공학석사학위논문

Vehicle routing problem considering reconnaissance and transportation

정찰 및 수송을 동시 고려한 차량경로문제

2019 년 2 월

서울대학교 대학원

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Abstract

Vehicle routing problem considering reconnaissance and transportation

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Troop movement involves transporting military personnel from one location to another using available means. To minimize damage from enemies, the military simultaneously uses reconnaissance and transportation units during troop movements. This thesis proposes vehicle routing problem considering reconnaissance and transportation (VRPCRT) for troop movements in wartime. VRPCRT is formulated as a mixed-integer programming model for minimizing the completion time of wartime troop movements. For this thesis, an ant colony optimization (ACO) algorithm for the VRPCRT was also developed and computational experiments were conducted to compare the performance of the ACO algorithm and that of the mixed-integer programming model. Furthermore, a sensitivity analysis of the change in the number of reconnaissance and transportation vehicles was performed, and the effects of each type of vehicle on troop movement were analyzed.

Keywords: Ant colony optimization, Vehicle routing problem, Wartime logistic

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Chapter 1

Introduction

Troop movement involves transportation of military personnel from one location to another using available means. In wartime, rapid and efficient troop movement offers many benefits in battle. For instance, efficient troop movement saves time and resources, which can be used for combat preparation and future operations. To win a battle, the commander must concentrate combat power at the opportune place and time to achieve a relative advantage over the enemy. Therefore, in the process of rearranging troops, efficient and rapid movement is essential.

The procedure for tactical troop movement in wartime consists of two parts. First, the reconnaissance troops patrol the area where the units and equipment will be transported. Second, the transportation troops move the units and equipment to the area where the reconnaissance troops have patrolled. Because of enemy threats, such as an ambush or surprise attack, the reconnaissance troops are deployed to protect the vehicle movement undertaken by the transportation unit during an operation. Figure 1 represents an example of the procedure for tactical troop movement in wartime.

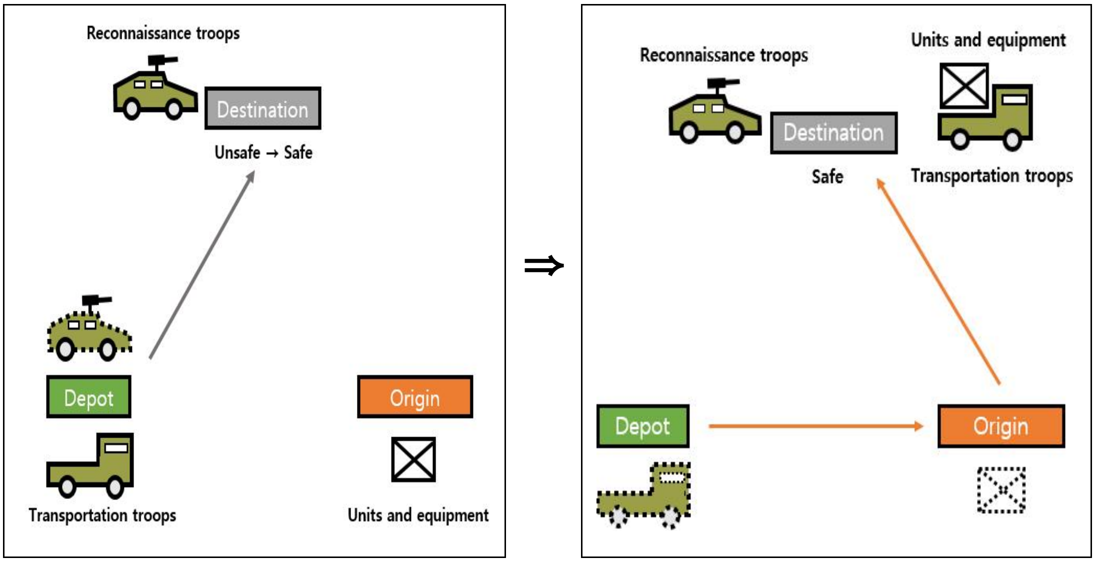

Figure 1. Procedure for tactical troop movement in wartime

Troop movement is usually performed using a ground vehicle or helicopter, and in some cases, the troops move on foot. Troop movement using vehicles is associated with a pickup and delivery problem (PDP), which is a modified form of a vehicle routing problem (VRP). Existing PDPs model realistic situations with constraints on vehicles in terms of time windows or capacity. However, for troop movement in wartime, more than the transportation vehicle route, as solely needed for existing PDPs, must be considered according to tactical troop movements; that is, both reconnaissance and transportation plans must be determined simultaneously for troop movement, which is essential, during wartime. Despite the importance of troop movement, existing transportation studies have limited application to troop movement because they have taken into account only transportation vehicles.

