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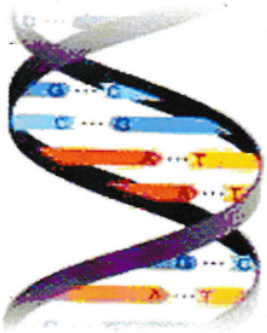

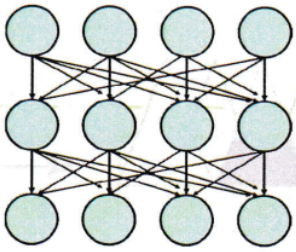

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Computer Experiments with a Clonal Selection Algorithm for the Travelling Salesperson Problem

Ayi Purbasari[1], Iping Supriana Suwardi[2], Oerip Santoso[3], and Rila Mandala[4]

[1]Informatics Department, Unpas Bandung
[2, 3, 4]School of Electrical Engineering and Informatics, Bandung Institute of Technology
[1]pbasari@unpas.ac.id, [2]iping@informatika.org, [3]oerip@informatika.org, [4]rila@informatika.org

Abstract

Clonal Selection Algorithm (CSA) is a popular algorithm from Artificial Immune System that using population based and selection that is inspired from Clonal Selection Theory. This research focused to observe the parameters to conclude the correlation between them. The research began with the implementation the CSA using C# language for combinatorial optimization problem, e.g. Travelling Salesperson Problem (TSP). The experiment is using dataset from TSPLIB for 2 kinds of dataset, e.g. Berlin52.tsp and tsp225.tsp. We concluded that number of node for the problem (non), population size parameter (N) and selection size parameter (n) are affecting the runtime result linearly and also affecting the best tour weight.

Keywords— Clonal Selection Algorithm, Artificial Immune System, Travelling Salesperson Problem.

Introduction

Bio-inspired are known as techniques to improve computational techniques by mimicking natural system and achieving similar desirable properties of the natural system. Famous bio-inspired are neural networks[10], genetic algorithms [6], ant colony optimization[5], and bee colony optimization[8]. Artificial immune systems (AIS) is another promising biological inspired computation based on metaphor and abstraction from theoretical of the vertebrateimmune system[12]. The field of AIS encompasses a spectrum of algorithms that exist inspired by the behavior and properties of immunological cells, specifically B-cells, T-cells and dendritic cells (DCs). AIS became a class of computationally intelligent systems, bridging between immunology and engineering.

The original research in AIS focus on applying immunological principles to computational problems in practical domains in a wide variety of domains, including machine learning, computer security, data mining, and optimization [11][1]. There are three classes of AIS algorithms derived from more simplified models: clonal selection, negative selection, and immune networks. Clonal Selection Algorithms (CSA) is the popular algorithms from AIS that using population based and selection that is inspired from Clonal Selection Theory[4]. This CSA are using for pattern recognition and optimization problem. Ulutas [14]stated that 23% of this algorithms are using for optimization problems.

However, this algorithm consists of many user-defined parameters that should be well understood. There are population size that randomly created selection size and cloning population size. This research focused to observe the parameters to conclude the correlation between them. The research began with the implementation the CSA using C# language for combinatorial optimization problem, e.g. Travelling Salesperson Problem (TSP). This experiment uses dataset from TSPLIB[13] for 2 kinds of dataset, e.g.Berlin52.tsp and tsp225.tsp. At the end of research, we concluded the correlation between population size parameter and selection size parameter to run time and convergent.

The paper is organized as follows. Section II reviewsthe clonalselection principle and algorithm. Section III contains implementation of clonal selection algorithms and defines user-defined parameters. Section IV briefly discusses the sensitivity analysis of the algorithm in relation to the user-defined parameters. Section V concludes the paper.

