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An Intelligent Artificial System : Artificial Immune based Hybrid Genetic Algorithm for the Vehicle Routing Problem

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Abstract: Vehicle routing problems are well-known combinational optimization problems with considerable economic significance. Considering the vehicle routing problem with limited capacity on tree is a problem that often naturally arises in railway, river, and rural road networks. In this paper, we describe an artificial immune system that is distributed, robust, dynamic, diverse and adaptive. It captures many features of the vertebrate immune system and proposed an intelligent artificial system which hybrid genetic and immune algorithm to solve the vehicle routing problem with limited capacity on tree. Computational results show the proposed technique to be very competitive with the best-known heuristic routing procedures providing some new best-known solutions.

Keywords: Dalgaard-Strulik model, energy, economic growth, time delay, limit cycle

1 Introduction

The vehicle routing problem (VRP) is a fundamental problem in combinatorial optimization with wide-ranging applications in practice. It forms the core of logistics planning and has been extensively studied by the operations research community. The last two decades have seen enormous improvements in the research communitys ability to solve these problems, due to better algorithms as well as better computational capabilities. Toth and Vigo [1] provide an update survey of problem variants, exact solution techniques, and heuristics for the vehicle routing problem. Vehicle routing problems are well-known combinational optimization problems with considerable economic significance. An important variant of the VRP arises when a fleet of vehicles characterized by different capacities and costs is available for distribution activities. Since it was first proposed by Dantzig and Ramser [2], hundreds of papers have been devoted to the exact and approximate solution of the many variants of this problem, such as the Capacitated VRP (CVRP), in which a homogeneous fleet of vehicles is available and the only constraint is the vehicle capacity, or the VRP with Time Windows (VRPTW), where customers may be served within a specified time interval and the schedule of the vehicle trips needs to be determined. In vehicle routing problem, customers with known demands are serviced by a homogeneous fleet of limited capacity vehicles. A fixed number k of identical vehicles, each with a capacity Q, is available at the central depot. Routes are assumed to start and end at the central depot. There are M customers (plus the depot), each customer provides a time interval during which a particular task must be complete such as loading or unloading the vehicle. The objective is to minimize the number of tours or routes, and then for the same number of tours, to minimize the total traveled distance. The total load on any vehicle associated with a given route does not exceed the vehicle capacity. The VRP is an NP-complete problem, preventing the use of exact algorithms for certain instances of the problem, and thus requiring the use of heuristic approaches.

This paper proposes one artificial intelligent system based on genetic and immune algorithm to solve VRP with limited capacity on tree, name ASIG-VRPCT. The concept of ASIG-VRPCT is from genetic and artificial immune systems are used genotypic-based distances to move from the infeasible region to the feasible region of a

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problem. We examine the basic problem including capacity constraints only, which has received greater attention in the literature, as well as the more recently studied variants including time window constraints. Moreover, we briefly review a related variant known as the Site-Dependent VRP (SDVRP), where there are compatibility relations between customers and vehicle types. Additional case studies and applications related to the solution of Heterogeneous VRPs can be found in Semet and Taillard [3], Rochat and Semet [4], Brandao and Mercer [5], Prins [6], Wu et al. [7] and Tavakkoli-Moghaddam et al. [8]. In addition, Engevall et al. [9] use a game-theoretic approach to model the problem of allocating the cost of the heterogeneous fleet to the customers. The ASIG-VRPCT is an algorithm with unsupervised of the solution. Although this may look like a limitation, the results achieved show a good performance of the proposed method.

The remainder of this paper is organized as follows. Section 2 presents an overview of a few algorithms to solve VRP; Section 3 introduced the Artificial immune system and in Section 4, the AIS-based hybrid genetic algorithm is presented; in Section 5 introduced the basic concepts of the proposed AIS-based hybrid genetic algorithm, ASIG-VRPCT, is detailed; the computational results are presented in Section 6. Finally, some conclusions and future research direction are presented in Section 7.