In this thesis, a VRP considering reconnaissance and transportation (VRPCRT) is proposed for troop movement in wartime. For the VRPCRT, the procedure of tactical troop movement was modeled mathematically and the routes of reconnaissance and transportation vehicles were determined simultaneously to complete troop movement in the shortest possible time under various constraints.

The VRPCRT is NP-hard because it is generalization of PDP. Due to complexity of NP-hard, many heuristic algorithms were developed to solve it. An ant colony optimization (ACO) algorithm based on the ant colony system (ACS) was proposed to solve the VRPCRT in this study.

1.1 Research Motivation and Contribution

The first contribution of the thesis comes from the proposed PDP as applied to the military field. PDPs are frequently used in real-life peacetime situations, such as those related to transportation or logistic systems. For instance, Chemla et al. [7] studied a PDP for a bike-sharing system and Swersey and Ballard [26] introduced a school bus–routing problem. Yan and Chen [29] applied the PDP to a carpooling system.

Despite clear applications for wartime, fewer PDPs have been used to study military situations compared to the implementation and research of them for peacetime, such as with transportation or logistic systems. For the study described in this thesis, by applying a PDP to the military field, procedures of troop movement were modeled with a VRPCRT.

For the second contribution, the VRPCRT was extended from the Dial-a-Ride Problem (DARP), which represents a multi-occupancy transportation system of door-to-door service [28]. Troop movement in wartime is related to a DARP because the origins and destinations of each unit are given when planning the transport. In the DARP, only transportation vehicle routes are determined, but in the VRPCRT, transportation and reconnaissance vehicle routes were determined. Constraints, such as pairing or precedence, in a DARP were included in the VRPCRT. Of note, in the VRPCRT, transportation vehicle routes were influenced by reconnaissance vehicle routes according to the procedure of troop movement; this condition was formulated as a time window constraint.

1.2 Organization of thesis

This thesis consists of six chapters. In Chapter 2, the literature review is presented. In Chapter 3, the mathematical model for the VRPCRT is described. In Chapter 4, the ACO algorithm for the VRPCRT is presented. In Chapter 5, the computational results are revealed. Finally, in Chapter 6, the conclusion is offered.

Chapter 2

Literature Review

2.1 Review of the pickup and delivery problem

The PDP has been studied for approximately 30 years and has been used in many areas of study. The PDP is classified into three types according to the structure of the problem and related constraints. One is the many-to-many (M-M) problem. In the M-M problem, any node can be an origin or destination for any commodity. For example, an M-M problem can be applied to inventory repositioning between retailers. Chemla et al. [7] studied an M-M type of PDP for bike-sharing systems. In their study, only one commodity and a capacitated single vehicle were allowed to visit a node several times. The authors proposed an efficient algorithm for the problem and a theoretical result concerning the algorithm.

Another PDP is the one-to-one problem (1-1). In the 1-1 problem, each object is assigned a given origin and destination. Dumas et al. [12] studied a pickup and delivery problem with time windows (PDPTW), which is a generalized VRP. In the problem, a vehicle route satisfies constraints, such as those related to transportation requests, capacity, time windows, and precedence. They presented an exact algorithm using column generation. Lau and Liang [18] proposed a two-phase-method algorithm for a PDPTW. In the first phase, the algorithm was constructed by combining an insertion and a sweeping heuristic to obtain an initial solution. In the second phase, a tabu search was used for improving the initial solution. Cordeau [9] dealt with the DARP. In the problem, various constraints, such as capacity, duration, paring, precedence, and time window constraints, were considered and introduced in a mixed-integer programming (MIP) formulation. A branch-and-cut algorithm, based on new valid inequalities for the DARP, was introduced. Malapert at el. [20] studied the PDP with two-dimensional loading constraints in which items were two-dimensional rectangles. Männel and Bortfeldt [21] proposed a PDP with three-dimensional loading constraints (3L-PDP). In the 3L-PDP, the vehicle capacity and requests were expressed in the form of a three-dimensional rectangle. Männel and Bortfeldt [21] used a hybrid algorithm for the model. Pankratz [24] came up with a grouping-genetic algorithm for the PDPTW. In the grouping-genetic algorithm, a gene stood for a group of requests instead of a single request.

