic) matrix (Theorem 3 in [Rudolph, G. (1994)]), from Lemma 1 and Theorem 5, we obtain that $\lambda_1 = 1$ is an eigenvalue of $CMSU_{11}$, i.e., $\lambda_1 = 1$ is an eigenvalue of $PU$, and $\lambda_1$ is simple. If we agree that the eigenvalues, $\lambda_1, \ldots, \lambda_k$, $k \leq 2^{(m+1)i}$, of $PU$ are in descending order $1 = \lambda_1 > |\lambda_2| \geq \cdots \geq |\lambda_k|$, with $m_1, m_2, \ldots, m_k$ being the (algebraic) multiplicities, respectively, the following inequality can be derived.

$$2^{(m+1)i} \sum_{i=2^{ml+1}}^{2^{(m+1)i}} v_i(n) \leq K'n^{m'_{max}-1}|\lambda_2|^n, \quad (4.12)$$

where $K' > 0$ and $m'_{max}$ is the maximal (algebraic) multiplicity of the eigenvalues of $PU$. That is, regardless the initial distribution of the populations, the probability of convergence to the global optimum is greater than or equal to $1 - K'n^{m'_{max}-1}|\lambda_2|^n$.

If $K'n^{m'_{max}-1}|\lambda_2|^n > 1$, that means either the fixed $n$ is not large enough, or $\lambda$ is not small enough, this equation is meaningless. For any optimization problem, we first need to
compute its transition matrix $CMS$, extend it to $PU$, find the eigenvalue $\lambda_2$, which is related to the convergence rate of the problem, of $PU$, and then apply $\lambda_2$ to $K' n^{m_{\text{max}}^{-1}} |\lambda_2|^n$. With $n$ satisfying $K' n^{m_{\text{max}}^{-1}} |\lambda_2|^n \leq 1$, we can obtain the CGA’s hardness of the problem (i.e., the applicability of CGA to the problem). Nevertheless, it is concluded that the computations described above are time consuming and impractical for the current state of the art. By the following subsection, we get that traces of the transition matrices $(PU)^n$ is highly related to $|\lambda_2|$. In Chapter 5, the relationship is modified and applied so that an alternative approach to substituting the estimation of $|\lambda_2|$ is proposed to estimate the applicability of the CGA to optimization problems. Chapter 7 uses the proposed method in Chapter 5 and provides a possible approximation method to estimate the number of generations needed for the global convergence.

4.1.1 Eigenvalues of Transition Matrices and Fix Points of Genetic Algorithm

The convergence rate is shown to be related to $|\lambda_2|$, the second largest eigenvalue of the transition matrix in absolute value. This subsection provides the relationship between the second largest eigenvalue of the transition matrix and the fix points of CGA.

Theorem 6 demonstrates that every square matrix is unitarily equivalent to a triangular matrix whose diagonal entries are the eigenvalues of the matrix. Hence, the transition matrix $(PU)^n$, representing transition probabilities for every $n$ generations of a CGA, can be written as

$$(PU)^n = (STS^*)^n = ST^n S^*,$$  \hspace{1cm} (4.13)

where $S$ is a unitary matrix and $T$ is upper triangular with diagonal entries are the eigenvalues of $PU$. Let the eigenvalues of $PU$ be denoted as $\lambda_1 = 1, \lambda_2, \ldots, \lambda_{2(m+1)}$ (in absolute descending order). Then $T^n$ is an upper triangular matrix with diagonal entries are $\lambda_1^n, \lambda_2^n, \ldots, \lambda_{2(m+1)}^n$.

Moreover, the trace of $(PU)^n$ is

$$\text{Trace}((PU)^n) = \text{Trace}((ST^n)S^*) = \text{Trace}(S^* ST^n) = \text{Trace}(T^n) = \sum_{i=1}^{2(m+1)} \lambda_i^n. \hspace{1cm} (4.14)$$
By the inequality
\[ \left| \sum_{i=1}^{2^{(m+1)}} \lambda_i^n \right| \leq \sum_{i=1}^{2^{(m+1)}} |\lambda_i|^n \leq 1 + (2^{(m+1)} - 1)|\lambda_2|^n, \tag{4.15} \]
it is obtained that
\[ \text{Trace}((PU)^n) \leq 1 + (2^{(m+1)} - 1)|\lambda_2|^n. \tag{4.16} \]
That is, $|\lambda_2|^n$ is bounded (from the left) by the trace of the transition matrix $(PU)^n$ with a constant multiple. Since $|\lambda_i| < 1$ for $i \in \{2, \ldots, 2^{(m+1)}\}$, there exists a number $M_1 > 0$ such that
\[ \text{Trace}((PU)^n) = 1 + \lambda_2^n + \cdots + \lambda_{2^{(m+1)}}^n \geq C_1, \quad \forall n \geq M_1, \]
where $C_1 \in (0, 1]$ is a constant. That implies that there exists a constant $K^n$ such that
\[ 1 + (2^{(m+1)} - 1)|\lambda_2|^n \leq 1 + (2^{(m+1)} - 1) \leq K^n \text{Trace}((PU)^n), \quad \forall n \geq M_1. \tag{4.17} \]
Equation (4.17) shows that if $n$ is large enough, $\text{Trace}((PU)^n)$ with a constant multiple can also form an upper bound for $|\lambda_2|^n$. Combined with Inequality (4.16), it can be known that computing bounds for $|\lambda_2|^n$ with $n \geq M_1$ is equivalent to computing the trace of the transition matrix to the power $n$. Additionally, the diagonal element of the transition matrix corresponding to each state shows probability of a fix point over the solutions in the CGA search space. The product of any distribution of transient states and the diagonal elements of the transition sub-matrix corresponding to the transient states represents the total probability of fix points, which are outside the set of optimal populations (absorbing states) of CGA. Note that a population $\xi^*$ is called an optimal population if there exists $i$, $1 \leq i \leq m + 1$, such that $\pi_i(\xi^*)$ is an optimal solution. For searching purpose, we do not want CGA to stay within a transient state too long since the state is already visited. The revisiting of a state will cost some time without any improvement of solutions. In other words, if the total probability of fixed points of CGA can be reduced, the probability of CGA to search other candidate states will be increased for the number of the states is finite.
4.2 Second Largest Eigenvalue versus Expected First Hitting Time

The research on computation time of GAs used to solve optimization problems is important for the foundation and theory of evolutionary algorithms. Both convergence rate and expected first hitting time express the information on time complexity.

From Ding’s work [Ding, L. and Yu, J. (2005)], the first hitting time \( \tau(\xi^*) = \min\{k \geq 0|\xi_k = \xi^*\} \),

where \( \xi^* \) is an optimal population, and \( \{\xi_k|k \in N\} \) is a discrete homogeneous Markov chain. Moreover, the expected first hitting time is calculated as

\[
E[\tau(\xi^*)] = \sum_{k\geq0} k \times P\{\tau(\xi^*) = k\}. \tag{4.18}
\]

As mentioned in Chapter 2, a Markov theorem tells us that the expected value of the transient time in which an arbitrary state \( i \) goes to any other state \( j \) is finite. That is, there exists \( 0 < M_1 < \infty \) such that

\[
E[\tau(\xi^*)] < M_1,
\]

since the optimal state is also a state in the state space of the Markov chain. With respect to the same problem, if the second largest eigenvalue in absolute value of \( PU \): \( \lambda_2 \neq 0 \) (i.e., CMS does not have identical rows), we can get that there exists \( 0 < C_1 < \infty \) such that

\[
E[\tau(\xi^*)] < C_1|\lambda_2|. \tag{4.19}
\]

For an arbitrary fitness function, an inequality similar as Inequality (4.19) can be derived. In fact, if a problem has the corresponding \( \lambda_2 \neq 0 \), it is possible to use \( \lambda_2 \) to estimate the first hitting time. Suppose \( \lambda_2 \neq 0 \) is given while \( m \) and \( l \) are also given. Based on the arrangement of eigenvalues in Section 4.1.1, the inequality

\[
1 + |\lambda_2|^n + |\lambda_3|^n + \cdots + |\lambda_{2(m+1)l}|^n \leq 1 + (2^{(m+1)l - 1})|\lambda_2|^n
\]

always holds. For a small \( \epsilon > 0 \), the solution of \( \epsilon = (2^{(m+1)l - 1})|\lambda_2|^n \) on \( n \) can be an estimation of the first hitting time.
CHAPTER 5. THE EVALUATION METRICS

5.1 The Bridge between Theory and Practice

Although the expected first hitting time and the convergence rate can be mathematically
computed, there is still a huge gap between the theoretical prediction and the estimation on the
applicability of GAs to problems in real world applications. As I know, the calculations on the
expected first hitting time or convergence rate include the computation on the corresponding
transition matrix of problems. To obtain the transition matrix with respect to a problem, the
matrices $C$, $M$, and $S$ should be considered. Since $S$ is derived from selection operator, in
which the proportional selection is applied, the construction time is much longer than the total
computation time on the fitness values of the entire search space. Hence, the theory is only an
ideal view. The real world demands a practical approach for the estimation on applicability of
GAs.

In order to derive a more practical approach, a direction related to Markov chain analysis
is suggested. It is introduced as follows.

5.1.1 Equivalent Forms in terms of Convergence

The extended transition matrix $PU$ is used to prove that the CGA with best solution
maintained converges to the global optimal solution. Because the computation time of the
transition matrix is not practical, $CMS$ and $PU$ cannot be computed directly. $PU$ includes
even more states than $CMS$. My goal is to find a way which can extract only the essential
properties of the transition matrix so that an evaluation metric can be formulated to evaluate
the applicability of CGAs to real-world problems.

Instead of $PU$, the transition matrix $CMS$ is used to develop the metric in the next section.
According to Theorem 3, the convergence of \((PU)^n\) as \(n \to \infty\) is proved; however, it does not show much information about the relationship between \((PU)^n\) and \((CMS)^n\), especially when \(n\) is finite. In order to further investigate the convergence behavior among \((PU)^n\), \((CMS)^n\), and \(A^n\) (the sub-matrix of \((PU)^n\) in Equation (3.10)) within finite steps (i.e., \(n \in N\) and \(n < \infty\)), Theorem 7 is formulated. Note that the term empirical convergence is defined in Definition 8.

**Theorem 7** The empirical convergence of \(\{CMS^n\}_{n \in N}\) at \(n = n_1\) and \(\{A^n\}_{n \in N}\) at \(n = n_2\) with respect to \(\epsilon = \frac{\epsilon}{2\sqrt{2^{(2^l-1)}}}\) implies the empirical convergence of \(\{PU^n\}_{n \in N}\) at \(n = k\) with respect to \(\epsilon\), where \(k \geq \max\{n_1,n_2\}\), \(A\) is the sub-matrix of \(PU\) in Equation (3.10), and \(\epsilon > 0\) is a sufficiently small number.

**Proof.** To prove the theorem, one has to first verify with respect to each row of blocks of \((PU)^n\), if all of the blocks are summed, the result is equal to \((CMS)^n\), for all \(n \in N\). The statement is proved by applying Mathematical Induction on \(n\) (the steps).

First, suppose that \(n = 2\). Based on the structure of \(PU\) (e.g., Figure 3.2), the property can be obtained that each row of blocks has exactly \(2^{ml}\) (the order of \(CMS\)) nonzero columns. Let all of the \(2^{ml}\) columns be named from left to right as \(column_1, column_2, \ldots, column_{2^{ml}}\). It can be shown that their positions within any row of blocks are distinct and sorted. That is, within a row of blocks, no matter which block it is in, \(column_1\) is always the first column in the block, \(column_2\) is always the second column in the block, and so on. To compute \(PU \cdot PU\), for any row \(i, 1 \leq i \leq 2^{(m+1)l}\), of the left \(PU\), the first nonzero entry, which is in the first column, is multiplied with the first row of the right \(PU\), the second nonzero entry, which is in the second column, is multiplied with the second row in the corresponding row of blocks of the right \(PU\), and so on. (Figure 5.1 shows an illustration of \(PU \cdot PU\), where \(m = 1\) and \(l = 3\).)

Since the \(2^{ml}\) nonzero entries in the \(i^{th}\) row of the left \(PU\) are from a row of \(CMS\), and rows with \(2^{ml}\) nonzero entries of the right \(PU\) are from rows of \(CMS\), it can be derived that

\[
Row_j((CMS)^2) = \sum_{g=1}^{2^l} Row_j((PU)^2)_{hg}, \tag{5.1}
\]

where \(j = (i \mod 2^{ml})\), \(Row_j(\cdot)\) indicates the \(j^{th}\) row in the block, \((PU)^2_{uw}\) is the block in the
the product of the 1st column and 1st row

the product of the 2nd column and 2nd row

the product of the 3rd column and 3rd row

the product of the 4th column and 4th row

the product of the 5th column and 5th row

the product of the 6th column and 6th row

the product of the 7th column and 7th row

the product of the 8th column and 8th row

Figure 5.1 An illustration of the Product $PU \cdot PU$

$u^{th}$ row and $v^{th}$ column of $(PU)^2$, and $h = \lceil \frac{i}{2^{ml}} \rceil$. From Equation (5.1), it can be obtained that with respect to each row of blocks of $(PU)^2$, if all of the blocks are summed, the result is equal to $(CMS)^2$. In other words, the statement holds for $n = 2$.

Suppose for $n = k$, the statement holds. That is, with respect to each row of blocks of $(PU)^k$, if all of the blocks are summed, the result is equal to $(CMS)^k$.

For $n = k + 1$, the product $PU \cdot (PU)^k$ needs to be computed. Let $(PU)^k_{uv}$ be the block in the $u^{th}$ row and $v^{th}$ column of $(PU)^k$. For any row $i$, $1 \leq i \leq 2^{(m+1)l}$, of $PU$, assume $C_1, C_2, \ldots, C_{2^{ml}}$ are the aforementioned nonzero entries, $j = (i \mod 2^{ml})$, and $h = \lceil \frac{i}{2^{ml}} \rceil$. Then, based on the rule for the product of two matrices, it is derived that

$$Row_j((PU)^{k+1}_{hw}) = \sum_{z=0}^{h-w-1} C_{w+z}Row_{w+z}((PU)^k_{(w+z)w}) + \sum_{x=h}^{2^{ml}} C_xRow_x((PU)^k_{hw}),$$

if $w \leq h$, and

$$Row_j((PU)^{k+1}_{hw}) = (0, \ldots, 0)_{2^{ml}},$$
if \( w > h \). Hence, it is obtained that

\[
\sum_{w=1}^{2^l} \text{Row}_j((PU)^{k+1}_{hw}) = \sum_{w=1}^{h} \text{Row}_j((PU)^{k+1}_{hw})
\]

\[
= C_1 \text{Row}_1((PU)^{k+1}_{11}) + C_2 \text{Row}_2((PU)^{k+1}_{21} + (PU)^{k+1}_{22}) + \\
C_3 \text{Row}_3((PU)^{k+1}_{31} + (PU)^{k+1}_{32} + (PU)^{k+1}_{33}) + \cdots + \\
C_{h-1} \text{Row}_{h-1}((PU)^{k+1}_{(h-1)1} + \cdots + (PU)^{k+1}_{(h-1)(h-1)}) + \\
C_h \text{Row}_h((PU)^{k+1}_{h1} + \cdots + (PU)^{k+1}_{hh}) + \\
C_{h+1} \text{Row}_{h+1}((PU)^{k+1}_{h1} + \cdots + (PU)^{k+1}_{hh}) + \\
\cdots + C_{2^m} \text{Row}_{2^m}((PU)^{k+1}_{11} + \cdots + (PU)^{k+1}_{hh}).
\]

Since it is already known that with respect to each row of blocks of \((PU)^k\), if all of the blocks are summed, the result is equal to \((CMS)^k\) (i.e., the statement holds for \(n = k\)), it can be derived that the right hand side (RHS) of Equation (5.2) is equal to \(\text{Row}_j((CMS)^{k+1})\). Hence, the statement holds for \(n = k + 1\). That is, with respect to each row of blocks of \((PU)^{k+1}\), if all of the blocks are summed, the result is equal to \((CMS)^{k+1}\).