2 Related Works

Hybrid genetic algorithms (HGAs) have, over the last decade, become almost standard tools for function optimization and combinatorial analysis: according to Goldberg et. al., real-world business and engineering applications are typically undertaken with some form of hybridization between the GA and a specialized search [10]. The reason for this is that HGAs generally have an improved performance, as has been demonstrated in such diverse areas as vehicle routing [11] and multiple protein sequence alignment [12]. Genetic algorithms [13],[14] are proposed by Lai and Jianag, are adaptive heuristic search methods that mimic evolution through natural selection. They work by combining selection, recombination and mutation operations. The selection will drive the population toward better solutions while recombination uses genes of selected parents to produce offspring that will form the next generation. Mutation is used to escape from local minima.

The VRP is a hard combinatorial problem. Naddef and Rinaldi [15], Baldacci et al. [16], proposed exact algorithms which can only solve relatively small instances and their computational times are highly variable. To this day, heuristics remain the only reliable approach for the solution of practical instances. In contrast to exact algorithms, heuristics are better suited to the solution of VRP variants involving side constraints such as time windows by Cordeau et al. [17], pickups and deliveries in Desaulniers et al. [18], periodic visits proposed by Cordeau et al. [19], etc.

In recent years several powerful heuristics have been proposed for the VRP and its variants, based on local search, population search and learning mechanisms principles. Local search includes descent algorithms by Ergun et al. [20], Osman [21] in simulated annealing, deterministic annealing by Golden et al. [22] and Li et al. [23], tabu search in Osman [21]; Taillard [24]; Gendreau et al. [25]; Xu and Kelly [26]; Rego and Roucairol [27] and Cordeau et al. [28]. The two best known types of population search heuristics are evolutionary algorithms proposed by Prins [29], Berger and Barkaoui [30] and adaptive memory procedures by Tarantilis and Kiranoudis [31].

The field of VRP heuristics is very active, as witnessed by the large number of recent articles listed in the previous paragraph. This chapter summarizes some of the most important new developments in the area of VRP heuristics and presents comparative computational results. Several surveys have recently been published on VRP heuristics proposed in Laporte and Semet [32]; Cordeau and Laporte [33].

From recent surveys, most metaheuristics proposed so far present some variability in average and best performances. Besides, reported average performance results can hardly support any claims acknowledging a dominating heuristic over the others [45-50]. No single method consistently matched the best-known minimum number of tours over all problem instances examined. Moreover, computational cost represents a sensitive issue to be satisfactorily addressed as well. As a result, a more robust, cost effective and stable algorithm still remains elusive. The main contribution of this paper is an attempt to design such a new technique. A version of a route-directed hybrid genetic and immune algorithm for the VRPCT is proposed.

3 Artificial Immune System (AIS)

In recent years, interest has been growing in the use of other biologically inspired models: in particular the immune system, as witnessed by the emergence of the field of Artificial Immune Systems (AIS). An artificial immune system is a type of optimization algorithm inspired by the principles. AIS can be defined as a computational system inspired by theoretical immunology, observed immune functions, principles and mechanisms in order to solve problems [34]. It is used to solve constrained global optimization [35]. Farmer et al. [36] were the first to suggest a way of representing the immune system in computer. Hajela et al. [37],[38] described the procedure for improving the performance of a constrained genetic search to simulate the mechanics of a biological immune system. Their objects are using the immune system capabilities to enhance the convergence of a GA approach, and handling the design of constraints in the GA based optimization. Nareli et al. [35] and Carlos et al. [39] proposed an artificial immune based method for handling constraints in GA. Their approach produced highly competitive results better than those of penalty function approaches for various function optimizations.