The third PDP is the one-to-many-to-one (1-M-1) problem. In the 1-M-1, some commodities must be delivered to the customers from the depot, and other commodities must be picked up from the customers and delivered to the depot. Montané and Galvao [23] dealt with the VRP using simultaneous pickup and delivery (VRPSPD) and developed a tabu search algorithm for it. Chen and Wu [8] also studied the VRPSDP and suggested a new hybrid heuristic algorithm by combining record-to-record travel and tabu lists. Çatay [6] introduced an effective ACO algorithm for the VRPSPD.

After the PDP was introduced, heuristic and meta-heuristic algorithms for solving it were developed. Tchoupo et al. [27] developed a meta-heuristic based on an ACO combined with dedicated local search algorithms for the PDPTW. Lu and Dessouky [19] presented a new insertion-based construction heuristic for the PDPTW. The crossing-length percentage (CLP), which is used to quantify the visual attractiveness of the solution, was introduced in their study. The CLP used in their heuristic algorithm improved the quality of the solution. Computational experiments showed that the proposed heuristic was better than a sequential-insertion heuristic and a parallel-insertion heuristic. Melachrinoudis et al. [22] proposed a double-request DARP with soft time windows and suggested a tabu search heuristic as the solution method.

In this study, transportation and reconnaissance vehicles are considered simultaneously and their routes are needed to be coordinated. Bae and Moon [2] extended a multi-depot VRP by considering two different types of service vehicles: delivery and installation. The service level, which refers to the time interval between delivery and installation, was proposed in the model. They also developed a new hybrid genetic algorithm. Aldaihani and Dessouky [1] studied the problem, which deals with integrating fixed route service (buses) and general PDP (taxis). They proposed a three stage heuristic construction algorithm that provide an approximate solution. The differences among VRP studies that deal with multi types of vehicles performing different task are summarized in Table 1.

Table 1. Characteristics of literature review

Authors	This thesis	Bae and Moon[2]	Aldaihani and Dessouky [1]
Application	Troop movement in wartime	Delivery and installation of electronics	Dial a ride
Vehicle types	Reconnaissance and transportation vehicle	Delivery and installation vehicle	Taxis and buses
Solution approach	Ant colony optimization algorithm	Genetic algorithm	Three-stage heuristic construction algorithm

2.2 Review of ant colony optimization algorithms

Dorigo et al. [11] introduced the ant system (AS), which was the first ACO algorithm used to solve the traveling salesman problem (TSP). They compared it with other meta-heuristics, such as the tabu search, simulated annealing, and a genetic algorithm. Bullnheimer el al. [5] introduced an AS in which all solutions were ranked and pheromone trails were updated according to the ranked solutions. Hu et al. [16] proposed the continuous orthogonal ant colony, in which the orthogonal design method was used to search the solutions effectively. Dorigo and Gambardella [10] introduced the ACS, which was extended from the AS. The local pheromone updating rule and new state transition rule were applied to the ACS. Stützle and Hoos [25] developed the MAX-MIN ant system (MMAS), which was derived from the AS. Only the best ants, found globally, were used to update the pheromone trails, which were limited for each solution to avoid stagnation in the MMAS. Blum and Dorigo [4] introduced the hyper-cube of the ACO, in which the pheromone value was limited between 0 and 1. Favaretto et al. [13] proposed an ACS for the VRP with multiple time windows. Fuellerer et al. [14] studied the two-dimensional loading-vehicle routing problem and proposed an ACO algorithm based on the AS.