Secondly, the empirical convergence of \((PU)^n\) with respect to \(\epsilon\) needs to be proved. Let \(u^{(n)}_{ij}\) be the element in the \(i^{th}\) row and \(j^{th}\) column of \((PU)^n\).

By Definition 8 and the fact that \(\{(CMS)^n\}\) converges empirically at \(n = n_1\) and \(\{A^n\}\) converges empirically at \(n = n_2\) with respect to the same \(\frac{\epsilon}{2\sqrt{2(2^l-1)}} > 0\), Inequality (5.3) and Inequality (5.4) are derived. For \(\frac{\epsilon}{2\sqrt{2(2^l-1)}} > 0\) and the constant \(n_1\),

\[
\left(\sum_{i,j=1}^{2^m} |v^{(n)}_{ij} - v^*_{ij}|^2\right)^{1/2} < \frac{\epsilon}{2\sqrt{2(2^l-1)}}, \forall n \geq n_1,
\]

where \(v^{(n)}_{ij}\) is the element in the \(i^{th}\) row and \(j^{th}\) column of \((CMS)^n\), and \(e(v^*)^T\) is the limit of \((CMS)^n\) (see Theorem 2). In addition, for \(\frac{\epsilon}{2\sqrt{2(2^l-1)}} > 0\) and the constant \(n_2\),

\[
\left(\sum_{i,j=1}^{2^{(m+1)}-2^m} |a^{(n)}_{ij} - 0|^2\right)^{1/2} < \frac{\epsilon}{2\sqrt{2(2^l-1)}}, \forall n \geq n_2,
\]
where \( a^{(n)}_{ij} \) is the element in the \( i \)th row and \( j \)th column of \( A^n \), and 0 is the limit of \( A^n \). Then \( \exists n_3 = \max\{n_1, n_2\} \) such that

\[
\sum_{i=2^{m+1}+1}^{2^{m+1}} \sum_{j=1}^{2^{ml}} |v_{ij}^{(n)} - v_j^*|^2 = \sum_{i=2^{m+1}+1}^{2^{m+1}} \sum_{j=1}^{2^{ml}} |v_{ij}^{(n)} + \sum_{k=0}^{2^l-2} a_{i,k}^{(n)} v_k^* + \sum_{k=0}^{2^l-2} a_{i,k}^{(n)}|^2
\]

\[
= \sum_{i=2^{m+1}+1}^{2^{m+1}} \sum_{j=1}^{2^{ml}} |v_{ij}^{(n)} - v_j^* - \sum_{k=0}^{2^l-2} a_{i,k}^{(n)}|^2
\]

\[
\leq \sum_{i=2^{m+1}+1}^{2^{m+1}} \sum_{j=1}^{2^{ml}} (1^2 + (-1)^2) |v_{ij}^{(n)} - v_j^*|^2
\]

(by Cauchy-Schwarz Inequality)

\[
\leq 2 \sum_{i=2^{m+1}+1}^{2^{m+1}} \sum_{j=1}^{2^{ml}} 2 \cdot |v_{ij}^{(n)} - v_j^*|^2 + 2(2^l - 1) \cdot 2^l \sum_{k=0}^{2^l-2} |a_{i,k}^{(n)}|^2
\]

(by Cauchy-Schwarz Inequality)

\[
\leq 2 \sum_{i=2^{m+1}+1}^{2^{m+1}} \sum_{j=1}^{2^{ml}} |v_{ij}^{(n)} - v_j^*|^2 + 2(2^l - 1) \sum_{i=2^{m+1}+1}^{2^{m+1}} \sum_{j=1}^{2^{ml}} (a_{i,k}^{(n)})^2
\]

\[
< 2 \cdot (2^l - 1) \cdot \frac{\epsilon^2}{8(2^l - 1)} + 2 \cdot (2^l - 1) \cdot \frac{\epsilon^2}{8(2^l - 1)} = \frac{\epsilon^2}{2}, \forall n \geq n_3.
\]

Then by Inequality (5.3) and Inequality (5.4),

\[
\sum_{i,j=1}^{2^{(m+1)l}} |v_{ij}^{(n)} - (PU)^*_{ij}|^2 < \frac{\epsilon^2}{8(2^l - 1)} + \frac{\epsilon^2}{8(2^l - 1)} + \frac{\epsilon^2}{2}
\]

\[
< \frac{\epsilon^2}{4} + \frac{\epsilon^2}{4} + \frac{\epsilon^2}{2} (1 \geq 1)
\]

\[
= \epsilon^2,
\]

where \((PU)^*_{ij}\) is the element in the \( i \)th row and \( j \)th column of the limit of \((PU)^n\).

That is, from the statement of Mathematical Induction and the fact that \(\{(CMS)^n\}\) converges empirically at \(n = n_1\) and \(\{A^n\}\) converges empirically at \(n = n_2\) with respect to the same \(\frac{\epsilon}{2\sqrt{2(2^l - 1)}}\), the empirical convergence of \(\{(PU)^n\}\) at \(n = k, k \geq \max\{n_1, n_2\}\), with respect to \(\epsilon\) is proved. \(\Box\)

Based on Inequality (3.4) and Inequality (4.12), it is implied that the convergence of \(\{(CMS)^n\}\) and \(\{A^n\}\) depend on \(|\lambda_{2,CMS}|\) (the second largest eigenvalue of CMS in absolute
value) and $|\lambda_2|$, respectively. Since $CMS$ is one of the diagonal blocks of $PU$, $|\lambda_{2,CMS}| \leq |\lambda_2|$. If $0 < \lambda_{2,CMS} < 1$, sufficiently small $\lambda_{2,CMS}$ implies that $n$ is large enough. Hence, $|\lambda_2|^n$ is small enough for the empirical convergence of $A^n$. Suppose after $(n-1)$ generations, the elements in $A^{n-1}$ satisfy

$$\left( \sum_{i,j=1}^{2 \cdot (m+1)l} |a_{ij}^{(n-1)} - 0|^2 \right)^{1/2} < \frac{\epsilon}{2 \cdot (m+1)l - 2 \cdot ml}, \text{ for some } \epsilon. \quad (5.5)$$

Then regardless of the initial distribution,

$$Pr\{\text{The } n^{th} \text{ Generation is an Optimal State}\} > 1 - \epsilon. \quad (5.6)$$

The proof of that is as follows. Suppose the initial distribution is $p_0 = (p_{0,1}, p_{0,2}, p_{0,3}, \ldots, p_{0,2 \cdot (m+1)l})$, where $p_{0,1}, \ldots, p_{0,2 \cdot ml}$ are corresponding to the absorbing states (related to the global optimal solution). Since $p_0$ is a probability distribution, it can be derived that $\sum_{i=2 \cdot ml+1}^{2 \cdot (m+1)l} p_{0,i} \leq 1$.

According to Equation (3.5) and Equation (3.10), we get

$$p_0(PU)^{n-1} = (p_{0,1}, \ldots, p_{0,2 \cdot ml}, p_{0,2 \cdot ml+1}, \ldots, p_{0,2 \cdot (m+1)l}) \begin{pmatrix} (CMSU_{11})^{n-1} & 0 \\ \sum_{i=0}^{n-2} A_i^{n-2-i} R(CMSU_{11})^i & A_{n-1} \end{pmatrix}. \quad (5.7)$$

From Inequality (5.5), it is derived that $a_{ij} < \frac{\epsilon}{2 \cdot (m+1)l - 2 \cdot ml}$ for all $i, j \in \{1, 2, \ldots, 2 \cdot (m+1)l - 2 \cdot ml \}$.

With Equation (5.7), we obtain that the probability for the $n^{th}$ generation (state) to be an transient state is

$$p_{0,2 \cdot ml+1} \cdot (a_{11} + a_{12} + \cdots + a_{1,2 \cdot (m+1)l - 2 \cdot ml}) + \cdots + p_{0,2 \cdot (m+1)l} \cdot (a_{2 \cdot (m+1)l - 2 \cdot ml,1} + \cdots + a_{2 \cdot (m+1)l - 2 \cdot ml,2 \cdot (m+1)l - 2 \cdot ml}) < p_{0,2 \cdot ml+1} \cdot \epsilon + \cdots + p_{0,2 \cdot (m+1)l} \cdot \epsilon < 1 \cdot \epsilon = \epsilon.$$

Hence, the probability for the $n^{th}$ generation (state) to be an optimal (absorbing) state is greater than $1 - \epsilon$. 
5.2 The Proposed Evaluation Metric

5.2.1 Overview of the Methodology

This section proposes an evaluation metric, which derives the applicability of a CGA to a problem from the estimated trace of the corresponding transition matrix. Through this method, a degree of convergence can be determined for each CGA run. According to that, researchers and engineers will be able to obtain a comprehensive view of the applicability of CGA and know how good the solutions generated by CGA, so that more correct decisions can be made. The general methodology diagram is illustrated in Figure 1.1.

5.2.2 Evaluating the Applicability of GAs from Run Time Data

The major concerns for the applicability of GAs to real-world problems are the computation time and the quality of the obtained solutions. Actually, there are tradeoffs between them. For instance, typically the longer the computation time, the better the solution is. Since they are tightly related, without loss of generality, we can fix one and utilize another to estimate the applicability of GAs to problems. Assumption 3 forces us to fix the computation time, whereas the quality of the obtained solution will be used to measure the problem applicability of GAs. Again, the discussion will be focused on CGA.

Due to the lack of information on the landscapes of fitness functions and encodings, it is difficult to analyze the quality of the obtained solution itself; however, the quality of the obtained solution can be measured indirectly through the degree of convergence under certain evaluation metrics from run time data. Theorem 8 functions as a support for the evaluation metric on degrees of convergence. The reason for employing the trace of \((CMS)^{n'}\), where \(n'\) is fixed, to estimate degrees of convergence is because it quantifies degrees of convergence. With it, a number on the degree of convergence of CGA will be given at the end of a CGA run. Based on that, one can determine whether or not the CGA run converges within \(n'\) generations.

**Theorem 8** The trace of \((CMS)^n\) converges to 1 as \(n \to \infty\).
Proof. By Theorem 1, 5, and Lemma 1, it is obtained that CMS has only one eigenvalue which is equal to 1 and others are less than 1.

Moreover, by Theorem 6, every square matrix is unitarily equivalent to a triangular matrix whose diagonal entries are the eigenvalues of the matrix. Hence, \((CMS)^n\) can be written as

\[
(CMS)^n = (STS^*)^n = ST^nS^*,
\]

where \(S\) is a unitary matrix and \(T\) is upper triangular. The diagonal entries of \(T\) are the eigenvalues of CMS. Let the eigenvalues of CMS be denoted as \(\lambda_1, \ldots, \lambda_{2ml}\) with \(1 = \lambda_1 > |\lambda_2| \geq \cdots \geq |\lambda_{2ml}|\). Then

\[
Trace((CMS)^n) = Trace((ST^n)S^*) = Trace(S^*ST^n) = Trace(T^n) = \sum_{i=1}^{2ml} \lambda_i^n. \tag{5.8}
\]

From Equation (5.8), the result, the trace of \((CMS)^n\) converges to 1 as \(n \to \infty\), is derived.

\(\square\)

In fact, Theorem 8 coincides with a result from Theorem 2. In Theorem 2, since CMS is regular, it converges to a positive stable stochastic matrix \(\Pi = ev^T\) as \(n \to \infty\), where \(e = (1, 1, \cdots, 1)^T\) is a \(2ml \times 1\) column vector in which all elements are of the value 1, and \(v^T = (v_1, v_2, \cdots, v_r)\) is a \(1 \times 2ml\) probability row vector with non-null entries. Based on that, the result, \(\lim_{n \to \infty} Trace((CMS)^n) = 1\), can be obtained.

5.2.3 Theoretical Framework for Approximating the Applicability of CGAs

This subsection mainly discusses the methodology adopted to evaluate the applicability of CGAs based on Theorem 8.

The overview of the idea includes:

1. Applying a Monte-Carlo-like simulation (Empirical Probability) [Leemis, L. H. and Park, S. K. (2005)] to estimate \(Trace((CMS)^{n'})\), \(n' \in N\), from states visited by a CGA run.

Note that \(n'\) should be chosen carefully so that \(n - n'\) can be a large number, where \(n\) is the number of generations.
2. Comparing the obtained $\text{Trace}((CMS)^{n'})$ with the “expected” value 1, and then deriving a value for the degree of convergence with respect to that CGA run.

In Assumption 3, $n$, the number of generations, is a reasonably large number and it is fixed. After a CGA run, there will be $n$ generations in total. Each generation corresponds to a state from the state space of the Markov transition matrix $CMS$. During a CGA run, a state representing the next generation will be generated after every selection operation. If all of the $n$ generations (states) are recorded, a list of $n$ states sorted chronologically will be generated at the end of each CGA run. With that list, a number $n' \in \mathbb{N}$, where $n' < n$ and $n - n'$ is a large number, is chosen. The starting states and the ending states are determined accordingly to estimate the trace of $(CMS)^{n'}$. Figure 5.2 illustrates this concept; it shows that for each generation (state) $i$, $1 \leq i \leq (n - n')$, given as a starting state, the $(i + n')^{th}$ generation (state) is the corresponding ending state. After the matching, there are $(n - n')$ pairs of (Starting State, Ending State). Based on the results, one can compute the frequency, or probability, of any starting state which goes back to itself. If all the obtained frequencies are summed up, the obtained value is the approximation of $\text{Trace}((CMS)^{n'})$. Note that an ending state of a pair can also be a starting state of another pair.

According to my empirical investigation, the transition matrix $CMS$ constructed by CGA has the property that its eigenvalues, which have large absolute values, are all real and positive if $p_m$ is small (e.g. $p_m < 0.45$). Only a few eigenvalues of $CMS$, whose absolute values are close to 0, are complex numbers. Intuitively, the transition matrix $M$ constructed by a small mutation probability $p_m$ is symmetric and strictly diagonally dominant (i.e., $M$ is a positive definite matrix). It has eigenvalues which are all real and positive. The sparse matrices $C$ and $S$ do not significantly impact the eigenvalues of $M$. Therefore, the eigenvalues of $CMS$ primarily depend on the eigenvalues of $M$. This fact implies that $\text{Trace}((CMS)^{n'})$ decreases to 1 as $n'$ increases.