The key immune procedure in the artificial immune system is the immune response. It is composed of interaction between the antigen and the antibody. Like the majority of GA applications, Hajela et al. [37],[38] had used a binary encoding for the strings representing the immune components (antigens and antibodies). The fitness of an individual was determined by its ability to recognize either a specific or a broad group of antigens, given by a function that measured the number of matching bits between a pair of strings, z= $sumt_i$, where $t_i = 1$ if there was a match in the ith location of the two strings, otherwise $t_i = 0$. The degree of recognition, known as the affinity between the immune cell and the antigen, is measured via a function that quantifies the strength of the match between the two. A simple immune components relationship can be seen in Fig. 3.1.

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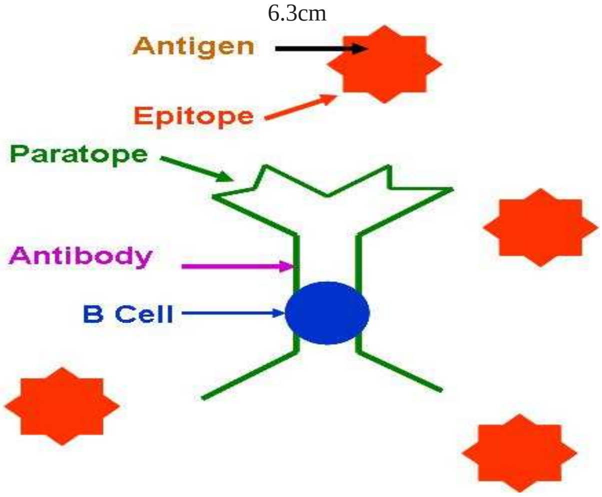

Figure 3.1: A simple immune components relationship

The proposed algorithm, the candidates n, the populations are divided into antigens and antibodies according to whether they satisfy minimize the number of tours or routes, distance and limited capacity. All feasible individuals are denominated as antigens and the remaining infeasible individuals as antibodies. The AIS-based algorithm drives the antibodies (infeasible individuals) towards the antigens (feasible) through evolution inspired by the immune principle, where the infeasible individuals with some form of penalty function. At the same time, the antigen part will also be driven to better position via crossover operator along with the local search algorithm. This idea is based on the model in Forrest [40].

4 AIS-based hybrid genetic algorithms

Evolutionary algorithms are a wide class of metaheuristics, also inspired from a natural metaphor, with Genetic Algorithms (Gas) being one of the best known. Basically, they mimic the way species evolve and adapt to their environment, according to the Darwinial principle of natural selection. Under this paradigm, a population of solutions (often encoded as bit or integer strings, known as chromosomes) evolves from one generation to the next through the application of operators that are similar to those found in nature, like selection of the fittest, genetic crossover and mutation. Through the selection process, only the best solutions are allowed to become parents and to generate offspring. The mating process, known as crossover, then takes two selected parent solutions and combines their most desirable features to create one or two offspring solutions. It is repeated until a new population of offspring is obtained. Finally each offspring is randomly perturbed by a mutation operator. Starting from a randomly or heuristically generated initial population, this cycle is repeated for a number of generations, and the best solution found is returned at the end.

GA is the most suitable method for NP complete and NP hard optimized problems [41],[42]. Despite the success of the GA in global optimization technique, the GA is used to solve the unconstrained problems [41]. An additional mechanism is required to incorporate constraints of a type into the fitness function. Various constraint handling methods are described in [43]. Penalty functions remain the most efficient technique for optimization problems. Constrained problem is transformed into unconstrained problems by adding penalty term with objective function. The performance of a penalty function depends on the type of functions adopted and on the values defined for its parameter (namely, penalty factor). It is difficult to decide suitable penalty parameters. Unsuitable penalty parameters result in poor performance even though the other parts of algorithms are designed well.