Chapter 3

Mathematical model

3.1 Problem description

This study was aimed at developing a model for tactical troop movement in wartime. The model was developed on a complete network. The node set, W, is partitioned into {J, P, D} for which J = {0} is the depot, P = {1, 2,…, n} is the set of origin nodes, and D = {n+1,…, 2n} is the set of destination nodes. Each arc is associated with travel time, t_{ij}. For the DARP, a request specifies the locations where people are picked up and where they are delivered [3]. The request described for the DARP applies equally to the VRPCRT. Each node $i \in$ W is associated with the number of troops, q_i, and the boarding and disembarking time, st_i, such that $q_0 = 0$, $st_0 = 0$, $q_i = -q_{n+i}$ $(i = 1, \dots, n)$. Each node $i \in$ D is associated with the reconnaissance time, sd_i. Set K contains reconnaissance vehicles with a maximum route time, r_k, and set S consists of transportation vehicles. Each transportation vehicle has capacity, Q_s, and maximum route time, r_s. Dual time windows were used for destination nodes. A time window [0, l_i^r] for the reconnaissance vehicle is associated with node $i \in$ D, for which l_i^r refers to the latest time for reconnaissance. A time window [a_i+sd_i, l_i^t] for the transportation vehicle is associated with node $i \in$ D for which l_i^t, a_i, and represent the latest time for transportation and arrival time of the reconnaissance vehicle, respectively. The time windows for transportation indicate that transportation vehicles can visit only destination nodes that have been patrolled by a reconnaissance vehicle.

The transportation vehicle in the troop movement procedure is similar to that of the DARP, which was designed to determine a route and schedule for pickup and delivery requests between origin and destination pairs [9]. In a DARP, the route of the transportation vehicle satisfies the precedence, pairing, capacity, maximum route time, and time window constraints. The precedence constraint means that a vehicle visits the origin before moving to a destination, and a pairing constraint is used so that the customer's pickup and delivery request is fulfilled by the same vehicle [28]. Figure 2 shows an example of requests and a vehicle route that satisfies the precedence and pairing constraints.

In the VRPCRT, reconnaissance vehicles visited only the destination nodes and necessarily satisfied the time window and maximum route time constraints. This reconnaissance activity at a destination during troop movement was performed by reconnaissance troops. Transportation vehicles satisfied the constraints of the DARP, such as pairing, precedence, capacity, and time window constraints, and thus, was used in the VRPCRT to describe the transportation troops that move units and equipment from an origin to a destination.

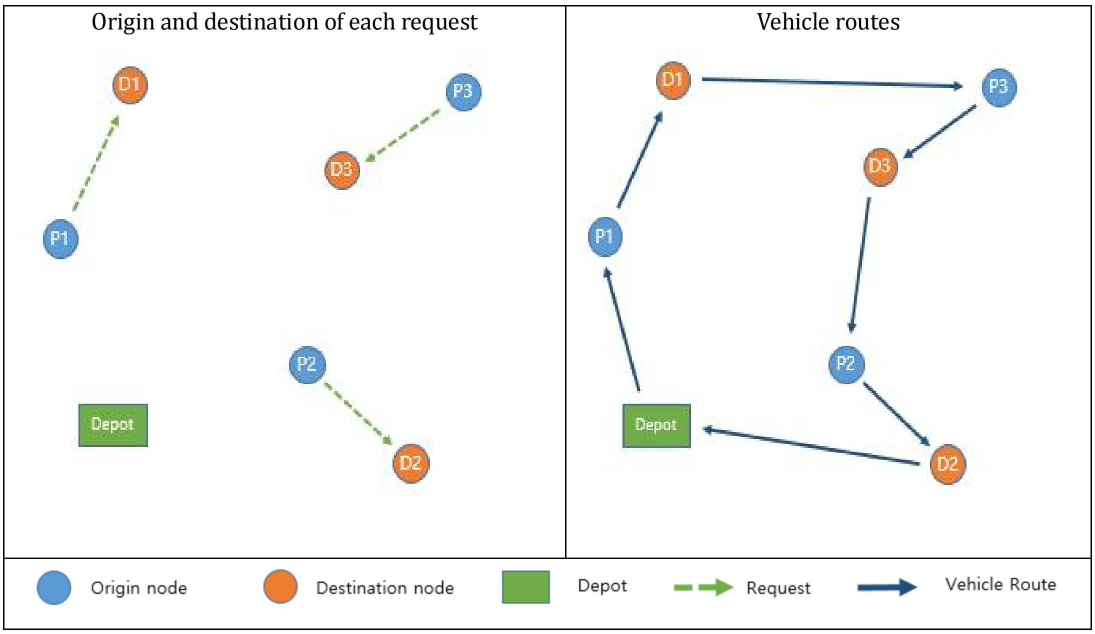

Figure 2. Vehicle route satisfying pairing and precedence constraints

Figure 3 represents the feasible routes for the reconnaissance and transportation vehicle in VRPCRT. Figure 3 shows that the transportation vehicle waits at the P1 node until the reconnaissance vehicle leaves the D1 node, and then it visits the D1 node after the reconnaissance vehicle at the D1 node has advanced to the D3 node. If the reconnaissance vehicle at the D1 node is delayed, then the arrival time for transportation vehicle at the D1 node is also delayed.