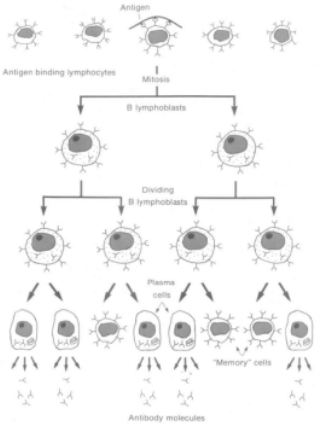

Figure 1 Simple overview of the clonal selection process, image taken from [3]

Clonal Selection Algorithm

Immune System Inspiration

Theimmunesystemconsistsofmorethan15%ofgenes in thehumangenome thatis

whyimmunefunctionplaysa vitalrolein humanhealth[9]. Theimmunesystemprotects humanhealthagainstexternalinvaders, suchas viruses, bacteria, and other pathogens, whileignoringself. The primary task of the immune system can be summarized as distinguishing between itself and non-self[7]. Most immune responses result from interactions amongvarious typesofcells, continually signalingtoone anothervia theirmechanisms.Mostimmunehas additional regulatorymechanisms resultsfromdifferentstates(resting/active, immature/mature, naive/effector/memory)of theircells.Therearetwokindof immuneresponses, innate immune response andacquired immune responses [7].

Artificial Immune System

Over the last few years, there has been an ever-increasing interest in the area of artificial immune systems (AIS) and their applications [11]. AIS uses ideas gleaned from immunology in order to develop adaptive systems capable of performing a wide range of tasks in various areas of research.AISalgorithms are inspiredfrom acquiredimmuneresponse[11].

Clonal Selection Theory

The clonal selection theory is a theory used to describe the functioning of acquired immunity, specifically the diversity of antibodies used to defend the organism from invasion[4] [3]. This theory postulated by Burnet (1957), stated that antibodies production is the selection process triggered by antigens as their enemies. The theory specifies that the organism have a pre-existing pool of heterogeneous antibodies that can recognize all antigens with some level of specificity[4] [3]. An antibody then chemically binds to the antigen if its receptors matched to an antigen. This chemically binding causes the cell to clone, replicate and produce more cells with the same receptor. During the cloning stage, cells genetic mutations occur and promote the match or affinity with the antigen. This allows the binding ability of the cells to improve with time and exposure to the antigen.

This is the simple overview of the clonal selection process:

There are B cells bind to specific antigens. Once bound, the B cells proliferates and produces many clone B cells. They differentiate into either plasma cells that produce antibodies or long lived memory cells.Antibody used to effector of the immune response and memory cells used if the antigen reappears. Beside B cells, there area another cells in acquired immunity, T cells. T cells consist of T Helper cells and T Killer cells. Their roles are to stimulate B cells and to neutralize the infected cells. These T cells are not to discussin clonal selection theory in detail.

Clonal Selection Algorithm Principle

Principle

The clonal selection theory is inspiring deCastro and Von Zuben to create clonal selection algorithms [4] name ClonalG. This figure below show the workflow of the Clonal Selection Algorithm technique:

Table 1 Clonal Selection Algorithms

Stage	Name	Description
1	Initialization	Initiallyindividual population(N) randomly.
2	Evaluation	a) Select Antigen – A single antigen is selected at random without replacement (for the current generation) from the pool of antigens. b) Exposure – The system is exposed to the selected antigen. Affinity values are calculated for all antibodies against the antigen. Affinity is a measure of similarity, and is problem dependent. It is common to use Hamming distance.
3	Selection and Clone	c) Selection – A set of n antibodies are selected from the entire antibody pool that have the highest affinity with the antigen. d) Cloning – The set of selected antibodies are then cloned in proportion to their affinity (rank based).
4	Hypermutation	The clones (set of duplicate antigens) are then subjected to an affinity maturation process to better match the antigen in question. Here, the degree of maturation is inversely proportional to their parent's affinity (rank based), meaning that the greater the affinity, the lower the mutation.
5	Editing Receptor	The d individuals in the remaining r antigen pool with the lowest affinity are replaced with new random antibodies.
6		Loop, Stage 1-5 until stop condition e.g. number of generation or convergent or optimal.

Selected antigens are antigens with highest affinity values that are calculated for all antibodies against the antigen. Affinity is a measure of similarity, and is problem dependent. It is common to use Hamming distance between two bit strings of equal length. Hamming distance is a simple measure that counts the number of point difference between two strings and is calculated as follows:

$$D = \sum_{i=1}^{L} \delta \qquad \begin{array}{l} \delta = 1, ab_i \neq ag_i \\ \delta = 0, ab_i = ag_i \end{array}$$

Where
D = the Hamming distance,
ab = the antibody,
ag = the antigen and
L = the length of the bit string.