**Theorem 9** Any square matrix with identical rows has only one nonzero eigenvalue, which is equal to the sum of any row of the matrix.
Figure 5.2  The Estimation on the Trace of \((CMS)^{n'}\)
Proof. Suppose that \( A \) is an arbitrary square matrix of order \( r \) with identical rows. First, the claim that 0 is an eigenvalue of \( A \) is going to be proved. Based on the definition of eigenvalues \( \text{Horn, R. A. and Johnson, C. R. \ (1985)} \), \( \lambda \) is an eigenvalue of \( A \) if and only if 
\[
det(A - \lambda I_r) = 0.
\]
Let \( \lambda = 0 \) and we have \( det(A - 0 \cdot I_r) = det(A) = 0 \) because \( A \) has identical rows. Hence, 0 is an eigenvalue of \( A \).

Secondly, it is claimed that the eigenspace of \( A \) corresponding to 0 (i.e., the (algebraic) multiplicity of 0) is \( r - 1 \). To compute that, the number of linearly independent eigenvectors corresponding to 0 should be calculated. Consider the equation
\[
Ax = 0 \cdot x, \ x \neq 0.
\]
Since \( A \) has identical rows, there is only one constraint for the \( r \)-dimensional vector \( x \). Therefore, there are \( r - 1 \) linearly independent eigenvectors corresponding to the eigenvalue 0. That is, the eigenspace of \( A \) corresponding to 0 is \( r - 1 \).

Now, let us prove that the only nonzero eigenvalue of \( A \) is the sum of any row of \( A \). Let \( x \) be an \( r \times 1 \) vector \( e = (1, 1, \ldots, 1)^T \). Then
\[
Ax = \begin{pmatrix}
a_{11} & a_{12} & \cdots & a_{1r} \\
a_{11} & a_{12} & \cdots & a_{1r} \\
\vdots & \vdots & \ddots & \vdots \\
a_{11} & a_{12} & \cdots & a_{1r}
\end{pmatrix}
\begin{pmatrix}
1 \\
1 \\
\vdots \\
1
\end{pmatrix} = (a_{11} + a_{12} + \cdots + a_{1r}) \begin{pmatrix}
1 \\
1 \\
\vdots \\
1
\end{pmatrix}.
\]
Hence, \( (a_{11} + a_{12} + \cdots + a_{1r}) \) is an eigenvalue of \( A \). \( \square \)

Theorem 9 tells us that any stochastic stationary state matrix has eigenvalues 1, 0, 0, ..., 0. Based on the discussion above, Theorem 8, and Theorem 9, to determine the degree of convergence one simply needs to compare the obtained value with 1. More specifically, all the diagonal blocks of \( A \) are principal submatrices of \( CMS \) and \( M \) is a positive definite matrix. By the theoretical result from the current state of the art in mathematics \( \text{Hwang, S. \ (2004)} \) and empirical study, the second largest eigenvalue of \( PU \), \( \lambda_2 \), is a little bit larger than, but very close to \( \lambda_{2,CMS} \). Hence, it can be derived that the trace of \((CMS)^{n'}\), where \( n' \in N \), needs to
be close to 1 first (i.e., $|\text{Obtained Value} - 1|$ close to 0), and then the global convergence occurs. That is, $(CMS)^{n'}$ has to be first close to its stationary state matrix, and then $A^{(n'+k)}$, where $k \in N$, is going to be close to 0. Therefore, if the value (or criterion) $|\text{Obtained Value} - 1|$ is close to 0, the degree of convergence is high.

The merit of this approach is that for every CGA run, a degree of convergence can be derived from run time data. With $n'$ being fixed, one can compare different encodings of the same problem, or obtain the values on how good the solutions are for several CGA runs with respect to different problems. Researchers can evaluate the best solution obtained by a CGA based on the degree of convergence.

5.2.4 Foundation of the Methodology

According to Theorem 8 and the discussion in previous subsection, it can be derived that the trace of $(CMS)^n$ determines the degree of convergence. In other words, to obtain the degree of convergence, one can calculate the trace of $(CMS)^n$ first. A traditional way to compute it is first to compute the transition matrix $CMS$; however, as mentioned, the construction time of $CMS$ takes more than the total computation time of all feasible solutions. Therefore, the traditional way is considered to be impractical due to the large computation time.

My methodology to approximate the trace of $(CMS)^{n'}$ is based on the following. In Figure 5.2, the first generation (state) is chosen at random from all feasible solutions. After the first generation is determined, the second generation can be generated by the crossover, mutation, and selection operators of a CGA accordingly. In the perspective of Markov chains, the distribution of the second generation is generated based on the product of the distribution of the first generation and the transition matrix $CMS$. Similarly, the distribution of the third generation is generated based on the product of the distribution of the first generation and the transition matrix $(CMS)^2$, and so on. In general, for $i \in N$, if the distribution of the $i^{th}$ generation is determined, the distribution of the $(i + n')^{th}$ generation can be generated based on the product of the distribution of the $i^{th}$ generation and the transition matrix $(CMS)^{n'}$. To estimate the trace of $(CMS)^{n'}$, the $i^{th}$ generation and the $(i + n')^{th}$ generation need to
be coupled \((i, n' \in N)\). Now consider the physical meaning of the trace of \((CMS)^{n'}\). The diagonal elements of \((CMS)^{n'}\) represent the probabilities of the fix points (states) from the \(i^{th}\) generation to the \((i + n')^{th}\) generation for a CGA. Therefore, the summation of the frequencies (probabilities) of any starting state going back to itself approximates the trace of \((CMS)^{n'}\).

A question about the distribution of samples may be raised. Besides the first generation, the \(i^{th}\) generation \((i \geq 2)\) is dependent on the \((i - 1)^{th}\) generation. That is, after the first generation, the starting state is not chosen uniformly. According to my investigation, this dependency will not cause any problem. On the other hand, it helps improve the accuracy of the approximation. Suppose the transition matrix

\[
(CMS)^{n'} = \begin{pmatrix}
t_{11} & t_{12} & \cdots & t_{1,2mi} \\
t_{21} & t_{22} & \cdots & \vdots \\
\vdots & \vdots & \ddots & \vdots \\
t_{2mi,1} & \cdots & \cdots & t_{2mi,2mi}
\end{pmatrix}.
\]

(5.9)

For the purpose of illustration, we may assume that \(t_{11}\) has a large value, say 0.99, and \(t_{2mi,2mi}\) has a small value, say 0.01. If the first state (i.e., the state corresponds to the element \(t_{11}\) in Equation (5.9)) is generated as the \(i^{th}\) generation \((i \leq n)\), in the \((i + n')^{th}\) generation, it has a high probability (0.99) to be chosen again. Other states have lower probability to become the \((i + n')^{th}\) generation. Similarly, if the last state is generated as the \(i^{th}\) generation, in the \((i + n')^{th}\) generation, it has merely 0.01 probability to be chosen again. Other states have a large probability to become the \((i + n')^{th}\) generation. Accordingly, a state with a large diagonal value has a high probability to become a starting state, and more samples will be collected for estimating it. A state with a small diagonal value may be ignored from the estimation. Compared with the samples collected uniformly, it increases the accuracy of the approximation since the number of samples is fixed (by \(n\) and \(n'\)) and the large diagonal values dominate the trace. If more samples with the starting states being the states with small diagonal values are gathered, fewer samples with starting states being the states with large diagonal values will be collected. In that case, the estimations of large diagonal values as well as the approximation of the trace may not be so accurate.
5.2.5 The Implementation and Data Structure of the Proposed Methodology

Many data structures, such as binary search trees, hash tables, and linked lists, can be applied to implement the proposed methodology. For the purpose of demonstration, binary search trees are applied (see Figure 5.3). Other data structures are also encouraged to be used to speed up the computation time.

For each node in the binary search tree, there are four fields. The first field is a number, the key of the node, representing the starting state converted from a binary string. The second field represents the number of ending states which are the same as the starting state in the first field, and the third field represents the total number of occurrences of the starting state in the first field. The fourth field represents the addresses for the roots of sub-trees.

The following shows how the proposed methodology is implemented:

1. Set the root of the tree to be NULL.

2. Record the first \( n' \) states as starting states using an array.

3. Start from the \( n' + 1 \) state, do 4) to 7) until the stop condition is satisfied.

4. Search for the corresponding starting state in the tree. If it is not found, insert the
corresponding starting state in the tree.

5. Compare the current state with the corresponding starting state. If it is the same as the starting state, add 1 to the second field.

6. Add 1 to the third field.

7. Replace the corresponding starting state with the current state in the array.

Since for each generation the selection operator selects individuals for the entire state, all of the states can be recorded at the same time as the selection. The recording will not increase the complexity of the computation time. In the next subsection, detailed information on the space and time complexity is calculated.

5.2.6 Complexity Analysis

5.2.6.1 Space Complexity

Based on the implementation in the previous section, an array and a binary search tree must be maintained during a CGA run. Each element in the array needs to record a binary string with length \( ml \). Since there are \( n' \) states preserved in the array, the space complexity of the array is \( O(n'ml) \). Moreover, there are \( (n - n') \) pairs of (Starting State, Ending State). Therefore, the tree has to maintain at most \( (n - n') \) nodes. Similar to the array, each node in the tree needs to record a binary string with length \( ml \), so the space complexity of the tree is \( O((n - n')ml) \). Hence, the total space complexity is \( O(nml) \).

5.2.6.2 Time Complexity

The extra time needed for the estimation is mainly from the time to search (or insert) the corresponding starting states in the tree (Step 4 in the previous section). Since there are in total \( (n - n') \) starting states, the tree has at most \( (n - n') \) nodes. The time to search each starting state (or insert a node) in the tree is \( O(\log(n - n')) \) in the average case and \( O((n - n')) \) in the worst case. That is, the total time complexity is \( O(n \cdot \log(n)) \) in the average case and
$O(n^2)$ in the worst case. However, a form of self-balancing binary search tree, such as red-black trees, can be used for improving the computation time. With that form, insertions and searches are $O(\log(n))$ in the worst case. In other words, the total time complexity becomes $O(n \cdot \log(n))$ in the worst case.

5.3 Experimental Validation of the Proposed Evaluation Metric

My goal for the experiments is to investigate the usability of the proposed evaluation metric. To facilitate the experimental comparisons in the following sections, we can fix the value of some of the CGA parameters. The fixed parameters are:

- the crossover probability $p_c$ is set to 0.5
- the mutation probability $p_m$ is set to 0.01 (a small value)

In addition, for the purpose of validation, several fitness functions, including 1-dimensional and 3-dimensional functions, with their known optimal solutions are selected as test functions.

5.3.1 One Dimensional Fitness Functions

Eight 1-dimensional fitness functions with different degrees of difficulty for CGAs are investigated and analyzed. The eight fitness function types are: a linear function, a quadratic function, a periodic function, a fraction function, two functions with isolation optimal points (called needle-in-a-haystack (NIAH) [Horn, J. and Goldberg, D. E. (1995); Horn, J. (1995)]), a function consisting of unequal spaced peaks of uniform heights, and a function consisting of unequal spaced peaks of nonuniform heights [Sareni, B. and Krahenbuhl, L. (1998); Petrowski, A. (1996)]. The fitness functions and their optimal fitness values are presented in Table 5.1 (the default value for the domains is $[0, 600]$).

5.3.2 Discussion of the Sizes of Samples

One may argue how we can be sure that the size of the samples is sufficient for deriving a proper approximation. To answer this question, experiments of sample sizes with respect to
Table 5.1  The Selected Fitness Functions

<table>
<thead>
<tr>
<th>Fitness Function</th>
<th>Optimal Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>( f_1(x) = x )</td>
<td>600</td>
</tr>
<tr>
<td>( f_2(x) = 360000 - x^2 )</td>
<td>360000</td>
</tr>
<tr>
<td>( f_3(x) = 1 + \sin(x) )</td>
<td>2</td>
</tr>
<tr>
<td>( f_4(x) = \frac{1}{\sqrt{x} + 1} )</td>
<td>1</td>
</tr>
</tbody>
</table>
| \( f_5(x) = \begin{cases} -x^2 + 90000, x < 300 \\
                        100000, x = 300 \\
                        -(x - 600)^2 + 90000, x > 300 \\
\end{cases} \) | 100000       |
| \( f_6(x) = \begin{cases} 100000, x = 0 \\
                        -(x - 300)^2 + 90000, x \neq 0 \\
\end{cases} \) | 100000       |
| \( f_7(x) = \sin(6\pi \cdot \frac{x}{3} - 0.05) \) | 1            |
| \( f_8(x) = e^{-2 \cdot (\ln(2) \cdot (\frac{x}{600} - 0.080854)^2 \cdot \sin(6\pi \cdot \frac{x}{3} - 0.05))} \) | 1            |

encoding sizes for a problem are conducted.

For the following observations, I apply the theoretical truth, if the power \( n' \) is fixed, the value \( \text{Trace}((CMS)^n') \) is fixed. With the setting on both the number of individuals in a generation \( m = 2 \) and the length of feasible solutions \( l = 2 \), \( CMS \) has a total of \( 2^4 = 16 \) states. Table 5.2 lists the average results for fitness function \( f_2 \) from 20 trials of CGA runs for the number of generations ranging from 5000 to 10000 with the actual traces compared. Note that similar results are also derived for other fitness functions.

Table 5.2  The Estimated \( \text{Trace}((CMS)^n') \) w.r.t. the Number of Generations and Power \( n' \)

<table>
<thead>
<tr>
<th>No. of Gens \ Power ( n' )</th>
<th>10</th>
<th>12</th>
<th>14</th>
<th>16</th>
<th>18</th>
<th>20</th>
</tr>
</thead>
<tbody>
<tr>
<td>5000</td>
<td>2.7331</td>
<td>2.5614</td>
<td>2.4094</td>
<td>2.2540</td>
<td>2.1660</td>
<td>2.0517</td>
</tr>
<tr>
<td>6000</td>
<td>2.7543</td>
<td>2.5584</td>
<td>2.4156</td>
<td>2.2564</td>
<td>2.1737</td>
<td>2.0527</td>
</tr>
<tr>
<td>7000</td>
<td>2.7579</td>
<td>2.5620</td>
<td>2.4104</td>
<td>2.2631</td>
<td>2.1715</td>
<td>2.0532</td>
</tr>
<tr>
<td>8000</td>
<td>2.7551</td>
<td>2.5592</td>
<td>2.4143</td>
<td>2.2613</td>
<td>2.1742</td>
<td>2.0556</td>
</tr>
<tr>
<td>9000</td>
<td>2.7507</td>
<td>2.5672</td>
<td>2.4070</td>
<td>2.2284</td>
<td>2.1716</td>
<td>2.0539</td>
</tr>
<tr>
<td>10000</td>
<td>2.7551</td>
<td>2.5558</td>
<td>2.4105</td>
<td>2.2708</td>
<td>2.1671</td>
<td>2.0548</td>
</tr>
<tr>
<td>Actual Traces</td>
<td>3.0441</td>
<td>3.1863</td>
<td>3.0771</td>
<td>2.9737</td>
<td>2.8763</td>
<td>2.7843</td>
</tr>
</tbody>
</table>

As we can see, with the same \( n' \), no matter how many generations exist, the results for estimated \( \text{Trace}((CMS)^n') \) are almost the same for each one, and are close to actual traces. Therefore, it is concluded that those numbers of generations are large enough for \( l = 2 \) and \( m = 2 \).

Now let the length \( l \) be set to 16. Table 5.3 shows the average results for fitness functions
f_1 and f_2 from 20 trials of CGA runs for the number of generations ranging from 5000 to 10000. Note that similar results are also derived for other fitness functions.