Hence, the transportation vehicle route was affected by the reconnaissance vehicle route because of the time window constraints of transportation as explained in the previous paragraph. In other words, the time windows of the transportation vehicles in the VRPCRT were not given as parameters because they depended on the reconnaissance vehicle routes.

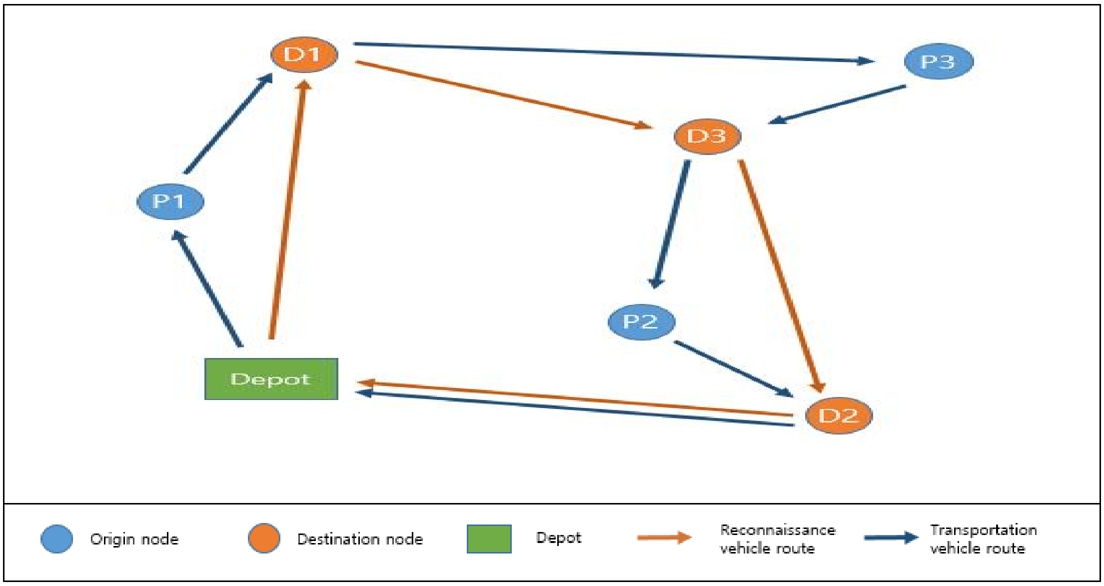

Figure 3. VRPCRT model

The following assumptions about the model were used to develop the VRPCRT:

(1) Two types of vehicles (reconnaissance and transportation) and two types of nodes (origin and destination) were used.

(2) All vehicles departed from and returned to the depot.

(3) Destination nodes must be visited exactly once by a reconnaissance vehicle, and origin and destination nodes must be visited once by a transportation vehicle.

(4) A transportation vehicle can only visit a destination node that has been patrolled by a reconnaissance vehicle.

(5) Requests of each troop must be served by a transportation vehicle.

(6) Numbers of troop at all nodes cannot exceed the capacity of the transportation vehicle.

(7) All vehicles must satisfy the time window constraints of each node and the maximum route time constraints.