Equation 1 - Hamming distance calculation

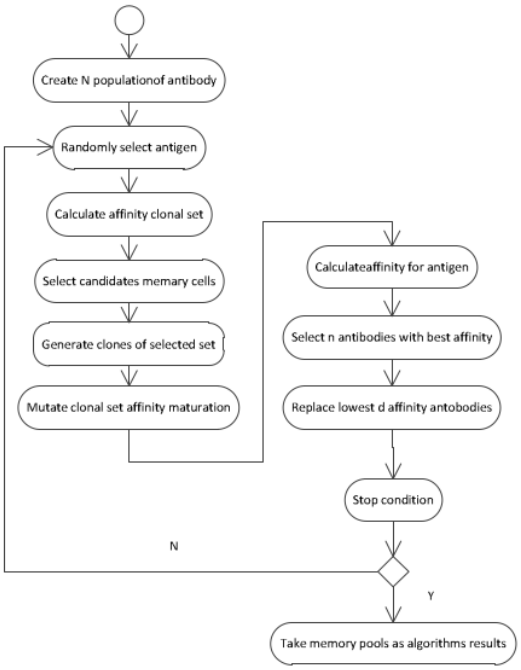

Figure 2 Overview of the Clonal Selection Algorithm [3]

An important aspect of this task is about the number of clones created from each of the n selected antibodies. This process is proportional to their affinity using a rank based measure. The set of selected antibodies is sorted in ascending order by their affinity to the antigen. The ordered list is then iterated, and the total number of clones prepared is:

$$N_c = \sum_{i=1}^{n} round(\beta . N)$$

Where:
Nc = the total number of clones,
n = the number of selected antibodies,
β = the clone factor

Equation 2 the total number of clones created for all antibodies per antigen exposure[4].

Parameters

As describes at Table 1 above, ClonalG has seven user defined parameters which include; antibody population size, memory pool size, selection pool size, remainder replacement size, clonal factor and number of generations as we can see in the following table. This algorithm needs random number generator seed.

Table 2 User defined parameter in Clonal Selection Algorithm

Parameter	Symbol	Value	Description
Antibody population size	N	Random	Specifies the total amount of resources, which is the total number of antibodies to be maintained by the system.
both the memory antibody pool	m	$m \leq N$	Portion of N allocated to the memory pool
the remainder antibody pool	r	$r = N - m$	The remainder antibody pool
Selection pool size	n	$n \in [1, n]$	The total number of antibodies with greatest affinity to draw from the antibody population for cloning on the presentation of each antigen.
Remainder replacement size	d	$d \in [0, r]$	Specifies the total number of lowest affinity antibodies to replace with random antibodies on each antigen exposure.
Clonal factor	β	$\beta \in [0, r]$	Specifies a scaling factor for the number of clones created for selected antibodies.
Number of generations	G		Specifies the total number of algorithm iterations to perform

Immune Engineering

Immune engineering is the process mapping between the immune system and the problem[12]. In this research, we used clonal selection algorithm to solve an optimization problem. Mapping between the immune system and an optimization problem is done as follows:

Table 3Immune system and an optimization problem.[2]

Immune system	Optimization problem
Pathogen	Problem(environmentofantigens)(e.g., city graphwhereinnodes representantigens)
Immuneresponse	Solution(e.g., shortestpath)
B-cells	Agents
Clonalselection	Creatingnewagentsinordertoexploretheenvironment(i.e., proliferation)
Positive/negativeselection	Selectionofuseless/badagentstokill themselves(i.e., apoptosis)

Implementation and Experiment Design

Implementation

This section describes the implementation of Clonal Selection Algorithm. We used C# programming to develop CSA program, and Travelling Salesperson Problem as a case study. The program is developed using Toshiba Portege Z935, Processor Intel®

Core™ i5-3317* CPU@1.70GHz. Using memory 4GB, 64-bit Operating System and Windows 7, Microsoft Visual Studio 2010 (10.0.30319.1 RTMRel), Microsoft.NET Framework version 4.0.30319 RTMRel, Visual C# Express 2010 01014-169-2560017-70895.