Table 5.3 The Estimated \( Trace((CMS)^{n'}) \) With Respect To the Number of Generations and Power \( n' \)

<table>
<thead>
<tr>
<th>No. of Gens</th>
<th>Fitness Function ( f_1 )</th>
<th>Fitness Function ( f_2 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>5000</td>
<td>10 15 20 25</td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>1.0645 1.0645</td>
<td></td>
</tr>
<tr>
<td>15</td>
<td>1.0887 1.0887</td>
<td></td>
</tr>
<tr>
<td>20</td>
<td>1.1031 1.1031</td>
<td></td>
</tr>
<tr>
<td>25</td>
<td>1.1233 1.1233</td>
<td></td>
</tr>
<tr>
<td>6000</td>
<td>10 15 20 25</td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>2.082 2.082</td>
<td></td>
</tr>
<tr>
<td>15</td>
<td>2.1031 2.1031</td>
<td></td>
</tr>
<tr>
<td>20</td>
<td>2.1233 2.1233</td>
<td></td>
</tr>
<tr>
<td>25</td>
<td>2.1435 2.1435</td>
<td></td>
</tr>
<tr>
<td>7000</td>
<td>10 15 20 25</td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>2.5041 2.5041</td>
<td></td>
</tr>
<tr>
<td>15</td>
<td>2.5243 2.5243</td>
<td></td>
</tr>
<tr>
<td>20</td>
<td>2.5446 2.5446</td>
<td></td>
</tr>
<tr>
<td>25</td>
<td>2.5650 2.5650</td>
<td></td>
</tr>
<tr>
<td>8000</td>
<td>10 15 20 25</td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>3.2504 3.2504</td>
<td></td>
</tr>
<tr>
<td>15</td>
<td>3.2707 3.2707</td>
<td></td>
</tr>
<tr>
<td>20</td>
<td>3.2910 3.2910</td>
<td></td>
</tr>
<tr>
<td>25</td>
<td>3.3113 3.3113</td>
<td></td>
</tr>
<tr>
<td>9000</td>
<td>10 15 20 25</td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>4.0506 4.0506</td>
<td></td>
</tr>
<tr>
<td>15</td>
<td>4.0708 4.0708</td>
<td></td>
</tr>
<tr>
<td>20</td>
<td>4.0910 4.0910</td>
<td></td>
</tr>
<tr>
<td>25</td>
<td>4.1112 4.1112</td>
<td></td>
</tr>
<tr>
<td>10000</td>
<td>10 15 20 25</td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>5.2504 5.2504</td>
<td></td>
</tr>
<tr>
<td>15</td>
<td>5.2707 5.2707</td>
<td></td>
</tr>
<tr>
<td>20</td>
<td>5.2910 5.2910</td>
<td></td>
</tr>
<tr>
<td>25</td>
<td>5.3113 5.3113</td>
<td></td>
</tr>
</tbody>
</table>

Table 5.3 shows that the results are different from previous results since as the number of generations increases, the estimated \( Trace((CMS)^{n'}) \) increases. This occurs because the numbers of samples for the \( 2^{32} \) states are relatively small. Some diagonal elements of \( (CMS)^{n'} \) will not be calculated by the small numbers of samples; however, based on the data from Table 5.3, we observe that both of the \( Trace((CMS)^{n'}) \) converge to 1 as \( n' \) increases. A conclusion can be drawn that although the number of samples sometimes may not be large enough for large \( l \)’s, for some \( n' \), the estimated \( Trace((CMS)^{n'}) \) is still referenceable. The setting of the \( n' \) depends on the setting of \( l \) and experiences.

As mentioned before, it is believed that large diagonal elements are easily estimated by the proposed metric. To verify, I have run several experiments. The result for \( f_2 \) is presented in Figure 5.5. Similar results can be derived for other fitness functions. As shown, the estimated \( Trace((CMS)^{n'}) \) increases rapidly before a large enough number of generations (e.g., \( n = 5000 \)) and after, it increases asymptotically to its actual value. If we choose the fixed number of generations close to the turning point (\( n = 5000 \)), a certain amount (percentage) of \( Trace((CMS)^{n'}) \) can be derived. The detailed data from Figure 5.5 is shown in Table 5.4.

Table 5.4 implies that when a state space has \( 2^9 = 512 \) states and the (fixed) number of generations is set to 2000, more than 50% of \( Trace((CMS)^{n'}) \) can be estimated if \( n' \) is between 10 and 26. In addition, small \( n' \) (e.g., \( n' = 10 \)) has better estimated precision than large \( n' \) (e.g., \( n' = 26 \)). However, the power \( n' \) cannot be set too small since with small \( n' \), relatively small eigenvalues are still not very close to zero, which causes some noise if the purpose is to
The Trace Values Comparison of Traces for \( f_2 \)
The Estimated Trace of CMS to the Power 10
The Actual Trace
The Number of Generations
(a) Power \( n' = 10 \)

The Trace Values Comparison of Traces for \( f_2 \)
The Estimated Trace of CMS to the Power 26
The Actual Trace
The Number of Generations
(b) Power \( n' = 26 \)

Figure 5.4 The relationship between estimated trace values, actual trace values, and numbers of generations with \( m = 3, l = 3 \)

predict a degree of convergence. In other words, \( (CMS)^{n'} \) with too small \( n' \) has large number of diagonal elements being not very close to zero, which makes the estimation difficult for the proposed metric because the sample size is relatively small with respect to the number of states in the state space.

5.3.3 Discussion of the Precision of the Estimation

Now, let us compare the estimated \( \text{Trace}((CMS)^{n'}) \) of fitness functions and their actual values. In order to accomplish this comparison, I have run the experiments on a High-Performance-Computer (HPC: hpc-class.iastate.edu). The maximal order of the transition matrices (square matrices) estimated for the actual trace values is \( 2^{10} \). In this case, we can either set \( (m, l) = (2, 5) \), or \( (m, l) = (5, 2) \). Both of them draw the same conclusion. Table 5.5 presents the estimated and actual values of \( \text{Trace}((CMS)^{n'}) \) for \( (m, l) = (2, 5) \) with the (fixed) number of generations being set to 10000. Other settings with \( ml \leq 10 \) have similar results.

In Table 5.5, if we compare the estimated \( \text{Trace}((CMS)^{n'}) \) with \( n' \) being fixed, we get that all of the estimated \( \text{Trace}((CMS)^{n'}) \) have close percentages of accuracy. The rates for
The Estimated Value and the Actual Value are between 50% and 60%. As we can see, those rates are larger than the percentages of visited states for most \( n' \). This coincides with the earlier conclusion that the states with large diagonal elements tend to be visited first. With this feature, we can be sure that if a fitness function has larger trace value for a certain \( n' \), the proposed evaluation metric will not underestimate its \( \text{Trace}((CMS)^{n'}) \) compared to the estimated traces of other fitness functions. For the same reason, small \( n' \) has better estimated precision than large \( n' \).

However, a concern may be raised that the discussion and observation above are based on the condition that the number of samples is greater than the number of states. The relation between estimated \( \text{Trace}((CMS)^{n'}) \) with a fixed \( n' \) and a number of generations \( n \) with \( n \) smaller than a predefined number of states is not specified. My empirical investigation shows that the estimated \( \text{Trace}((CMS)^{n'}) \) and the number of generations \( n \) are linearly related if \( n \) is less than the number of states. Figure 5.5 illustrates their relationship with respect to \( f_2 \) and \( f_8 \) when the setting is \((n', m, l) = (10, 2, 16)\). That means, the estimated traces with respect to fitness functions should have close percentages of accuracy with \( n \) smaller than the number of states, if they have close percentages of accuracy with \( n \) larger than or equal to the number of states.
5.3.4 Discussion of the Convergence Trend

Another feature in the data shown in Table 5.3 is that with the number of generations being fixed, the estimated $\text{Trace}((CMS)^{n'})$ decreases as $n'$ increases. Therefore, the convergence trend of the estimated $\text{Trace}((CMS)^{n'})$ remains the same as the convergence trend of the theoretical value of $\text{Trace}((CMS)^{n'})$. This feature can be applied to evaluate the degrees of convergence asserted earlier in this dissertation.

To analyze the convergence trends of the estimated $\text{Trace}((CMS)^{n'})$ with respect to the fitness functions, the number of individuals within a generation $m$ is set to 2, the length of an individual (a feasible solution) $l$ is set to 16, the number of generations is fixed to 10000, and the power $n'$ of $(CMS)^{n'}$ is set from 10 to 24, respectively. The derived result, shown in Figure 5.6, is the average over 40 trials of CGA runs. For the purpose of verification, a set of numerical data representing the range for numbers of generations at which the CGA with best solution maintained over time has probability of 80% to reach the global (or near) optimal solution, shown in Table 5.6, is derived from 1000 trials.

Figure 5.6 shows the relationship between $n'$ and the estimated $\text{Trace}((CMS)^{n'})$, and demonstrates that no matter what type the fitness function, as $n'$ increases, the estimated $\text{Trace}((CMS)^{n'})$ decreases. All of the estimated values of $\text{Trace}((CMS)^{n'})$ approach to a value between 0 and 1 with increasing $n'$. This result coincides with Theorem 8 and discussions in both Section 5.3.2 and Section 5.3.3. Moreover, the fitness functions are clustered based on their difficulties for CGAs. Depending on different scales for clustering, two or more clusters can be identified in the figure. In my opinion, fitness functions $f_1, f_2, f_4, f_5$, and $f_6$ can be considered to be in the same cluster, fitness functions $f_3$ and $f_8$ are in another, and $f_7$ is in the other. Compared with Table 5.6, we obtain that except for the fitness function $f_4$, the clustering in Figure 5.6 is consistent with the set of numerical data in Table 5.6. Since the landscape of the fitness function $f_4$ is almost flat, the fitness value is not sensitive with respect to the modifications of the value $x$. With this type of fitness function, proportional selection cannot discriminate “good” solutions from “bad” ones. Therefore, during a CGA run, most states have large probabilities of remaining the same in the next generation. In other words,
this type of fitness function results in a transition matrix which has a large number of diagonal entries which are not close to 0 and have values close to each other. This feature will cause problems for the proposed methodology since there may not be enough samples to reach all of the states and accurately estimate $\text{Trace}((CMS)^{n'})$, $n' \in N$. However, besides $f_4$, the clustering shows that the proposed evaluation metric has the ability to distinguish the degrees of difficulty of the CGA.

### 5.3.5 Discussions on the Confidence Intervals

Further investigation on the relationship between $n'$ and the estimated value $\text{Trace}((CMS)^{n'})$ generated by the proposed evaluation metric is conducted. The distributions for the estimated
traces generated by the metric with respect to \( f_1 \) to \( f_8 \) are illustrated in Figure 5.7 to Figure 5.14, respectively. The settings remain the same as in the previous discussion on the convergence trend. The 95\% standard confidence intervals (SCIs) are computed for all of the fitness functions \( f_1 \) to \( f_8 \) (see Figure 5.15 to Figure 5.22). Note that the evaluation metric cannot derive 100\% of true trace values (see Section 5.3.3). The 95\% SCIs merely can tell us something about the true mean value (i.e., the mean of all possible outcomes) generated by the metric, which is certain percentage of the true trace value.

The SCI tends to shrink as \( n' \) increases. Among \( f_1 \) to \( f_8 \), \( f_7 \) has the largest confidence intervals for \( n' = 10 \) and \( n' = 24 \), whose lengths are around 2.02 and 0.60 (less than 1), respectively. In Figure 5.23, the 95\% SCIs for \( f_1 \), \( f_3 \), and \( f_7 \) representing the three clusters mentioned in the previous discussion are compared. The SCIs for \( f_1 \) do not overlap with the SCIs for \( f_3 \). Similarly, the SCIs for \( f_3 \) do not overlap with the SCIs for \( f_7 \). It confirms that the clustering of fitness functions with respect to the estimated values of \( \text{Trace}((CMS)^{n'}) \) derived by the evaluation metric is valid and has a strong discrimination. In reality, except \( f_4 \), \( f_7 \) is the most difficult fitness function among \( f_1 \) to \( f_8 \) for the CGA with the setting \((m, l) = (2, 16)\) (see Table 5.6).

In the literature, researchers who investigate confidence intervals have asserted that the actual coverage probability of the SCI may sometimes not be equal to the nominal level claimed, especially when the sample is small [Brown, L. D. and Cai, T. T. and DasGupta, A. (2001)]. Several alternative intervals are recommended. The Wilson interval (WI) is one of them and used to compare with the SCI here (see Figure 5.24 to Figure 5.31). As we can see, the WI also tends to shrink as \( n' \) increases. Most of the mean values and the lengths of WIs are slightly smaller than those of SCIs. Figure 5.32 shows the mean values of WI and SCI for the fitness functions \( f_1 \) and \( f_8 \), respectively. Carefully comparing the WIs and SCIs for the eight fitness functions, we can get that when \( n' \geq 14 \), the two intervals overlap each other. No matter which interval (WI or SCI) is used for the comparison, the clusters formed earlier are still valid.
Table 5.4  The Data of Figure 5.4(a) and 5.4(b)

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<th>No. of Gens</th>
<th>Estimated Value</th>
<th>Actual Value</th>
<th>%</th>
<th>Estimated Value</th>
<th>Actual Value</th>
<th>%</th>
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Figure 5.7  The Distribution with respect to $f_1$
### Table 5.5 Comparison with Actual Trace Values

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**Percentages of Visited States (%)**

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<th>Fitness $f_4$</th>
<th>Fitness $f_5$</th>
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**Percentages of Visited States (%)**

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<th>Fitness $f_4$</th>
<th>Fitness $f_5$</th>
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**Percentages of Visited States (%)**

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</tr>
</thead>
<tbody>
<tr>
<td>30.37</td>
<td>31.74</td>
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Figure 5.8  The Distribution with respect to $f_2$
Figure 5.9  The Distribution with respect to $f_3$
Figure 5.10  The Distribution with respect to $f_4$
Figure 5.11  The Distribution with respect to $f_5$
Figure 5.12 The Distribution with respect to $f_6$
Figure 5.13  The Distribution with respect to $f_7$
Figure 5.14  The Distribution with respect to $f_8$
Figure 5.15 95% SCI for $f_1$

Figure 5.16 95% SCI for $f_2$

Figure 5.17 95% SCI for $f_3$

Figure 5.18 95% SCI for $f_4$

Figure 5.19 95% SCI for $f_5$

Figure 5.20 95% SCI for $f_6$

Figure 5.21 95% SCI for $f_7$

Figure 5.22 95% SCI for $f_8$
Figure 5.23 The Comparison of 95% SCIs for the Estimated Trace Values Generated by the Proposed Evaluation Metric
Figure 5.24 95% WI for $f_1$

Figure 5.25 95% WI for $f_2$

Figure 5.26 95% WI for $f_3$

Figure 5.27 95% WI for $f_4$

Figure 5.28 95% WI for $f_5$

Figure 5.29 95% WI for $f_6$

Figure 5.30 95% WI for $f_7$

Figure 5.31 95% WI for $f_8$
Table 5.6 The Range for Numbers of Generations at which the CGA with Best Solution Maintained Over Time Has Probability of 80% (out of 1000 Trials) to Reach the Global (or Near) Optimal Solution

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<td>$f_8$</td>
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5.3.6 Discussions on the Smallest Number of Samples Needed for the Estimation

Through above discussions, we know that the proposed evaluation metric has the ability to determine the order of fitness functions sorted by the difficulty levels for CGAs. This subsection simply discusses the smallest number of samples needed for the estimation. Similar as before, the fitness functions, except $f_4$, with the setting $(n', m, l) = (10, 2, 16)$ are investigated. Assume that for the same $n'$, using a larger number of samples derives the estimated Trace($((CMS)^{n'})$) closer to the actual trace value. The order of fitness functions when the number of generations $n = 20000$ is compared with smaller numbers of generations. When $n = 20000$, the order of the fitness functions from the most difficult one (i.e., the one has the largest Trace($((CMS)^{10})$)) to the easiest one is

$$f_7 \rightarrow f_8 \rightarrow f_3 \rightarrow f_6 \rightarrow f_5 \rightarrow f_1 \rightarrow f_2$$

Note that when $n = 10000$, the order of fitness functions is exactly the same as the above order. Figure 5.33 shows the results obtained from using smaller numbers of generations.