3.2 The model formulation

An MIP model was developed for troop movement in wartime. Sets, parameters, and decision variables of the model are described as follows:

Sets

P : set of origin nodes for requests
P = {1, 2, 3,..., n} where n is the total number of requests

D : set of destination nodes for requests
D = {n+1, n+2,..., 2n} where n is the total number of requests

J : depot, J = {0}

W : set of all nodes, W = P ∪ D ∪ J

K : set of reconnaissance vehicles

S : set of transportation vehicles

U : P ∪ D

Decision variables

a_i: arrival time of the reconnaissance vehicle at node i $\quad \forall\, i \in D$

b_i: arrival time of the transportation vehicle at node i $\quad \forall\, i \in U$

a_{jk}: arrival time of the reconnaissance vehicle at the depot $\forall\, j \in \mathrm{J},\ \ k \in \mathrm{K}$

b_{js}: arrival time of the transportation vehicle at the depot $\forall\, j \in \mathrm{J},\ \ s \in \mathrm{S}$

$$x_{ijk} = \begin{cases} 1, & \text{if reconnaissance vehicle visits node } j \text{ from node } i \\ 0, & \text{otherwise} \end{cases}$$

$\forall\, i,j \in \mathrm{D} \cup \mathrm{J},\ \ k \in \mathrm{K}$

$$x_{ijs} = \begin{cases} 1, & \text{if transportation vehicle visits node } j \text{ from node } i \\ 0, & \text{otherwise} \end{cases}$$

$\forall\, i,j \in \mathrm{W},\ \ s \in \mathrm{S}$

Q_{is}: number of troops in transportation vehicle S after visiting node i

$\forall\, i \in \mathrm{U},\ \ s \in \mathrm{S}$

Parameters

l_i^r: latest time for reconnaissance at node i $\forall\, i \in \mathrm{D}$

l_i^t: latest time for transportation at node i $\forall\, i \in \mathrm{D}$

t_{ij}: travel time between nodes i and j $\forall\, i,j \in \mathrm{W}$

q_i: number of troops to board at node i $\forall\, i \in \mathrm{P}$

q_{n+i}: number of troops that disembark at node i $(-q_i)$ $\forall\, i \in \mathrm{D}$

sd_i: reconnaissance time at node i $\forall\, i \in \mathrm{D}$

st_i: boarding and disembarking times at node i $\forall\, i \in \mathrm{U}$

r_k: maximum route time for vehicle k $\forall\, k \in \mathrm{K}$

r_s: maximum route time for vehicle s $\forall\, s \in \mathrm{S}$

Q_s: capacity for vehicle s $\forall\, s \in \mathrm{S}$

M: big M

The formulation of VRPCRT can be stated as follows:

Minimize τ

$$b_i \le \tau \qquad \forall\, i \in \mathrm{W} \tag{1}$$

$$\sum_{k \in K} \sum_{i \in D \cup J} x_{ijk} = 1 \qquad \forall\, j \in \mathrm{D} \tag{2}$$

$$\sum_{s \in S} \sum_{i \in W} x_{ijs} = 1 \qquad \forall\, j \in \mathrm{U} \tag{3}$$

$$\sum_{\mathrm{i}\in\mathrm{D}\cup\mathrm{J}} x_{ijk} = \sum_{\mathrm{i}\in\mathrm{D}\cup\mathrm{J}} x_{jik} \qquad \forall\, j \in \mathrm{D} \cup \mathrm{J},\ k \in \mathrm{K} \tag{4}$$

$$\sum_{\mathrm{j}\in\mathrm{W}} x_{ijs} = \sum_{\mathrm{j}\in\mathrm{W}} x_{jis} \qquad \forall\, i \in \mathrm{W},\ s \in \mathrm{S} \tag{5}$$

$$\sum_{\mathrm{j}\in\mathrm{D}} x_{ijk} = 1 \qquad \forall\, i \in \mathrm{J}, \quad k \in \mathrm{K} \tag{6}$$

$$\sum_{j\in P} x_{ijs} = 1 \qquad \forall\, i \in \mathrm{J},\ s \in \mathrm{S} \tag{7}$$

$$\sum_{j\in W} x_{ijs} = \sum_{j\in W} x_{n+i,\, js} \qquad \forall\, i \in \mathrm{P},\ s \in \mathrm{S} \tag{8}$$

$$L_i = b_{n+i} - (b_i + st_i) \qquad \forall\, i \in \mathrm{P},\ s \in \mathrm{S} \tag{9}$$

$$t_{i,n+i} \leq L_i \qquad \forall\, i \in \mathrm{P},\ s \in \mathrm{S} \tag{10}$$

$$a_j \geq a_i + sd_i + t_{ij} + M\left(\sum_{k\in K} x_{ijk} - 1\right) \qquad \forall\, i \in \mathrm{D} \cup \mathrm{J},\ j \in \mathrm{D} \tag{11}$$