The Travelling Salesperson Problem (TSP) datasets are taken from TSPLIB [13]. This research is using two kinds of datasets, Berlin52.tsp with 52 nodes and Tsp225.tsp with 225 nodes.

Figures below show dataset of Berlin52.tsp and dataset of tsp225.tsp:

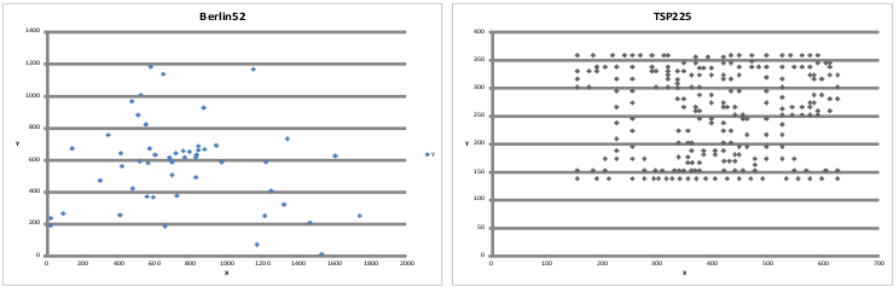

Figure 3 Dataset of Berlin52.tsp and dataset of tsp225.tsp

Experimenal Design

There are two parameters investigated were N (number of population) and n (number of best affinity selected). These parameters were investigated to see their affected to run time and convergent. The non, the number of node, consist of 52 and 225. The nog, the number of generation is set to 1000. This experimental environment is the same with the implementation environment.

The figure 3 besides is the computation model for experimental design:

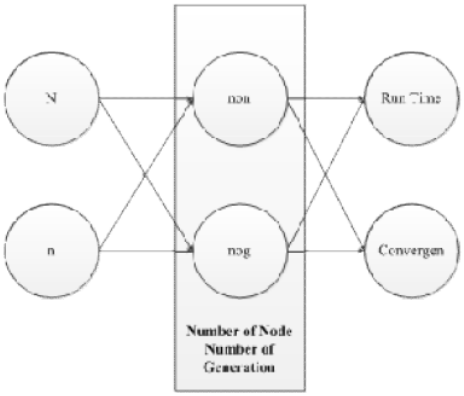

Figure 4 Experimental Design

Result and Discussion
This section provides the result of experiment:

Result: Best Cost and Convergen
Best cost
In the following graph, we can see that the weight of the best tour is obtained with n = 25and N = 100. The best weight is10673.27 ingeneration 532. Best tour obtained by: 11, 50, 32, 42, 35, 39, 37, 4, 9, 8, 7, 40, 16, 20, 30, 0, 31, 18, 44, 48, 21, 19, 49, 28, 29, 1, 6, 41, 22, 15, 34, 33, 36, 14, 3, 45, 43, 17, 2, 38, 47, 5, 23, 24, 27, 25, 26, 12, 46, 13, 51, 10.

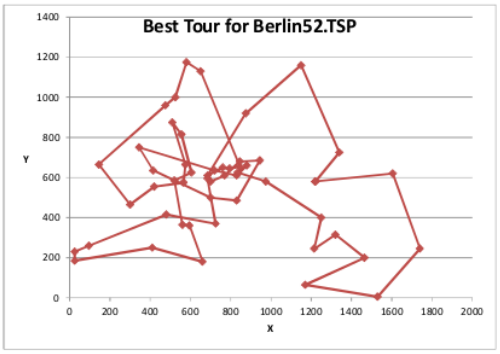

Figure 5 Best Tour for Berlin52.TSP

Varying Nand Varying n for Berlin52.TSP
In the following graph shows the varying N for Berlin52.TSP. As we can see, the best tour is obtained for N = 100 and n = 10. Best weight is 12312.47and it is obtained in generation 401.