As we can see, when the number of generations increases, the estimated traces increase linearly. This result is similar as the result in Figure 5.5. From $n = 500$ to $n = 8500$, the two lines representing the trace values for $f_5$ and $f_6$ are tangled. This is also the case when $n$ is around 20000. When $n = 500$, the traces for $f_7$ and $f_8$ already have larger values than
Figure 5.32 The means of WI and SCI for fitness functions $f_1$ and $f_8$, respectively.

X-Axis: The Number of Generations $n$; Y-Axis: Estimated Trace of CMS to the Power 10

Figure 5.33 The order of fitness functions w.r.t. smaller numbers of generations.
the traces for other fitness functions; however, the difference of the traces for any two fitness functions is very small, which may cause problems. For instance, we cannot know whether the fitness function which has a smaller trace is actually the easier one or not. When \( n = 1000 \), we get the exact same order of fitness functions presented above. This shows that the smallest number of samples needed for the setting \((n', m, l) = (10, 2, 16)\) can be around 1000. Compared with the number of states \(2^{32}\) and the number of feasible solutions in the solution space \(2^{16}\), it is a small number.

5.3.7 Multi-Dimensional Fitness Functions

In order to present more evidence for verifying my proposed methodology, five 3-dimensional fitness functions are selected, including Ackley’s, Rastrigin’s, and Sphere functions, with different degrees of difficulty for CGAs [Tang, K. and Yao, X. and Suganthan, P. N. and MacNish, C. and Chen, Y. P. and Chen, C. M and Yang, Z. (2007)]. Ackley’s, Rastrigin’s, and Sphere functions are designed to be minimized. The selection technique utilized in all experiments in this dissertation, roulette wheel selection, enables a CGA to maximize fitness functions. Hence, those fitness functions are slightly adjusted in this experiment. The five fitness functions investigated are in Table 5.7. Intuitively, the fitness functions \(f_9\) and \(f_{10}\) are relatively simple among the five, since both of them only have one optimal solution. Comparing the features of the rest of the fitness functions, Ackley’s function is more difficult for a CGA than Rastrigin’s

<table>
<thead>
<tr>
<th>Fitness Function</th>
<th>Optimal Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>(f_9(x) = (\sum_{i=1}^{3} x_i) + 16), where (x_1, x_2, x_3 \in [-5, 5])</td>
<td>31</td>
</tr>
<tr>
<td>(Sphere Function - Unimodal and Separable)</td>
<td></td>
</tr>
<tr>
<td>(f_{10}(x) = -x_1 x_2 x_3 + 76), where (x_1, x_2, x_3 \in [-5, 5])</td>
<td>76</td>
</tr>
<tr>
<td>(Ackley’s Function 1 - Multimodal, and Non-separable)</td>
<td></td>
</tr>
<tr>
<td>(f_{11}(x) = -(-20 e^{-0.2 \sqrt{\sum_{i=1}^{3} x_i^2}} - e^3 \sum_{i=1}^{3} \cos(2 \pi x_i) + 20 + e) + 15), where (x_1, x_2, x_3 \in [-5, 5])</td>
<td>15</td>
</tr>
<tr>
<td>(Ackley’s Function 2 - Multimodal, and Non-separable)</td>
<td></td>
</tr>
<tr>
<td>(f_{12}(x) = -(-20 e^{-0.2 \sqrt{\sum_{i=1}^{3} x_i^2}} - e^3 \sum_{i=1}^{3} \cos(2 \pi x_i) + 20 + e) + 23), where (x_1, x_2, x_3 \in [-32.768, 32.768])</td>
<td>23</td>
</tr>
<tr>
<td>(Rastrigin’s Function - Multimodal, and Separable)</td>
<td></td>
</tr>
<tr>
<td>(f_{13}(x) = -(\sum_{i=1}^{3} x_i^2 - 10 \cos(2 \pi x_i) + 10)) + 135), where (x_1, x_2, x_3 \in [-5, 5])</td>
<td>135</td>
</tr>
</tbody>
</table>
function, since Ackley’s function is not only multimodal, but also non-separable (i.e., it cannot be rewritten as a sum of several functions of just one variable) [Hadley, G. (1964)]. Separable functions can be optimized for each variable in turn. Non-separable functions are more difficult to optimize as the accurate search direction depends on two or more genes. The result of this experiment, shown in Figure 5.34, is the average from 40 trials of CGA runs. The confidence intervals with respect to the settings of \( n' \) are similar to the results derived for 1-dimensional fitness functions. From Figure 5.34, the estimated trace derived by \( f_{12} \) is larger than that of \( f_{11} \) since the range \([-32.768, 32.768]\) includes more peaks than the range \([-5, 5]\). The degree of difficulty of \( f_{12} \) is higher than that of \( f_{11} \) for a CGA. Moreover, when fitness functions are multi-dimensional, the traces estimated by the proposed evaluation metric still coincide with the earlier assertion that more difficult fitness functions, with respect to a CGA, result in higher estimated traces. The proposed evaluation metric has the ability to determine the best fitness function for a CGA among a set of fitness functions.
5.3.7.1 Observations on the Experiments

Due to the fact that usually the sample size is relatively small compared to the state space size, the estimated $Trace((CMS)^n')$ is only a small percentage of the actual $Trace((CMS)^n')$. The criterion (i.e., $|\text{Obtained Value} - 1|$) discussed in Section 5.2.3 for determining a degree of convergence should be slightly adjusted. Since the actual $Trace((CMS)^n')$ is greater than or equal to 0 for all $n \in N$, any percentage of $Trace((CMS)^n')$ should be greater than or equal to 0. The criterion can be modified to $|\text{Obtained Value} - 0|$ (i.e., Obtained Value) to reflect that the smaller the estimated $Trace((CMS)^n')$, the higher the degree of convergence.

From the experiments, the probability that multiple encoded points have equal fitness values is low, even for periodic functions. That is, in the real world, there is usually one global optimal solution in the search space of CGAs. Different settings of $m$ and $l$ may cause different orders of fitness functions sorted by difficulty to a certain CGA configuration. The reason is that the number of points encoded in a search space for discovering the landscape of a fitness function is based on $l$. Small $l$ implies a small number of points encoded in a search space. In that case, a non-smooth fitness function may become a smooth one due to the lack of points. The setting of $m$ impacts probabilities of selecting individuals. Another observation is that different domains of a fitness function encoded in a search space have a high possibility to result in different degrees of difficulties for a CGA, which is because more of the landscape of the fitness function, such as peaks, and valleys, is included in a larger domain.

In addition, before running a CGA with the evaluation metric, one has to check:

1. Sensitivity of the fitness function;

2. Fitness values of the encoding 0000…0 and 1111…1;

3. If the isolation points are known, the fitness values of those points should be computed in advance.

Checking the sensitivity of the fitness function helps researchers determine whether or not the defined fitness function has a low discrimination for “good” and “bad” solutions. In real-world applications, CGAs with non-sensitive fitness functions are rare. Practitioners apply
CGAs to obtain (near) optimal solutions. If the fitness function is almost flat for a CGA, it is meaningless to spend time searching for the global optimal solution. Besides, the low discrimination fitness function can always be reformulated to improve the performance of CGAs. Through the second step, the isolation points of the fitness function in the extreme locations can be known beforehand. This step is essential because the isolation points other than 0000...0 and 1111...1 are relatively easy to produce by chance through crossover and mutation operators. Checking the extreme cases first helps CGAs to have a better chance to find the global optimal solution.
CHAPTER 6.  The Estimation of Global Convergence

This chapter presents an approach to using the proposed evaluation metric in Chapter 5 for estimating the number of generations needed for the best solution generated by a CGA to converge to the global optima of a fitness function.

6.1 The Overview of the Estimation

The estimation includes the following three phases (see Figure 6.1):

- the empirical estimation on $\text{Trace}(CMS^{n'})$ and $\text{Trace}(CMS^{n'+k})$, for some $n', k \in \mathbb{N}$,
- the generation of a fitting curve based on $\text{Trace}(CMS^{n'})$ and $\text{Trace}(CMS^{n'+k})$, and
- the derivation of the least number of generations needed (for global convergence) from the fitting curve and a small fixed $\epsilon$.

Each phase is introduced below.

6.1.1 The Empirical Estimation on the Traces and the Fitting Curve

In the experiments of Chapter 5, estimated traces derived by the proposed evaluation metric are merely certain proportions of the actual ones. Without any other information, the exact actual trace is difficult to determine from the estimated trace. To closely estimate a trace, one has to know the number of states visited by a CGA run, which can be computed by directly counting the number of nodes in the linked list in Figure 5.3. Being aware of the number of states visited by a CGA run, the proportion of the visited states over the total number of states is derived, which is used to estimate the actual trace below.
Figure 6.1  The Overview of the Estimation
Due to the limitation of the computer capability, the maximal order of the transition matrices (square matrices) estimated for the actual traces is $2^{10}$. For this reason, the setting $m = 2$ is used to develop the entire estimation framework as an illustration. Similar frameworks can be derived by the same way for other settings of $m$. Table 6.1 and Table 6.2 show the relationships among the estimated trace, the proportion of the visited states over the total number of states, and the actual trace with respect to the fitness function $f_1(x) = x$. Note that the actual traces for the settings $l > 5$ are guessed by fitting a curve to the previous four points (i.e., $(m, l) = (2, 2), (2, 3), (2, 4)$ and $(2, 5)$).

<table>
<thead>
<tr>
<th>Settings</th>
<th>$m = 2, l = 2$</th>
<th>$m = 2, l = 3$</th>
<th>$m = 2, l = 4$</th>
<th>$m = 2, l = 5$</th>
<th>$m = 2, l = 6$</th>
<th>$m = 2, l = 7$</th>
<th>$m = 2, l = 8$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of Generations: 500</td>
<td>18</td>
<td>27</td>
<td>54</td>
<td>89</td>
<td>121</td>
<td>157</td>
<td>186</td>
</tr>
<tr>
<td>Percentages of Visited States (%)</td>
<td>62.50</td>
<td>42.19</td>
<td>21.09</td>
<td>8.69</td>
<td>2.95</td>
<td>0.96</td>
<td>0.28</td>
</tr>
<tr>
<td>Estimated Trace by the Proposed Metric</td>
<td>1.9425</td>
<td>2.094</td>
<td>3.0592</td>
<td>4.1131</td>
<td>4.4298</td>
<td>4.6717</td>
<td>3.9965</td>
</tr>
<tr>
<td>Estimated Trace/Percentages of Visited States ($\times 500$)</td>
<td>0.9019</td>
<td>6.5644</td>
<td>17.1131</td>
<td>31.3240</td>
<td>48.9540</td>
<td>60.6661</td>
<td>125.4194</td>
</tr>
<tr>
<td>$(\times 500)/$The Actual Trace</td>
<td>0.9837</td>
<td>1.9733</td>
<td>3.6767</td>
<td>2.3842</td>
<td>4.5454</td>
<td>6.6464</td>
<td>10.5079</td>
</tr>
<tr>
<td>Number of Generations: 1000</td>
<td>13</td>
<td>35</td>
<td>77</td>
<td>141</td>
<td>208</td>
<td>284</td>
<td>352</td>
</tr>
<tr>
<td>Percentages of Visited States (%)</td>
<td>81.25</td>
<td>54.69</td>
<td>30.08</td>
<td>13.77</td>
<td>5.08</td>
<td>1.73</td>
<td>0.54</td>
</tr>
<tr>
<td>Estimated Trace/Percentages of Visited States ($\times 1000$)</td>
<td>2.7166</td>
<td>5.8435</td>
<td>15.9527</td>
<td>44.0021</td>
<td>135.6001</td>
<td>401.7019</td>
<td>1224.4665</td>
</tr>
<tr>
<td>$(\times 1000)/$The Actual Trace</td>
<td>0.8221</td>
<td>0.9399</td>
<td>1.4202</td>
<td>2.2193</td>
<td>3.7666</td>
<td>6.1224</td>
<td>9.2504</td>
</tr>
<tr>
<td>Number of Generations: 2000</td>
<td>13</td>
<td>39</td>
<td>90</td>
<td>176</td>
<td>275</td>
<td>398</td>
<td>507</td>
</tr>
<tr>
<td>Percentages of Visited States (%)</td>
<td>81.65</td>
<td>60.94</td>
<td>35.16</td>
<td>17.19</td>
<td>6.81</td>
<td>2.43</td>
<td>0.77</td>
</tr>
<tr>
<td>Estimated Trace/Percentages of Visited States ($\times 2000$)</td>
<td>2.7489</td>
<td>5.7410</td>
<td>14.8255</td>
<td>42.2382</td>
<td>127.3931</td>
<td>383.6346</td>
<td>1292.6409</td>
</tr>
<tr>
<td>$(\times 2000)/$The Actual Trace</td>
<td>0.8865</td>
<td>0.9516</td>
<td>1.3081</td>
<td>2.1307</td>
<td>3.5268</td>
<td>5.8439</td>
<td>9.0753</td>
</tr>
<tr>
<td>Number of Generations: 5000</td>
<td>14</td>
<td>42</td>
<td>100</td>
<td>203</td>
<td>335</td>
<td>498</td>
<td>647</td>
</tr>
<tr>
<td>Percentages of Visited States (%)</td>
<td>87.30</td>
<td>65.63</td>
<td>35.06</td>
<td>19.92</td>
<td>8.18</td>
<td>1.04</td>
<td>0.59</td>
</tr>
<tr>
<td>Estimated Trace by the Proposed Metric</td>
<td>2.6475</td>
<td>5.2041</td>
<td>5.7226</td>
<td>7.7670</td>
<td>10.0029</td>
<td>11.7726</td>
<td>11.5273</td>
</tr>
<tr>
<td>Estimated Trace/Percentages of Visited States ($\times 5000$)</td>
<td>2.6475</td>
<td>5.4265</td>
<td>14.2601</td>
<td>39.1179</td>
<td>122.3023</td>
<td>367.5734</td>
<td>1167.6285</td>
</tr>
<tr>
<td>$(\times 5000)/$The Actual Trace</td>
<td>0.8012</td>
<td>0.9038</td>
<td>1.3864</td>
<td>1.9738</td>
<td>3.3882</td>
<td>5.5993</td>
<td>9.7800</td>
</tr>
</tbody>
</table>