$$b_j \geq b_i + st_i + t_{ij} + M\left(\sum_{s\in S} x_{ijs} - 1\right) \qquad \forall\, i \in \mathrm{W}, \quad j \in \mathrm{U} \tag{12}$$

$$r_k \geq a_{jk} \geq a_i + sd_i + t_{ij} + M(x_{ijk} - 1) \qquad \forall\, i \in \mathrm{D},\ j \in \mathrm{J},\ k \in \mathrm{K} \tag{13}$$

$$r_s \geq b_{js} \geq b_i + st_i + t_{ij} + M(x_{ijs} - 1) \qquad \forall\, i \in \mathrm{U},\ j \in \mathrm{J},\ s \in \mathrm{S} \tag{14}$$

$$a_i + sd_i \leq l_i^r \qquad \forall\, i \in \mathrm{D} \tag{15}$$

$$a_i + sd_i \leq b_i \leq l_i^t \qquad \forall\, i \in \mathrm{D} \tag{16}$$

$$Q_S \geq Q_{js} \geq Q_{is} + q_j + M(x_{ijs} - 1) \geq 0 \qquad \forall\, i,j \in \mathrm{W},\ s \in \mathrm{S} \tag{17}$$

$$a_j = b_j = st_j = sd_j = x_{iis} = x_{iik} = Q_{js} = 0 \tag{18}$$

$$\forall\, i \in \mathrm{W},\ j \in \mathrm{J},\ k \in \mathrm{K},\ s \in \mathrm{S}$$

The objective function minimizes the maximum arrival time of any transportation vehicle. Constraints (2) represents the destination nodes must be visited exactly once by a reconnaissance vehicle. Constraints (3) means that the origin and destination nodes must be visited once by a transportation vehicle. Constraints (4) and (5) ensure that the vehicle that visited the node is the same vehicle that is leaving the node. Constraints (6) and (7) refer to the reconnaissance and transportation vehicle, respectively, that departs from the depot. Constraints (8) indicates that each request is served by the same transportation vehicle. Constraints (9) and (10) guarantee that the transportation vehicle visits the origin nodes before the destination nodes. Constraints (11) and (12) represent relationships between the arrival time of the reconnaissance and transportation vehicles to nodes. Constraints (13) and (14) are related to the maximum route time for the reconnaissance and transportation vehicles. Constraints (15) and (16) specify the time window constraints, and constraints (17) dictates the vehicle capacity constraint. Constraints (18) represents the depot time and initial conditions at the depot.

3.3 Numerical example

In this section, the VRPCRT was validated by solving the numerical example through Xpress-IVE Version 1.24 optimization software. Small data sets consisting of 7 nodes are presented in the numerical example. The nodes in this example consist of three origins, three destinations, and one depot. Travel times between each node and the parameters for the model are presented in Tables 2 and 3, respectively. All parameters for this example were generated randomly.

Table 2. Travel times between nodes in the numerical example

	P1	P2	P3	D1	D2	D3	Depot
P1	0	49	42	69	41	30	54
P2	49	0	78	49	69	62	102
P3	42	78	0	70	14	67	45
D1	69	49	70	0	56	95	110
D2	41	69	14	56	0	69	58
D3	30	62	67	95	69	0	58

Depot	54	102	45	110	58	58	0

The routes and arrival times of each vehicle are described in Table 4 and illustrated Figure 4. The optimal value provided by the model was 228, which refers to the completion time of the troop movement. Transportation vehicles satisfied the precedence, paring, and capacity constraints in the numerical example, and both transportation and reconnaissance vehicles satisfied the time window and the maximum route time constraints in the numerical example.

The main feature of the VRPCRT is that the reconnaissance vehicle route affects the route of the transportation vehicle. In other words, transportation vehicles must visit the destination nodes that the reconnaissance vehicles have patrolled. In this example, all transportation vehicles visited the destination nodes after the reconnaissance vehicles completed the assignment such that transportation vehicle 1 waited at the P1 node until after the reconnaissance vehicle completed duty at the D1 node.