Our proposed approach incorporates an emulation of AIS with GA and uses genotypic-based distances to move from the infeasible region of a problem. In our approach, GA is hybridized by incorporating three heuristic schemes. In the first scheme, artificial immune search mechanism is used to handle the constraints instead of penalty function. This mechanism is based on similarities between chromosomes, so no additional evaluation on fitness function is required. The second scheme is to use the local search function along with crossover to drive the antigen into the better position. With this second hybrid approach, local search function is applied to each newly generated offspring to move it to a local optimum before inserting it into the new population. In the third approach, clone selection algorithm with hyper-mutation is used to preserve the diversity. The selected clone cells are subject to an affinity maturation process, which improves their affinity to the selective antigens. Also, we use the search engine of the genetic algorithm to conduct the search towards the global optimum. In our algorithm both antigen and antibodies re represented as binary strings and a matching rule is used to estimate the similarity between an antigen and an antibody.

4.1 Vehicle Routing Problem with limited Capacity on Tree

The vehicle routing problem with limited capacity can be modeled as a rooted tree $T = (N_0, E)$, the root of T (representing the depot) is a unique node in N_0. The set of nodes other than the depot is denoted by N. Edge set E and $(i, j) \in E$, i is closer to the root than j, then i is the parent of j and j is a child of i. Node i is an ancestor of node j if i lies on the unique simple path from the root to j. We will use the convention that the tree is represented topologically downward. Therefore, a node is below its ancestors and above its descendants. A leaf node of the graph is a node that does not have children. A sub-tree S is a connected sub-graph of T. The root of a sub-tree S, denoted by r_S, is the node in S that is closet to the depot. The weight of a sub-tree is the sum of weights of the edges in the sub-tree.

Given a subset of nodes $L \subset N_0$, the minimal covering sub-tree is the union of all paths from each node in L to the depot. Observe that the covering sub-tree is rooted at the depot. The covering sub-tree is the minimum set of edges that need to be traversed in order to visit each node in L.

Without loss of generality, we assume that the degree of the depot is 1. Consider the situation where there is no fixed cost associated with the use of a vehicle. Observe that a route that includes the depot as a non-terminal node can be broken up into multiple routes, each route originating and terminating at the depot with no change in the objective value. Thus, in this situation, the problem may simply be decomposed into multiple smaller problems, one for each sub-tree incident to the depot node. Figure 4.1 illustrates this situation. On the other hand, when there is a fixed cost associated with a route, we add a new node and connect it to the depot by an edge whose cost equals the fixed cost. We make this new node the depot. Finally, we wet the demand of the old depot node to zero and solve the ASIG-VRPCT on this network where the depot has degree 1.

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A tour for each vehicle consists of a path from the depot to the first node in the vehicle tour, a set of arcs connecting nodes in the vehicle tour in increasing order of node index, and a path from the last node in the tour back to the depot.

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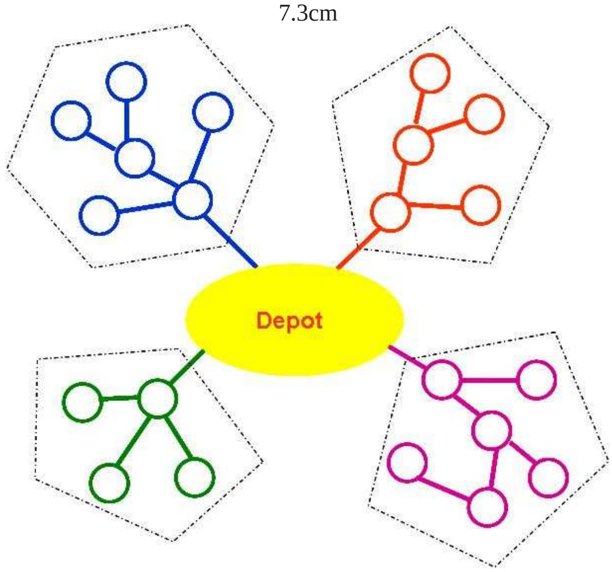

Figure 4.1: A tree in which the degree of the depot is greater than 1 can be split into multiple sub-trees

The following four sets of binary variables in our formulation. The decision variables are shown in Table 1.