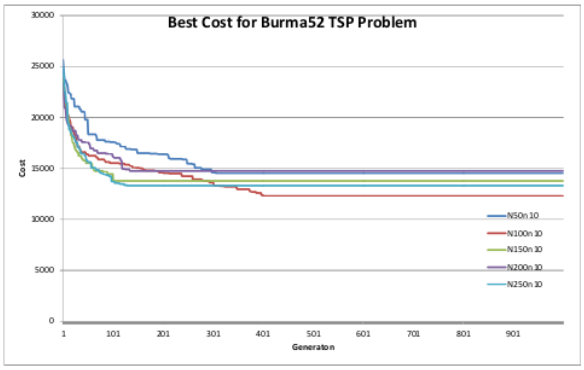

Figure 6 Varying N for Berlin52.TSP

The following graph is showing the best tour for Berlin52.TSP in varying n. The best tour is obtained for N = 100 and n = 25. Best weight is 10673.27 ingeneration 532.

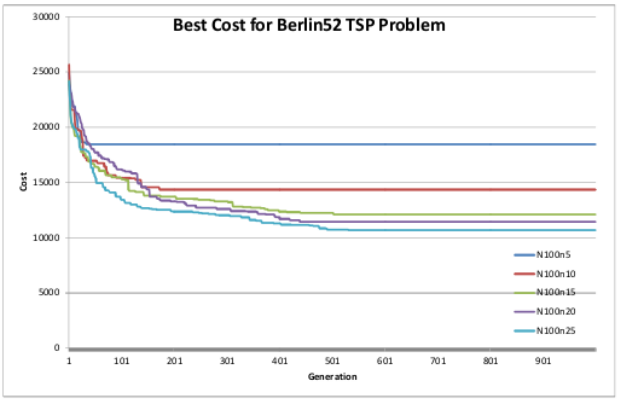

Figure 7 Varying n for Berlin52.TSP

Varying N and Varying n (TSP225)

In the following graph shows the varying N for TSP225.TSP. As we can see, the best tour is obtained for N = 250 and n = 10. Best weight is 28987.83and it is obtained in generation554.

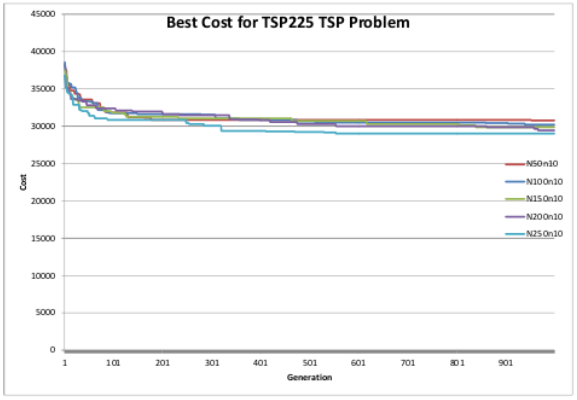

Figure 8 Varying N for TSP225.TSP

This is the graph showing the best tour for Berlin52.TSP in varying n. The best tour is obtained for N = 100 and n = 20. Best weight is 28730ingeneration 987.

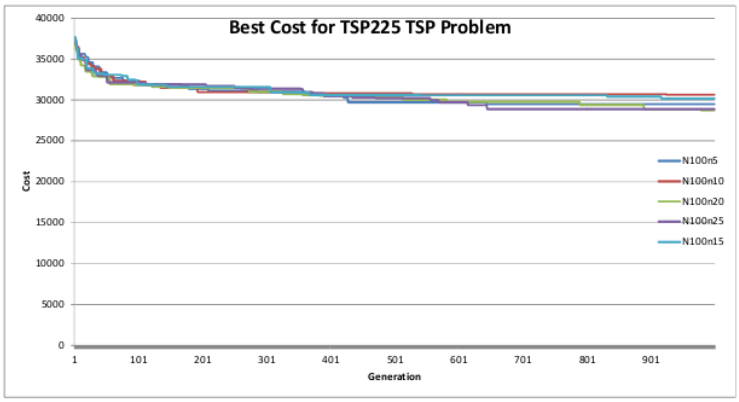

Figure 9 Varying n for TSP225.TSP

Result: Runtime

In this section, we will see the runtime result for both varying N and n for dataset Berlin52 and TSP225.