Table 6.1 The Relationships among the Estimated Trace, the Proportion of the Visited States over the Total Number of States ($n = 10$)

As shown in both Table 6.1 and Table 6.2, the value, derived by dividing the estimated trace by the proportion of the visited states over the total number of states, is greater than the actual trace when setting $m = 2$ and $l \geq 4$. Moreover, the relationship between the value and
<table>
<thead>
<tr>
<th>Number of Generations: 500</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>(Average) Number of States Visited</td>
<td>10</td>
</tr>
<tr>
<td>Estimated Trace by the Proposed Metric</td>
<td>1.8528</td>
</tr>
<tr>
<td>Estimated Trace/Percentages of Visited States (%</td>
<td>2.9644</td>
</tr>
<tr>
<td><em>(x</em>500)/(The Actual Trace)</td>
<td>0.9303</td>
</tr>
<tr>
<td>Number of Generations: 1000</td>
<td></td>
</tr>
<tr>
<td>(Average) Number of States Visited</td>
<td>13</td>
</tr>
<tr>
<td>Estimated Trace by the Proposed Metric</td>
<td>2.0982</td>
</tr>
<tr>
<td>Estimated Trace/Percentages of Visited States (%</td>
<td>2.5824</td>
</tr>
<tr>
<td><em>(x</em>1000)/(The Actual Trace)</td>
<td>0.8164</td>
</tr>
<tr>
<td>Number of Generations: 1500</td>
<td></td>
</tr>
<tr>
<td>(Average) Number of States Visited</td>
<td>13</td>
</tr>
<tr>
<td>Estimated Trace by the Proposed Metric</td>
<td>2.1311</td>
</tr>
<tr>
<td>Estimated Trace/Percentages of Visited States (%</td>
<td>2.6282</td>
</tr>
<tr>
<td><em>(x</em>1500)/(The Actual Trace)</td>
<td>0.8231</td>
</tr>
<tr>
<td>Number of Generations: 2000</td>
<td></td>
</tr>
<tr>
<td>(Average) Number of States Visited</td>
<td>14</td>
</tr>
<tr>
<td>Estimated Trace by the Proposed Metric</td>
<td>2.1711</td>
</tr>
<tr>
<td>Estimated Trace/Percentages of Visited States (%</td>
<td>2.4812</td>
</tr>
<tr>
<td><em>(x</em>2000)/(The Actual Trace)</td>
<td>0.7796</td>
</tr>
<tr>
<td>Number of Generations: 5000</td>
<td></td>
</tr>
<tr>
<td>(Average) Number of States Visited</td>
<td>15</td>
</tr>
<tr>
<td>Estimated Trace by the Proposed Metric</td>
<td>2.3152</td>
</tr>
<tr>
<td>Estimated Trace/Percentages of Visited States (%</td>
<td>2.4696</td>
</tr>
<tr>
<td><em>(x</em>5000)/(The Actual Trace)</td>
<td>0.7760</td>
</tr>
<tr>
<td>The Actual Trace</td>
<td>3.1866</td>
</tr>
</tbody>
</table>

Table 6.2 The Relationships among the Estimated Trace, the Proportion of the Visited States over the Total Number of States ($n' = 12$)
the setting of $l$ is shown in Figure 6.2, which is based on the results from the setting $n' = 10$. Figure 6.3 shows the difference between the setting $n' = 10$ (the power of $CMS$) and $n' = 12$ when the number of generations is set to 2000. The observations on other fitness functions have similar results, although the values are slightly different.

Based on my investigation, different fitness functions, with fixed numbers of generations, have different multiple functions (as shown in Figure 6.2) for actual traces, but all of them can be fitted by the curve $y = \alpha^{l-3}$ when $l \geq 4$, where $\alpha \geq 1$. Note that different settings on the number of generations have different values for $\alpha$. For each fitness function, we can always compute its own multiple functions to derive the (estimated) actual traces for estimating the number of generations for the empirical global convergence; however, that idea has some drawbacks. We have to compute everything for each fitness function, which costs a lot of computation time. In addition, computation errors of the multiple functions may sometimes result in the situation that the estimated $\lambda_2$ (i.e., the second largest eigenvalue in absolute value), denoted as $\hat{\lambda}_2$, is greater than 1. In order to conquer the above problems and provide a robust method for the estimation, the entire estimation framework is analyzed and simplified. The following explains how the framework works.

Let us discuss the equation planned to be used as the fitting curve in Figure 6.1 first.
Theoretically, the curve should be $y = f(x) = 1 + m_2 \lambda_2^2 + m_3 \lambda_3^2 + \cdots + m_q \lambda_q^x$, where $m_2, \ldots, m_q$ and $\lambda_2, \ldots, \lambda_q$ are defined in Theorem 4 in Chapter 3; however, to include all of the parameters $(m_2, \ldots, m_q$ and $\lambda_2, \ldots, \lambda_q)$ costs a lot of computation overhead. As it is commonly known that $\lambda_2, \ldots, \lambda_q$ are all less than 1, for a large enough $x$, the terms $m_3 \lambda_3^2, \ldots, m_q \lambda_q^x$ can be ignored. The equation $y = f(x) = 1 + m_2 \lambda_2^2$ is thusly applied to fit the curve. In this case, merely two points are needed for the fitting. Note that in order to obtain more precise results, higher dimensional fitting curves using the existing fitting techniques, such as least squares fitting, can be applied here, but more points are needed for the fitting.

With the two points version, a proper set of fitness functions with different difficulty levels is chosen for estimating $\lambda_2$. With an arbitrary setting of $m$ and $l$, the estimations of $\lambda_2$ derived by three pairs of points, $(n' = 10, n' = 12)$, $(n' = 10, n' = 20)$, and $(n' = 20, n' = 22)$, are compared. Based on the results, it is considered true that $\hat{\lambda}_2$ computed based on the pair $(n' = 20, n' = 22)$ is always the largest. For instance, with respect to the fitness function $y = f_3(x) = 1 + \sin(x)$ with the setting $m$ equal to 2 and $l$ equal to 5, $\hat{\lambda}_2$ derived by the pair $(n' = 10, n' = 12)$ is equal to 0.9554, $\hat{\lambda}_2$ derived by the pair $(n' = 10, n' = 20)$ is equal to 0.9578, and $\hat{\lambda}_2$ derived by the pair $(n' = 20, n' = 22)$ is equal to 0.9612. The reason is that, at the point $x = 10$, $m_3 \lambda_3^2 + \cdots + m_q \lambda_q^x$ is not really close to 0, which causes some noises for the estimation. Although the $\hat{\lambda}_2$ derived by the pair $(n' = 20, n' = 22)$ is the best among
Figure 6.4 The relationship between the actual curve and the curve fitted by the pair \((n'=10, n'=12)\)

the three, the noises caused by \(m_3\lambda_3^x + \cdots + m_q\lambda_q^x\) still exist, which makes the estimated \(\lambda_2\) slightly smaller than the actual \(\lambda_2\). The fitting curves based on those three \(\hat{\lambda}_2\)'s and their corresponding \(\hat{m}_2\)'s are drawn in Figure 6.4, Figure 6.5, and Figure 6.6, respectively, where \(\hat{m}_2\) represents the estimated \(m_2\). Comparing three of them, the curve generated by the pair \((n'=20, n'=22)\) is the best fit for the actual curve. Note that the \(n'\) cannot be too large when it is applied to estimate \(\lambda_2\) for any fitness function. Too large \(n'\) may cause some errors due to precision problems.

This paragraph mainly discusses and analyzes the approach adopted for estimating traces with certain powers \(n'\) and the corresponding \(\lambda_2\). Consider an arbitrary fitness function. With respect to this fitness function, we can compute two multiple functions for both \(n'=20\) and \(n'=22\). Suppose the value of the multiple function for \(n'=20\) at \(l=16\) is \(Mul_{20}(16)\), and the value of the multiple function for \(n'=22\) at \(l=16\) is \(Mul_{22}(16)\). The traces for \(n'=20\) and \(n'=22\) are \(\frac{\text{Estimated Trace (n'=20)}}{\text{Percentages of Visited States}} / Mul_{20}(16)\) and \(\frac{\text{Estimated Trace (n'=22)}}{\text{Percentages of Visited States}} / Mul_{22}(16)\), respectively. Note that the fraction \(\frac{\text{Estimated Trace}}{\text{Percentages of Visited States}}\) is used for estimating traces because the proportion of visited states roughly presents the percentages of traces discovered by the
The Actual Curve and The Fitting Curve for the Pair (n'=10, n'=20)
X-Axis: The Power of CMS – n'

Figure 6.5  The relationship between the actual curve and the curve fitted by the pair (n' = 10, n' = 20)

The Actual Curve and The Fitting Curve for the Pair (n'=20, n'=22)
X-Axis: The Power of CMS – n'

Figure 6.6  The relationship between the actual curve and the curve fitted by the pair (n' = 20, n' = 22)
evaluation metric. From Table 6.1 and Table 6.2, we know that the fraction overestimates the
traces by some multiples when \( l \geq 4 \). The multiple functions are leveraged to solve the over-
estimated problem. The reason for the overestimation is that usually the sum of the relatively
larger diagonal elements is discovered and computed by the evaluation metric. The amount
is already included in the estimated trace. Estimating the sum of smaller diagonal elements
using the sum of the relatively larger diagonal elements causes the problem. After deriving the
estimated traces for \( n' = 20 \) and \( n' = 22 \), the equations

\[
\begin{align*}
1 + m_2 \lambda_2^{20} &= \text{Trace}((CMS)^{20}) \\
1 + m_2 \lambda_2^{22} &= \text{Trace}((CMS)^{22})
\end{align*}
\]

are applied to estimate \( \lambda_2 \). From the equations, we obtain

\[
\hat{\lambda}_2^2 = \frac{\text{Trace}((CMS)^{22})}{\text{Trace}((CMS)^{20}) - 1} - \frac{\text{Trace}((CMS)^{20})}{\text{Trace}((CMS)^{22})} + \frac{\text{Trace}((CMS)^{22}) - 1}{\text{Trace}((CMS)^{20})} - \frac{\text{Trace}((CMS)^{22})}{\text{Trace}((CMS)^{20})(\text{Trace}((CMS)^{20}) - 1)}.
\]

(6.1)

Note that the second term of the last line in Equation (6.1) can be ignored if \( \text{Trace}((CMS)^{20}) \) is
large enough (e.g., \( \text{Trace}((CMS)^{20}) \geq 1000 \)). We use a function \( \text{Correction}(\text{Trace}((CMS)^{20}), \text{Trace}((CMS)^{22})) \) to denote it. Combined with the computations mentioned earlier, Equation (6.1) becomes

\[
\hat{\lambda}_2^2 = \frac{\text{Estimated Trace (n' = 22)}}{\text{Percentages of Visited States}/M_{l22}(l)} - \frac{\text{Estimated Trace (n' = 20)}}{\text{Percentages of Visited States}/M_{l20}(l)} - \text{Correction}(\text{Trace}((CMS)^{20}), \text{Trace}((CMS)^{22}))
\]

(6.2)

which can be re-written as

\[
\hat{\lambda}_2^2 = \frac{M_{l20}(l)}{M_{l22}(l)} \left( \frac{\text{Estimated Trace (n' = 22)}}{\text{Percentages of Visited States}} \right) - \frac{\text{Estimated Trace (n' = 20)}}{\text{Percentages of Visited States}} - \text{Correction}(\text{Trace}((CMS)^{20}), \text{Trace}((CMS)^{22})).
\]

(6.3)
If both of $\text{Trace}((CMS)^{20})$ and $\text{Trace}((CMS)^{22})$ are estimated by the proposed evaluation metric at the same time (i.e., they are computed using the same set of random numbers), Equation (6.3) can be simplified and re-written as

$$\hat{\lambda}^2_2 = \frac{M_{ul20}(l)}{M_{ul22}(l)} \left( \frac{\text{Estimated Trace (}n' = 22\text{)}}{\text{Estimated Trace (}n' = 20\text{)}} \right) - \text{Correction}(\text{Trace}((CMS)^{20}), \text{Trace}((CMS)^{22})),$$

(6.4)

since both of them have the same value for Percentages of Visited States.

Now let us carefully consider an approximation equation for Equation (6.4) using the limited known information. As mentioned before, it is time consuming to compute the multiple functions for each fitness function. In order to get more precise results, one may choose to perform that. My goal is to simplify the computation process. Hence, an approximation approach is suggested. Based on my observation, the results show that with respect to the same setting of $l$, the rates $\frac{M_{ul20}(l)}{M_{ul22}(l)}$ of different fitness functions are close; however, fitness functions which have smaller numbers of states visited by the CGA tend to have slightly larger rates. The fitness function $f_7(x) = \sin^6(5\pi[x^{3/4} - 0.05])$ is chosen as the referenced fitness function. (Note that other fitness functions can also be used as the referenced fitness function.) For different $l$ ($l \geq 4$), the rate $\frac{M_{ul20}(l)}{M_{ul22}(l)}$ of $f_7$ (when the number of generations $n$ is set to 2000) is approximate to

$$\frac{M_{ul20}(l)}{M_{ul22}(l)} \approx (1.0072)^{l-3}.$$

Some adjusted coefficients need to be applied for other fitness functions. The one suggested is the fraction $\frac{\text{The Number of States Visited for } f_7}{\text{The Number of States Visited for the Fitness Function}}$ for a specific fitness function. The approximation equation for Equation (6.4) can be

$$\hat{\lambda}^2_2 \approx (1.0072)^{l-3}(\text{The Adjusted Coefficient}) \left( \frac{\text{Estimated Trace (}n' = 22\text{)}}{\text{Estimated Trace (}n' = 20\text{)}} \right),$$

(6.5)

where $l \geq 4$. The $\text{Correction}(\text{Trace}((CMS)^{20}), \text{Trace}((CMS)^{22}))$ is ignored because for most of the cases, we need Equation (6.5) to estimate $\lambda_2$ for large-scale problems; in which case, $l$ is greater than 14. When $l \geq 14$ and $n' = 20$, the traces are around or greater than 1000.
6.2 The Number of Generations for the Empirical Global Convergence

After obtaining \( \hat{\lambda}_2 \), the equation \( 1 + m_2 \lambda_2^{20} = \text{Trace}((CMS)^{20}) \) is used to estimate \( m_2 \). Before that, \( \text{Trace}((CMS)^{20}) \) needs to be computed first. By the computation in the previous section, for each fitness function, \( \text{Trace}((CMS)^{20}) \) is equal to the fraction \( \frac{\text{Estimated Trace (n’=20)} \text{ Percentages of Visited States}}{\text{Mult}_{20}(l)} \) divided by a number \( \text{Mult}_{20}(l) \) corresponding to the fitness function. According to the results on the values of \( \text{Mult}_{20}(l) \) for fitness functions in the observed set, the largest \( \text{Mult}_{20}(l) \) is around ten times of the smallest one. As mentioned before, it is not very efficient to compute the multiple functions for each fitness function. Hence, using one of the multiple functions instead of all of them is suggested. Note that the selection of the value \( \text{Mult}_{20}(l) \) only impacts \( \hat{m}_2 \), which is employed in computing \( n \) from the equation \( 1 + m_2 \lambda_2^n = 1 + \epsilon \) (as in Figure 6.1), in the entire estimation framework. An equivalent equation for \( 1 + m_2 \lambda_2^n = 1 + \epsilon \) is

\[
    n = \frac{\log(\frac{\epsilon}{m_2^n})}{\log(\lambda_2)}.
\]

From Equation (6.6), we can get that \( \lambda_2 \) is more sensitive than \( m_2 \). Moreover, Figure 6.6 shows that the fitting curve computed by the proposed estimation method is eventually lower than the curve drawn by the actual traces after \( n \) exceeds a value. That means the number of generations for the global convergence estimated by the proposed method is smaller than the actual one. Hence, smaller \( \text{Mult}_{20}(l) \) is suggested to be leveraged so that larger \( \hat{m}_2 \) can be used to solve \( n \) in Equation (6.6).