Table 1. The decision variables

variable	value	meaning
x_{ij}	1	if node i immediately precedes node j in the vehicle tour
	0	otherwise
y_{ij}	1	if node i and j are visited by the same vehicle
	0	otherwise
w_i	1	if node i is the first node visited in the vehicle tour
	0	Otherwise
z_i	1	if node i is last node visited in the vehicle tour
	0	otherwise

The VRPCT model uses the following data that is available as input which is shown in Table 2.

We may now state our formulation as follows, assuming that nodes are indexed in depth first order.

$$Minimize \sum_{i=1}^{n} S_i(w_i + z_i) + \sum_{i=1}^{n-1} \sum_{j=j+1}^{n} L_{ij} x_{ij}, \qquad (1)$$

Table 2. Input Parameters

Parameters	Meaning
D_i	Demand at node i
L_{ij}	Shortest path distance between nodes i and j
S_i	Shortest path distance between nodes i and depot
N	Set of all nodes other than the depot; $N = \{1,2,\ldots,n\}$
C	Capacity of each vehicle
V_k^{min}	A lower bound on the number of vehicles required to service nodes $\{k,\ldots,n\}$

$$Subject to D_i + \sum_{j=i+1}^{n} D_j y_{ij} \leq C \forall i \in N, \tag{2}$$

$$y_{ij} + y_{jk} - y_{ik} \leq 1 \forall i,j,k \in N, i < j < k, \tag{3}$$

$$x_{ij} - y_{ij} \leq 0 \forall i,j \in N, \tag{4}$$

$$w_j + \sum i = 1^{j-1} x_{ij} = 1 \forall j \in N, \tag{5}$$

$$z_i + \sum j = i + 1^n x_{ij} = 1 \forall i \in N, \tag{6}$$

$$w_i, x_{ij}, y_{ij}, z_i \in 0, 1 \forall i,j \in N, i < j, \tag{7}$$

The objective function is to minimize the distance of all traversed arcs. Constraint (2) is the vehicle capacity constraint. Although there is no explicit concept of a vehicle in the formulation, capacity constraints are captured by summing demand over nodes that are n the same vehicle. Constraint (3) creates a clique among nodes in the same vehicle, if nodes i and j are in the same vehicle, and nodes j and k are in the same vehicle, then nodes i and k must be in the same vehicle. Constraint (4) enforces that node i cannot precede node j unless they are both in the same vehicle. Constraint (5) and (6) force the demand at a node to be served by exactly one vehicle. Constraint (7) enforces that all variables are binary. An interesting observation is that the integrality of x, w and z variables can be relaxed (i.e., $0 \leq x,w,z \leq 1$) without affecting the integrality of the solution. However, we observed that in practice, the problem was solved faster if all variables were specified to be binary.

4.2 Clone selection algorithm

The clone selection principle describes the basic features of an immune response to an antigenic stimulus [44]. The clone selection algorithm is shown to be capable of solving complex machine-learning tasks, like pattern recognition and multi-modal optimization. It establishes the idea that only those cells that recognize the antigen are selected to proliferate. The selection cells are subjected to an affinity maturation process, which improves their affinity towards the selective antigens. The feature of the clone selection theory is that, the new cells are copies of their parents (clone) subjected to a mutation mechanism with high rates (somatic hypermutation). In this section, the clone selection principle is used for driving the antibody population to an antigen population with heuristic mutation between antigen and antibody. In this mutation, for each antibody, we have selected the path which is not satisfying the constraints and then replaced it with the path present in the randomly selected antigen. The steps for clone selection algorithm are as follows:

1. The population is divided into antigens and antibodies.
2. An antigen (Ag) is selected randomly from the antigen population (α).
3. The a1 best antibodies are selected from the antibody population (β), based on an affinity measure with antigen and these immune cells (where population size is P_n) are cloned.
4. Each cell in clone population is submitted to a hypermutation scheme, where the hypermutation is inversely proportional to the affinity of the antibody; the higher affinity cells are mutated with lower mutation probability. A high mutation probability is followed in lower affinity cells. This step helps for preserving the diversity. The maturated antibody population is denominated as Anti.
5. The affinity of each mutated cell to the antigen (selected in step 2) is evaluated. The low affinity population in P_n is replaced by the high affinity population present in Anti. The replacement is done as follows: if both are infeasible then choose the individual with high affinity. The proposed algorithm is shown in Figure 4.2.

4.3 Chromosome representation

We have used the chromosome representation, which is shown in Figure 4.3. Each individual is represented by means of k bits, where k is the number of destined nodes. Each bit in the chromosome corresponds to path in the routing, from root to each node. For the given problems, chromosome representation is depicted in Figure 4.3.

```
Cloneal_selection( )
{
    Division( );
    Selection_AG(Ag,α);
    Similarity_Measure(Ag,β,aff[ ]);
    // array aff[ ] contains the affinity values of antibodies
    Selection_AB(a1, β, aff[ ]); //a1 antibodies are selected
    Clone(a1,Pn,aff[ ]);
    Hypermutation(Pn,aff[ ],a1); //a1 is maturated cells
    Similarity_Measure(Ag, a1,aff[ ]);
    Replacement( );
}
```

Figure 4.2: Clone Selection algorithm

G_1	G_2	...	G_j	...	G_k

Figure 4.3: Chromosome representation

4.4 Routing table

For a given graph, $G = (V, E)$, the proposed algorithm assumes that a routing table, which has R possible routes. Figure 4.4 shows the routing table relation with chromosome.

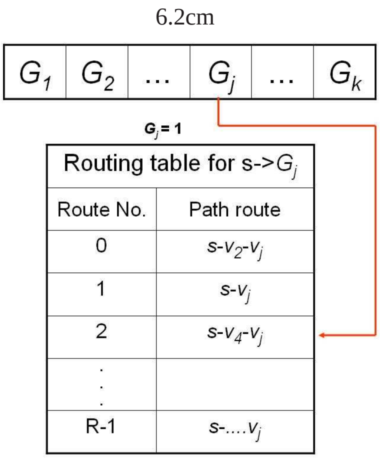

Figure 4.4: Routing table relations with chromosome

Gene $G_j = 1$, then the algorithm first find out the integer values in 0,1,2,.,R-1 which is the routing tables s ($s \to v_j$) route number.Using that route number, the path route from s to v_j is selected from the routing table. For example, a gene, 100101, the correct row entry numbers of routing tables $s \to v_j$,$s \to v_3$ and $s \to v_6$. In Figure 4.4, $G_j = 1$, the integer value, 2 is given by the algorithm, and hence the corresponding path route $s \to v_4 \to v_j$ is selected.

4.5 Mutation and crossover

Crossover is used to cross breed the individuals. Using crossover operator, information between two chromosomes are exchanged which mimic the mating process. We have adopted m point crossover with the probability of 0.54, which is shown in Figure 4.5. A pair of high fitted parents is selected from the population randomly based on fitness function values and the crossover operator chooses m cutting points randomly and alternatively interchanges each segment between two parents. The random number, m is chosen with range of 1-6. The operation for 4 point crossover is depicted in Figure 4.5. Using the output of crossover offspring finds the local maximum offspring. Those resultant offspring are added into population for next generations.

The mutation operator introduces new genetic material by randomly selecting and changing the single gene. Two mutation operators namely single gene mutation operator, gene segment shifting operators are used for avoiding the local minimum. Gene shifting probability is 0.004 and mutation probability is 0.05.