Varying N (Berlin 52 and TSP225)

The following graph is shown the runtime result for varying N Berlin52.TSP and TSP225.TSP

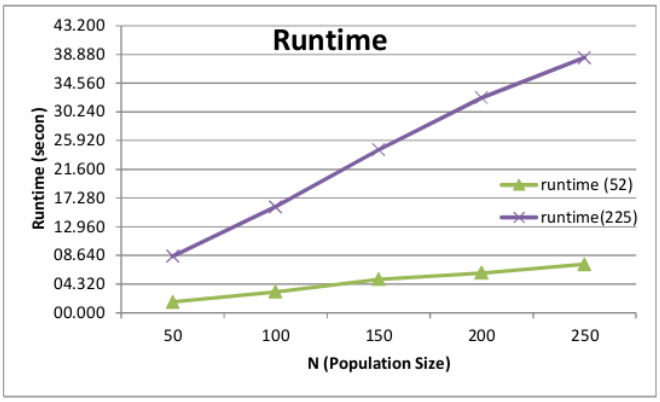

Figure 10 Runtime Result Varying N for Berlin52.TSP and TSP225.TSP

As we can see, the best execution is obtained by N = 50 for Berlin52.TP and by N = 50 for TSP225.tsp.

Varying n (Berlin 52 and TSP225)
The following graph is shown the runtime result for varying n Berlin52.TSP and TSP225.TSP

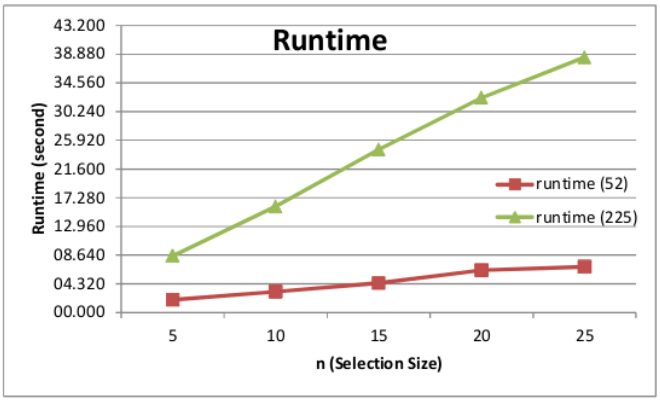

Figure 11 Runtime Result Varying n for Berlin52.TSP and TSP225.TSP

As we can see, the best execution is obtained by n = 5 for Berlin52.TP and by n = 5 for TSP225.tsp.

Regression Anaysist
In this following section, we will see the summary of the best cost and runtime result for all dataset andthe variant. Here the table that summarize all experiments:

Table 4the Experiment Summarize

No	#Node	N	n	Generation	Best Cost	Runtime
1	52	50	10	307	14526.97	01.635
2	52	100	10	401	12312.47	03.168
3	52	100	5	120	16138.76	01.920
4	52	100	10	173	14348.51	03.152
5	52	100	15	503	12113.04	04.449
6	52	100	20	440	11440.16	06.369
7	52	100	25	532	10673.27	06.890
8	52	150	10	101	13775.85	05.051
9	52	200	10	134	14767.7	06.007
10	52	250	10	129	13307.51	07.314
11	255	50	10	953	30748.77	08.520
12	255	100	10	940	30201.6	15.949
13	255	100	5	644	29501.97	09.199

14	255	100	10	925	30651.66	16.547
15	255	100	15	917	30182.59	22.980
16	255	100	20	987	28730	30.438
17	255	100	25	645	28902.08	40.309
18	255	150	10	840	29880.97	24.532
19	255	200	10	967	29472.77	32.349
20	255	250	10	554	28987.83	38.408

Using multiple regressing, we can see the relationship between number of node (non), parameters N and n, and the runtime result (r) and weight (w) for the best tour.

Here the estimating model for runtime results:

r =.000.010 * non +.000.001*N+.000.001 * n + (.000.264)

Here the estimating model for best tour weight results:

W = (166.065.083) * non + (4.588.662)*N+ 80.717.241 * n + 11792.523.698

Discussion

Sensitivity of n – n does affect the best tour obtained and increases in n, increased the computational complexity of the algorithm, thus slowing its execution.

Sensitivity of N – N does affect the best tour obtained and increases in n, increased the computational complexity of the algorithm, thus slowing its execution.

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