6.3 The Verification of the Proposed Estimation Framework

The one-dimensional fitness functions \( f_1 \) to \( f_8 \) in Chapter 5, with the setting \( (m, l) = (2, 16) \), are used for the verification. Table 6.3 shows the pair \( (\hat{\lambda}_2, \hat{m}_2) \) with respect to each fitness function computed by the proposed methodology. Note that \( \text{Mult}_{20}(16) = 158.5566 \approx 159 \) (from the observed set) is applied to derive \( \hat{m}_2 \).

Figure 6.7 to Figure 6.10 shows the cumulative distribution function (CDF) for fitness functions \( f_1 \) to \( f_8 \), respectively. It is estimated by observing the convergence trends of the fitness functions from 1000 trials. More specifically, 1000 trials of the CGA (with best solution
Table 6.3 The Pair ($\lambda_2, \hat{m}_2$) with respect to Each Fitness Function

<table>
<thead>
<tr>
<th>Fitness Function</th>
<th>$\lambda_2$</th>
<th>$\hat{m}_2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$f_1$</td>
<td>0.8490</td>
<td>102814</td>
</tr>
<tr>
<td>$f_2$</td>
<td>0.8434</td>
<td>150613</td>
</tr>
<tr>
<td>$f_3$</td>
<td>0.8890</td>
<td>76333</td>
</tr>
<tr>
<td>$f_4$</td>
<td>0.9339</td>
<td>26663</td>
</tr>
<tr>
<td>$f_5$</td>
<td>0.8646</td>
<td>87450</td>
</tr>
<tr>
<td>$f_6$</td>
<td>0.8699</td>
<td>84670</td>
</tr>
<tr>
<td>$f_7$</td>
<td>0.9439</td>
<td>85533</td>
</tr>
<tr>
<td>$f_8$</td>
<td>0.9165</td>
<td>12535</td>
</tr>
</tbody>
</table>

maintained) are run for each fitness function. The CDFs with the length of the bin being 500 are generated. For the non-periodic fitness functions, the trials, in which the CGA reach the global optimal solutions, are counted. Note that the isolation points of the fitness functions $f_5$ and $f_6$ are ignored here. That is, as long as the best solutions maintained reach 90000.0, the trials of the CGA are considered converging to the global optimal solutions. Sometimes, they can reach 100000.0. However, based on my observation, the best solutions have certain difficulty to reach 100000.0 for all trials even for a very large $n$. For the periodic fitness functions $f_3$ and $f_7$, it is almost impossible for their best solutions to reach only a single point since they have more than one global optimal solutions. Therefore, for $f_3$ and $f_7$, with the best solutions maintained over time, when for the first time $x$ (best solutions) satisfy

$$ |f_i(x) - \text{Global Optimal Value}| < 10^{-6}, $$

the trials are considered converging to the global optimal solutions. For those figures, the maximum number of generations is set to 70000. In other words, the trials which run more than 70000 generations are not shown in the figures.

In order to compare the CDFs of the CGA with respect to those fitness functions, the bin, representing a range for numbers of generations, which first reaches probability of 80% in the CDF for each fitness function is listed in Table 6.4. (The second column of Table 6.4 repeatedly shows the $\hat{\lambda}_2$ column in Table 6.3.) In Table 6.4, the second column which is derived using my
proposed methodology and the third column show similar results. That is, the difficulty of the CGA with respect to the fitness functions $f_2$, $f_1$, $f_5$, and $f_6$ is the least. The difficulty of the CGA with respect to $f_7$ and $f_4$ is the greatest. This implies that the proposed methodology can derive close values for the corresponding $\lambda_2$.

### Table 6.4  The Bins Which First Reach 80% in CDFs

<table>
<thead>
<tr>
<th>Fitness Function</th>
<th>$\lambda_2$</th>
<th>80% in CDFs</th>
</tr>
</thead>
<tbody>
<tr>
<td>$f_1$</td>
<td>0.8490</td>
<td>15500 – 16000</td>
</tr>
<tr>
<td>$f_2$</td>
<td>0.8434</td>
<td>14500 – 15000</td>
</tr>
<tr>
<td>$f_3$</td>
<td>0.8890</td>
<td>24000 – 24500</td>
</tr>
<tr>
<td>$f_4$</td>
<td>0.9339</td>
<td>&gt; 70000</td>
</tr>
<tr>
<td>$f_5$</td>
<td>0.8646</td>
<td>16000 – 16500</td>
</tr>
<tr>
<td>$f_6$</td>
<td>0.8699</td>
<td>16500 – 17000</td>
</tr>
<tr>
<td>$f_7$</td>
<td>0.9439</td>
<td>57000 – 57500</td>
</tr>
<tr>
<td>$f_8$</td>
<td>0.9165</td>
<td>44000 – 44500</td>
</tr>
</tbody>
</table>

### Table 6.5  The Empirical Global Convergence for Each Fitness Function

<table>
<thead>
<tr>
<th>Fitness Function</th>
<th>Condition</th>
<th>$\epsilon = 0.003$</th>
<th>$\epsilon = 0.000003$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Derived Number of Generations</td>
<td>Probability (Out of 40)</td>
</tr>
<tr>
<td>$f_1$</td>
<td>Best Value ≥ 594</td>
<td>106</td>
<td>0.8250</td>
</tr>
<tr>
<td>$f_2$</td>
<td>Best Value ≥ 35640</td>
<td>105</td>
<td>1.0000</td>
</tr>
<tr>
<td>$f_3$</td>
<td>Best Value ≥ 1.98</td>
<td>145</td>
<td>1.0000</td>
</tr>
<tr>
<td>$f_4$</td>
<td>Best Value ≥ 0.99</td>
<td>234</td>
<td>1.0000</td>
</tr>
<tr>
<td>$f_5$</td>
<td>Best Value ≥ 89100</td>
<td>119</td>
<td>1.0000</td>
</tr>
<tr>
<td>$f_6$</td>
<td>Best Value ≥ 89100</td>
<td>124</td>
<td>0.9000</td>
</tr>
<tr>
<td>$f_7$</td>
<td>Best Value ≥ 0.99</td>
<td>298</td>
<td>1.0000</td>
</tr>
<tr>
<td>$f_8$</td>
<td>Best Value ≥ 0.99</td>
<td>175</td>
<td>0.9250</td>
</tr>
</tbody>
</table>

Table 6.5 shows the results derived by the proposed methodology. With respect to different settings of $\epsilon$, the probabilities of satisfying the condition that the best solution maintained over time is greater than or equal to 0.99 multiple of the global optimal solution are different. The result from small $\epsilon$ has higher probability to satisfy the condition. Comparing the numbers of generations derived by the proposed method and the upper bounds of the third column in Table 6.4, we can get that the latter ones are in certain multiples of the former ones. Except
$f_4$ (i.e., the unknown one), the multiples are in between 138 and 255 for $\epsilon = 0.003$, and in between 99 and 176 for $\epsilon = 0.000003$, respectively. Hence, the number of generations derived by the proposed method is useful for providing some information about the empirical global convergence if a certain multiple greater than 255 (e.g., 260) is applied to it and $\epsilon$ is set to be less than 0.003.

Another important result derived from Table 6.3 and Table 6.5 is that, the convergence mainly depends on the value $\lambda_2$, while $m_2$, related to the constant in Inequality (4.3), does not have significant impact on it. For instance, the $\hat{m}_2$ with respect to $f_2$ is much larger than the $\hat{m}_2$ with respect to $f_1$, but in the Derived Number of Generations columns in Table 6.5 for both $\epsilon = 0.003$ and $\epsilon = 0.000003$, the Derived Number of Generations for $f_2$ is a little bit less than that for $f_1$. The values of $\hat{\lambda}_2$ mainly control the order. Equation (6.6) explains this result. Further, this result coincides with my earlier result (see Inequality (4.3)) and many work in the literature that the second largest eigenvalue represents the convergence rate of a Markov chain (see Definition 7 for convergence rate).
Figure 6.7 The CDF for Number of Trials to Find the Global Optimal Solution with respect to $f_1$ and $f_2$ (X-Axis represents the number of generations; Y-Axis represents the cumulated number of trials to find the global optimal solution (out of 1000 trials))
Figure 6.8  The CDF for Number of Trials to Find the Global Optimal Solution with respect to $f_3$ and $f_4$ (X-Axis represents the number of generations; Y-Axis represents the cumulated number of trials to find the global optimal solution (out of 1000 trials))
Figure 6.9 The CDF for Number of Trials to Find the Global Optimal Solution with respect to $f_5$ and $f_6$ (X-Axis represents the number of generations; Y-Axis represents the cumulated number of trials to find the global optimal solution (out of 1000 trials))
Figure 6.10 The CDF for Number of Trials to Find the Global Optimal Solution with respect to $f_7$ and $f_8$ (X-Axis represents the number of generations; Y-Axis represents the cumulated number of trials to find the global optimal solution (out of 1000 trials))
CHAPTER 7. A Case Study - Evolutionary Testing

7.1 Overview of Evolutionary Testing

Software testing is a critical element of software quality assurance and represents the ultimate review of specification, design, and coding [Pressman, R. S. (2005)]. Due to its importance, at least 50% of the total cost (including human effort) involved in a software development project is typically consumed by testing [Beizer, B. (1990); Tracey, N. and Clark, J. and Mander, K. (1998)]. Although a lot of effort has been allocated to the task of testing, complete testing is usually impossible in practice because of the vast amount of possible input situations [Wegener, J. (2005)]. For the same reason, effective methods for automatic test data generation are in great demand. Many techniques focusing on that purpose have been proposed and developed. Evolutionary Testing (ET) is one of them and it gradually forms an important branch of the research area in automatic test data generation.

ET exploits evolutionary algorithms (EAs), such as GA, to generate test data. According to the objectives of testing [Pressman, R. S. (2005)], it is believed that ET has its potential to become a major technique for automatically generating test data since it possesses the following features:

- Like Random Testing (RT), it has the ability to search feasible solutions in the search space. However, unlike RT, it can guide solutions to the desired ones through an evaluation criterion. With guidance, ET is capable of producing effective solutions even for complex and poorly understood search spaces with many dimensions. Without it, ET behaves exactly the same as RT. Hence, ET is more powerful than RT.

- ET is able to recombine the input data based on the higher fitness values. That is, it has
the capability to adjust the input data from the testing history, and create the desired ones.

A better encoding of EAs is one that can explore more possible solutions within a fixed time duration. In other words, a good design for ET can cover lots of combinations of inputs and discover errors with a high probability.

Among all the software testing activities (i.e., test case design, test execution, monitoring, test evaluation, test planning, test organization, and test documentation), test case design is essential. Systematic generation of test cases based on the test design is indispensable to the quality of software. However, for most of the test objectives, it is difficult to automate the generation of test cases due to the reasons listed below [Sthamer, H. and Wegener, J. and Baresel, A. (2002)]:

- The generation of test cases for functional testing is usually impossible because in general no formal specifications can be applied in industrial practice.
- Structural testing is difficult to automate due to the limits of symbolic execution.
- No specialized methods and tools exist for testing the temporal behavior of systems.
- A generation of test cases for testing safety constraints is generally impossible.

Hence, test cases have to be defined manually, which is not efficient. Therefore, the researchers have sought other techniques, e.g., ET, to effectively solve these problems.

According to the literature review, ET has been applied for functional testing (black box testing), structural testing (white box testing), and real-time testing [Last, M. and Eyal1, S. and Kandel, A. (2006); Michael, C. C. and McGraw, G. and Schatz, M. A. (2001); Baresel, A. and Pohlheim, H. and Sadeghipour, S. (2003); Baresel, A. and Binkley, D. and Harman, M. and Korel, B. (2004); McMinn, P. (2004); Wegener, J. (2005)] to automatically generate test data. Among all of the existing work, structural testing is the method that has been investigated and developed the most.
In structural testing, various methods to analyze the coverage of program structures have been proposed. Depending on their test aims, fitness functions of ET are formulated. The fitness functions summarized below are commonly seen in the literature.

The test data generation problem for structural testing is to find a set of program inputs that achieves the desired coverage [Tracey, N. and Clark, J. and Mander, K. (1998)]. This type of problems has been converted to optimization problems since the test criteria are specifically known. Most of the work defines the fitness function based on the test criterions. The methods to construct fitness functions can be categorized in Figure 7.1 [McMinn, P. (2004)].

![Figure 7.1 Classification of Dynamic Structural Test Data Generation Techniques Using EAs [McMinn, P. (2004)]](image)

From Figure 7.1, we can see that researchers started to apply EAs for software testing around two decades ago. They first set their goal in terms of coverage. For instance, the fitness functions are designed to penalize the individuals that follow already covered paths. Later, they found that it is difficult for the coverage-oriented approach to discover some specific paths. It gradually changed to structure-oriented approach. In this approach, researchers employed different information to form the fitness functions. The most updated one has combined control and branch distance together. The branch distance is usually normalized to the range $[0, 1)$ [McMinn, P. (2004); McMinn, P. and Binkley, D. and Harman, M. (2005)]. With it (fractional part), one may evaluate two feasible solutions with the same fitness value on the approach level (integer part) [Levin, S. and Yehudai, A. (2007)]. The basic form of that to be minimized is
Fitness = Approach Level + Branch Distance, \hspace{1cm} (7.1)

where the Approach Level is the number of target condition statements which are not executed by the given test data, and Branch Distance is the distance from the test data to the input values of the target branch, and it can be computed in various ways. The formula to calculate both depend on the test goal, i.e., which types of coverage are needed [McMinn, P. and Holcombe, M. (2003); McMinn, P. (2004); Wegener, J. (2005)].

7.2 The Flag Problem

Many works have applied EA for structural testing using fitness functions to guide the feasible solutions to form sets of test data for the desired branches. However, problems exist that inhibit the search and have not been perfectly solved yet. The flag problem is one of them. Typically, it occurs when the source code has flag variables. A flag variable is any variable that takes on one of two or more (finite) discrete values [Baresel, A. and Binkley, D. and Harman, M. and Korel, B. (2004)]. For instance, boolean variables are flag variables. In the following, an example is given to show how the flag variable influences the performance of the search.

Suppose Figure 7.2 is part of the tested source code.

1. flag = false;
2. ... /*Nothing related to ‘flag’*/
3. if (switch == 5) flag = true;
4. ... /*Nothing related to ‘flag’*/
5. if (flag) /* Test aim */

Figure 7.2 An Example: The Source Code

In Figure 7.2, there is an boolean variable called flag. The test aim is in line 5, in which flag should be equal to 1 (TRUE). In that case, part of the fitness function related to the flag variable should be of some formula like |flag − 1|, i.e., the absolute value of (flag − 1). Now,
given two or more sets of input test data automatically generated by EA, if all of them do not go to the branch in which the variable `switch` is equal to 5 before line 3, all of the fitness values related to the flag variable are equal to $|0 - 1|$. That is, the fitness values related to the flag variable are the same for all sets of test data with `flag` not being TRUE in line 5. Hence, the fitness function does not provide any guidance for reaching the test aim as the flag can be always FALSE and cannot become TRUE. The search degenerates to random search.