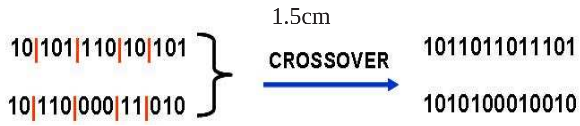

Figure 4.5: '4' point crossover operation

5 ASIG-VRPCT algorithm

The proposed ASIG-VRPCT algorithm is shown in Figure 5.1. The algorithm describes the genetic operation with affinity measure between antigen and antibody. First we randomly generate an initial population with population size P. $Inject_vaccine$( ) is used to add a single copy of a feasible solution into the initial population. Then, we divided the population into two groups. All feasible solutions are grouped into antigens and infeasible solutions are name as antibodies. If most of the individuals are infeasible, then we have applied the best individual in the population as the antigens, where best refer to the individual with the lowest amount of constraint violation.

In initialize( ) function, a sample of antibodies of size β is selected from the antibody pool and an antigen (Ag)

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```
ASIG-VRPCT( )
{
    Population Initalization ( );
    Inject_vaccine ( );
    Divide population into antibodies and antigens ( );
    Initialize ( );
    Repeat {
        Selection(Ag,β);
        Similarity_Measure((Ag,β antibodies);
    }
    until (4* antibody population size);
    crossever_Ab ( );
    Mutation ( );
    {
        Repeat{
            Clonal Selection with hypermutation ( );
            // for antibodies
            crossever_Ab ( );
            Mutation ( );
        } until (maximum generation);
    }   //the converged solution is the optimized solution
}
```

Figure 5.1: ASIG-VRPCT algorithms

is chosen at random from the antigen population with our replacement. In $Similarity_Measure$( ), each antibody in the sample is compared against the antigen selected, and we have computed the similarity measure K between the antibody and antigen as follows

$$K = \sum i = 1^L t_i, \tag{8}$$

Where $t_i = 1$ if there is a matching at position i=1,2,,L (L is the length of the chromosome) to $t_i = 0$ if there is no match. K represents a distance measured at the genotypic level (i.e. at the level of the chromosome encoding). The antibody (Ab) with highest score has the match score added to its fitness value (i.e. add the K value to the antibodys affinity). The affinity of other antibodies remains unchanged. The antibodies are then returned to the antibody population and process (selection, $fitness_function$) is repeated four times of antibody population. Based on these values, the crossover operation among antibodies is performed with the probability of 0.54. The offspring produced by crossover is improved. Crossover operation between the antigens is performed with the probability of 0.54. Mutation operation between the antigens is performed with the probability of 0.05. Mutation operation between antibodies is also performed with the probability 0.05.

Clone selection with hypermutation algorithm is applied to the antibodies. In $crossover_Ab$( ), we randomly choose m and apply m point crossover operator with the probability 0.54 based on the fitness function over antigens. In mutation( ), we have performed mutation operation among antigens with the probability of 0.05. Here both mutation and crossover helps to move the antigens to a better position. The converged solution is minimized the number of tours or routes, and then for the same number of tours, to minimize the total traveled distance. Finally we run the dynamic algorithm for adapting the changes at run time. In this work, hybridizing of GA is carried out as following:

1.Embedding the local search function to move solutions towards local optima after each generation which results in a significant improvement in the overall performance;
2.Incorporating the AIS based method for handling constraints;
3.Using the clone selection method for maintaining a good balance between diversity and convergence;
4.It follows the search engine of the genetic algorithm to conduct the search towards the global optimum for chromosomes and embeds the dynamic algorithm into the GA for handling dynamism.

6 Simulation and results

Our simulation built on IBM Pentium IV personal computer equipped with 2.8 GHz CPU, 4 GB RAM, 500GB HDD, and Windows XP OS. The performance of ASIG-VRPCT Algorithm was compared with VLSVRPs algorithm [23] and DVRP [29] algorithm. The parameter list is shown in Table 3. Figure 6.1 shows the effect of number of generation with travel distance which depicts the convergence property of various algorithms. For Figure 6.1, we can observe that after 160 generations, algorithms converge to optimized solutions.

Table 3. Parameter list

Parameter	Value
Population size	100
Crossover probability	054
Mutation probability	0.05
Degree constraint	6
Maximum number of generation	200
Group size	35%
Gene shifting probability	0.004

Figure 6.2 depicts the routing number versus group size. The routing number generated by our algorithm

compared with that of other algorithms. The group size is 30, the routing number for ASIG-VRPCT yields better performance than that of other algorithms (VLSVRPs and DVRP). When the group size is greater than 60, ASIG-VRPCT yields better performance than other algorithms. This is because of the fast convergence property of ASIG-VRPCT in large solution space.

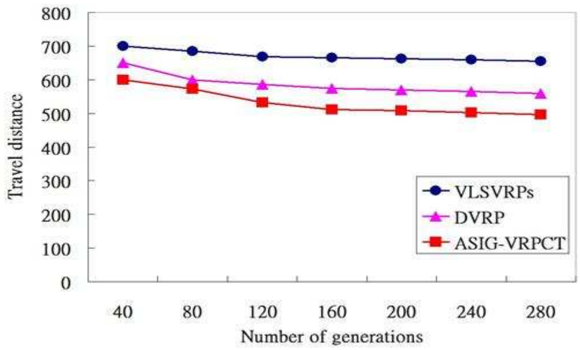

Figure 6.1 Convergence property of algorithms

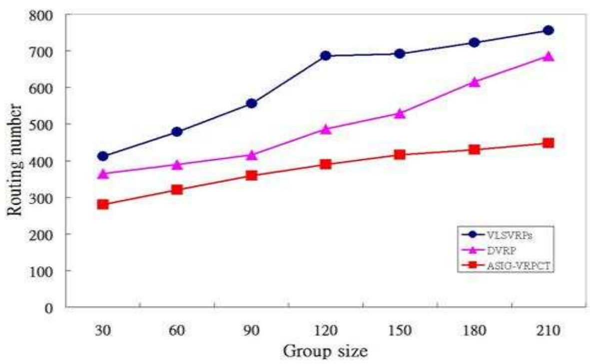

Figure 6.2 Routing number versus group size

In our simulation, the execution time required by each algorithm is presented in Figure 6.3. As seen in Figure 6.3, ASIG-VRPCT required less execution time because of applying hybrid genetic algorithm to solve the VRP. Artificial immune algorithm for handling constraints, clone selection method is helpful for increasing the convergence speed and to obtain the optimized results.

7 Conclusion

In this paper, we proposed an artificial immune based hybrid genetic algorithm for solving the vehicle routing problem with limited capacity on tree. Instead of penalty function, we have used artificial immune based algorithm

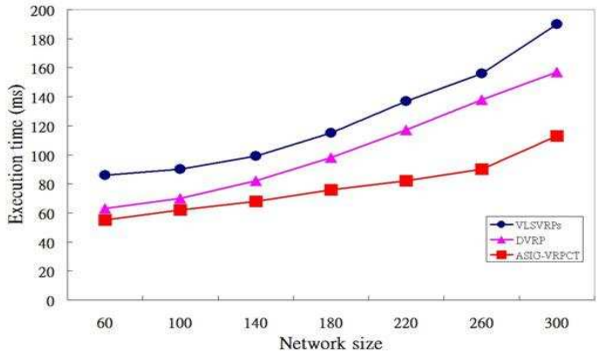

Figure 6.3 Routing number versus group size

for dealing the infeasible chromosomes, which avoids the difficulties faced by penalty methods. Random point crossover technique helps to speed up the convergence. Hypermutation with clone selection method effectively move the solution to global optimized solution. Experimental results show that our algorithm yield solutions comparable to that of best previously known heuristics.

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