### 7.3 Discussion

The reason of selecting ET as a case study is that

- There is a difficult flag problem in the context of ET so that the difficult problems can be compared with easier problems (i.e., the problems dealing with testing of flag-free programs);

- From the final fitness value, we can always get information about the quality of solutions.

The `Approach_Level` (i.e., integer part) represents which branch the generated test case is located in.

### 7.4 Experiment Settings

The flag problem is a difficult problem for ET. In order to demonstrate that the proposed evaluation metric has the ability to discern the applicability of CGAs for real-world optimization problems, two types of programs are designed (see Figure 7.3 and Figure 7.4). A corresponding fitness function is formulated for each program (see Table 7.1). CGA with best solution maintained over time is applied to generate test cases for those types of programs with respect to the fitness functions.

The first type of the program (called $P_1$) has flags which are discrete values. For this type of program, the fitness function formulated using Equation 7.1 has isolation points. The second type of the program (called $P_2$) is a flag-free program.
\( f_{14} \) and \( f_{15} \) in Table 7.1 are the corresponding fitness functions for \( P_1 \) and \( P_2 \), respectively. The function \textit{Approach Level} in Table 7.1 is in Figure 7.5.

The CGA with best solution maintained is applied to generate test cases corresponding to \( P_1 \) and \( P_2 \) with their fitness functions, respectively. With the setting \( n = 10000, l = 16, \) and \( m = 2 \), the result in Section 7.5 is derived.

In order to further verify that the proposed methodology in Chapter 6 is valid, \( \lambda_2 \) and \( m_2 \) are computed for both fitness functions. The result is also presented in Section 7.5.

### 7.5 The Result of the Case Study

Table 7.2 presents the average values of \( \text{Trace}(CMS)^{n'} \) derived from the proposed evaluation metric from 40 trials. \( f_{15} \) with \( P_2 \) has lower estimated \( \text{Trace}(CMS)^{n'} \) for all \( n' \) because it is easier than the other for ET. The results coincide the conclusions made from Chapter 5. From the results, we can also know that the isolation points occasionally can be visited under the condition that they are always encoded as points in the search space of CGAs.

Table 7.3 shows the values of \( \lambda_2, m_2 \), and the corresponding information for both fitness functions. \( \lambda_2 \) for the fitness function \( f_{14} \) is much greater than \( \lambda_2 \) for the fitness function \( f_{15} \).
Table 7.1 The Fitness Functions of $P_1$ and $P_2$

<table>
<thead>
<tr>
<th>Program</th>
<th>Fitness Function</th>
</tr>
</thead>
<tbody>
<tr>
<td>$P_1$</td>
<td>$f_{14} = 5 - (\text{Approach Level} + \frac{1}{109}(</td>
</tr>
<tr>
<td>$P_2$</td>
<td>$f_{15} = 5 - (\text{Approach Level} + \frac{1}{1190}(f'_a(a) + f'_b(b) + f'_c(c) + f'_d(d)))$, where</td>
</tr>
<tr>
<td></td>
<td>$f'_a(a) = \begin{cases}</td>
</tr>
<tr>
<td></td>
<td>$f'_b(b) = \begin{cases}</td>
</tr>
<tr>
<td></td>
<td>$f'_c(c) = \begin{cases}</td>
</tr>
<tr>
<td></td>
<td>$f'_d(d) = \begin{cases}</td>
</tr>
</tbody>
</table>

Therefore, the number of generations derived from the proposed approximation method with respect to $f_{14}$ is much greater than that with respect to $f_{15}$ with $\epsilon = 0.000003$. The results here are also consistent with the conclusions made from previous two chapters. Since the fitness functions $f_{14}$ and $f_{15}$ are multi-dimensional, it may not be appropriate to compare the results derived in Table 6.3, Table 6.5, and their corresponding data.

In order to verify the number of generations derived in Table 7.3, the PDFs and CDFs with respect to both fitness functions are investigated. Figure 7.6 shows the number of trials needed (and the corresponding CDF) to reach the global optimal solution with respect to $f_{14}$ out of 1000 trials. When the number of generations equals to 70000, the CDF in Figure 7.6 merely reaches the probability around 50%. Comparing to the PDF and CDF with respect to $f_{15}$ (not shown here), $f_{15}$ is much easier for the CGA since all of the 1000 trials reach the global optimal solution (i.e., the branch of the test aim) within 500 generations. This result is consistent with the derived numbers of generations in Table 7.3.
Figure 7.5  The Control Flow Graph for $P_1$ and $P_2$

Table 7.2  The Results of the Estimated $Trace((CMS)^n')$

<table>
<thead>
<tr>
<th>n'</th>
<th>$f_{14}$ corresponding to $P_1$</th>
<th>$f_{15}$ corresponding to $P_2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>10</td>
<td>14.3495</td>
<td>13.9687</td>
</tr>
<tr>
<td>12</td>
<td>8.4146</td>
<td>7.9792</td>
</tr>
<tr>
<td>14</td>
<td>4.9971</td>
<td>4.7871</td>
</tr>
<tr>
<td>16</td>
<td>2.9591</td>
<td>2.7624</td>
</tr>
<tr>
<td>18</td>
<td>2.1697</td>
<td>1.8531</td>
</tr>
<tr>
<td>20</td>
<td>1.6540</td>
<td>1.5847</td>
</tr>
<tr>
<td>22</td>
<td>1.5015</td>
<td>1.3598</td>
</tr>
<tr>
<td>24</td>
<td>1.3851</td>
<td>1.2680</td>
</tr>
<tr>
<td>26</td>
<td>1.2795</td>
<td>1.1730</td>
</tr>
<tr>
<td>Average Best Value</td>
<td>4.2517</td>
<td>4.9296</td>
</tr>
</tbody>
</table>
Table 7.3  The Corresponding Information for Fitness Functions $f_{14}$ and $f_{15}$

<table>
<thead>
<tr>
<th>Fitness Function with Information</th>
<th>$\lambda_2$</th>
<th>$m_2$</th>
<th>The Number of Generations Derived from the Proposed Approximation Method $\epsilon = 0.000003$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$f_{14}$</td>
<td>0.9819</td>
<td>9313</td>
<td>1197</td>
</tr>
<tr>
<td>Trace Values for $n = 2000$:</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$n' = 20$: 0.3180</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$n' = 22$: 0.3033</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>The Number of States Visited: 1329</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$f_{15}$</td>
<td>0.9313</td>
<td>5016</td>
<td>299</td>
</tr>
<tr>
<td>Trace Values for $n = 2000$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$n' = 20$: 0.2476</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$n' = 22$: 0.2134</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>The Number of States Visited: 1333</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Figure 7.6 The PDF and CDF for Number of Trials to Find the Global Optimal Solution with respect to $f_{14}$ (X-Axis represents the number of generations; Y-Axis represents the cumulated number of trials to find the global optimal solution (out of 1000 trials))
CHAPTER 8. The Generalization of the Proposed Methodology

As aforementioned, the proposed evaluation metric is based on the condition that CMS is regular, which is obtained from the assumption that CGA is applied to solve the optimization problems. In this chapter, I am going to prove that in addition to CGA, the evaluation metric can be applied to any type of selection, and crossover operators, as long as bit mutation is performed after selection and crossover operators.

**Theorem 10** Regardless of the types of selection and crossover operators, the transition matrix SCM is regular if and only if bit mutation is performed after selection and crossover.

**Proof.** Since $S$ and $C$ are stochastic matrices, $SC$ is a stochastic matrix (i.e., sum of elements in a row is equal to 1 and each element of $SC$ is nonnegative). Moreover, because bit mutation is performed, for all $i$ and $j$, the element $m_{ij}$ in $M$ is

$$m_{ij} = \prod_{k=1}^{m} p_{m}^{H(\pi_k(i),\pi_k(j))}(1 - p_{m})^{1-H(\pi_k(i),\pi_k(j))},$$

where $H(\cdot, \cdot)$ is the Hamming distance of the strings (chromosomes). Hence, $m_{ij}$ is positive for all $i$ and $j$. That means $M$ is positive.

Since $SC$ is a stochastic matrix and $M$ is positive, $SCM$ is positive. Therefore, $SCM$ is regular.\[\square\]

With the condition that $SCM$ is regular, the evaluation metric can be generally applied — not limited to certain types of selection and crossover operators. The corresponding properties investigated and checked in previous chapters should also be further investigated if different selection or crossover operators are used.
Theorem 11 The transition matrix $A$ constructed by Rudolph’s version can be converted to a transition matrix $B$ in Vose’s version. Moreover, the statement that $A$ is positive implies that $B$ is positive.

Proof. Let us consider an arbitrary state, $State_i$, of the transition matrix $A$ constructed by Rudolph’s version. Suppose the number of different individuals in $State_i$ is $r$, each individual is assigned a distinct number between 1 and $r$, and $m_j, j \in \{1, 2, \ldots, r\}$, is the corresponding number of occurrences for $Individual_j$ (in State $i$). Note that $m_1 + m_2 + \cdots + m_r = m$.

By Rudolph’s state representation, there are $\frac{m!}{m_1!m_2!\cdots m_r!}$ states which are a permutation of individuals in $State_i$ in the transition matrix $A$. In Vose’s version, those states, including $State_i$, are all in one state since each state represents only the number of occurrences of the individuals. To convert the transition matrix $A$ in Rudolph’s version to a transition matrix $B$ in Vose’s version, one can simply add up the columns that correspond to the destination states (in Rudolph’s version) considered as the same states in Vose’s version. Similarly, the rows which correspond to the source states (in Rudolph’s version) considered as the same states in Vose’s version are added up. For the computation of rows, a multiple of $1/\frac{m!}{m_1!m_2!\cdots m_r!}$ needs to be applied to the result. The reason is that given a state with $r$ different individuals in Vose’s version, there is $1/\frac{m!}{m_1!m_2!\cdots m_r!}$ possibility that this state is permutation $k$, where $k \in \{1, 2, \ldots, \frac{m!}{m_1!m_2!\cdots m_r!}\}$, in Rudolph’s version (see Figure 8.1).

Based on the computation above, we get that if $A$ is positive, then $B$ is positive since the adding and multiplying manipulations of positive numbers are still positive. □

In Rudolph’s paper [Rudolph, G. (1994)], it is shown that CMS constructed by CGA is positive. With Theorem 10, we know that SCM constructed by a GA, with bit mutation being performed after any selection and crossover operations, is also positive. The proposed evaluation metric can be generalized to a GA with bit mutation being performed after any selection and crossover operations using Vose’s version for state representation, since the converted transition matrix in Vose’s version is positive (also regular). More experiments on the performance of the proposed evaluation metric with states being represented by Vose’s version need to be conducted. I believe that the estimated trace of a transition matrix in Vose’s version
Figure 8.1 An Illustration of the Conversion

will be more accurate than the estimated trace of the transition matrix in Rudolph’s version. This will be one of the directions of my future work.
CHAPTER 9. Conclusion and Future Work

The conclusion of this dissertation includes three sections. The first section describes the contributions of this work; the second section discusses the limitations of the evaluation metric and the proposed approximation approach. In the final section, future work is suggested.

9.1 Contributions of this Work

The contributions of this work include the following:

- The convergence rate of $PU$ (the extended transition matrix) from Perron’s Formula is derived (see Chapter 4).

- A research framework is proposed for estimating the applicability of CGAs for real-world optimization problems. I have formulated several corresponding theorems, conducted experiments for the proposed framework, and analyzed the experimental results (see Chapter 5). I have also studied several cases in Software Testing to validate the evaluation metric (see Chapter 6).

- With my evaluation metric, researchers can decide a cluster of better fitness functions among a set of fitness functions by taking a set of fitness functions as input with the same GA configuration. This feature is very important for real-world optimization problems, since researchers or practitioners may consider using more than one fitness function when they attempt to solve optimization problems. The evaluation metric can rank the fitness functions from the best to the worst by sorting the fitness functions by degrees of convergence.
The traditional way (also the only existing computational and analyzable way) to discriminate the fitness functions with respect to a GA configuration is to compute their Markov transition matrices. With a number of $2^{ml}$ states, at least $2^{ml} \times 2^{ml} \times m$ fitness evaluations need to be performed, which costs a lot of time and is impractical for large-scale real-world applications. Another method, comparison of the fitness values after a fixed number of generations, is not a practical method, since the chosen fixed number may be too large, so that all of the transition matrices empirically converge to their limits.

- An approximation approach is presented for applying the proposed evaluation metric to estimate the number of generations for the global convergence of GAs (Chapter 7).

### 9.2 Limitations

Both the evaluation metric and the proposed approximation approach have limitations, discussed as follows:

- The proposed evaluation metric has the ability to rank the difficulties of fitness functions with respect to a configuration of GAs. However, it is difficult for the metric to derive a precise value of trace.

- A small $n$ makes the metric arduous to predict the relative convergence behavior of a flat fitness function. This limitation can be solved by using large $n$. For a large enough $n$, a close numerical value related to the degree of convergence can be derived. However, the number $n$ may be too large to make the metric practical.

- The proposed approximation approach for predicting the number of generations for the global convergence of GAs has difficulty in dealing with fitness functions that contain isolation points. The empirical results show that with respect to such a fitness function, when $n$ is equal to the number of generations derived from the approximation, the best solution maintained over time reaches a global optimal solution of the fitness function.
other than the isolation points in 40 continuous trials. Only a few of the trials obtain the best solutions equal to the isolation points.

Further investigation is needed to tackle the aforementioned limitations.

9.3 Future Work

My future work will be focused on improving the precision of the proposed evaluation metric. Currently, the metric is able to evaluate the applicability of CGA with best solution maintained over time, and is extended to a more general case in Chapter 7 (e.g., the applicability of EAs that perform bit mutation after selection and crossover operators). Further investigation on more classes of EAs is necessary. Chapter 8 also proves that the state representation using Rudolph’s version can be converted to the state representation using Vose’s version. I believe that this conversion is helpful for improving the precision of the trace estimated by the proposed evaluation metric, since certain states represented using Rudolph’s version are combined into a state in Vose’s version. The diagonal elements of the transition matrices constructed by Vose’s version have larger values than those of the transition matrices constructed by Rudolph’s version, and the state space in Vose’s version is smaller than that in Rudolph’s version. These reasons make the estimation easier in Vose’s version. More research work and experiments need to be conducted along this line.

An alternative approach or adjustment to the approximation method is another future direction. The approximation method currently can predict the number of generations for the global convergence of GAs by multiplying the derived values with certain multiples; however, a solution to deal with its limitation is needed. I plan to investigate the Markov transition matrices constructed by the fitness functions with isolation points and solve the problem by either adjusting the proposed approximation or developing a novel approach.

The design of fitness functions of multi-objective problems is the other direction for future research. If the fitness functions cannot be well-formed for multi-objective problems, some of the objectives will not be considered during the GA runs. In the future, I plan to derive suitable rules to guide other researchers in dealing with this problem.
BIBLIOGRAPHY