Table 3. Parameters in the numerical example

- Number of reconnaissance vehicles: 1
- Number of transportation vehicles: 2
- Boarding and disembarking time: 3
- Reconnaissance time: 15
- Latest time for reconnaissance at destination node: 250
- Latest time for transportation at destination node: 300
- Maximum route time for reconnaissance vehicle: 400
- Maximum route time for transportation vehicle: 400
- Capacity of transportation vehicle: 50
- Number of troops to board: P1(10), P2(15), P3(25)

Table 4. Results from the numerical example

Reconnaissance vehicle 1	Depot	D3	D2	D1	Depot	
Arrival time		58	142	213		
Transportation vehicle 1	Depot	P3	D3	P1	D1	Depot
Arrival time		45	115	148	228	
Waiting time				8		
Transportation Vehicle 2	Depot	P2	D2	Depot		
Arrival time		102	174			

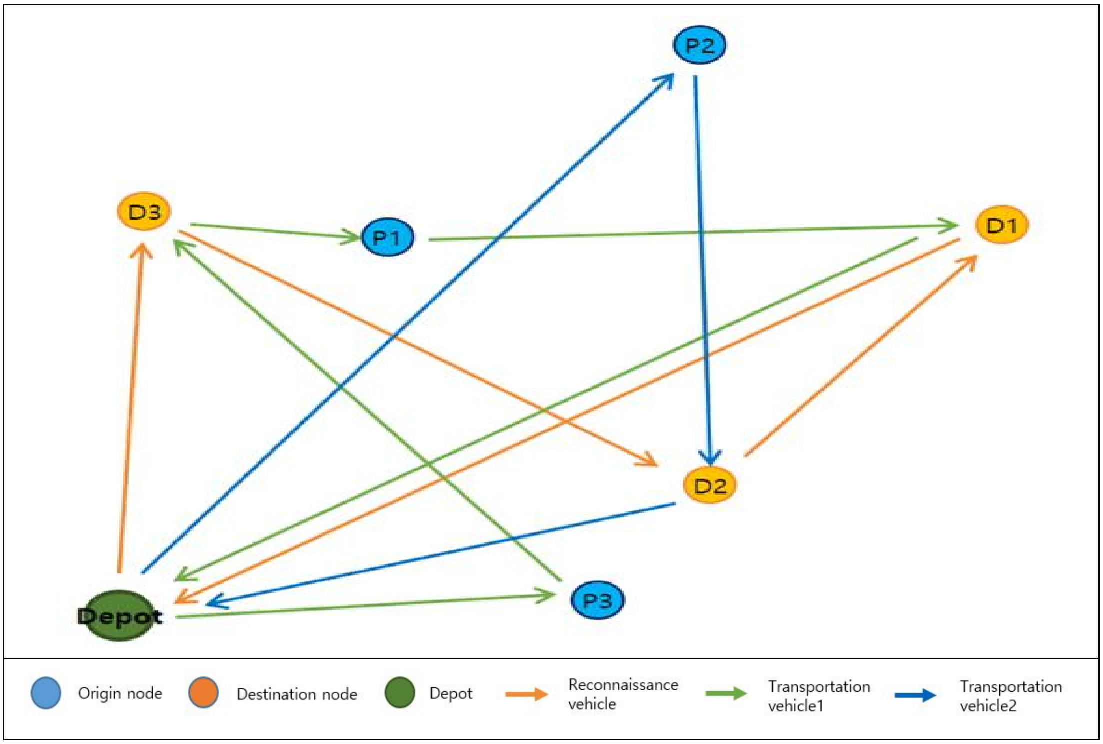

Figure 4. Each vehicle route in the numerical example

Chapter 4

Ant colony optimization algorithm

In this section, the proposed ACO algorithm for the VRPCRT is described. The ACO algorithm is a meta-heuristic developed to solve combinatorial optimization problems, such as the TSP or VRP. The ACO algorithm was based on the idea that ants leave pheromone trails when they are searching for food. The pheromone affects the way the ants move, so it is an important factor for the ACO algorithm. In the natural world, the pheromone accumulates along the route of ants searching for food or evaporates over time. Similarly, the pheromone accumulates or evaporates according to the parameters and rules of the ACO algorithm.

The proposed ACO algorithm for the VRPCRT in the study is based on the ACS algorithm that featuring local pheromone updating and transition rule that differ from the AS [11]. The proposed ACO algorithm was also modified by considering characteristics of the VRPCRT.

The process for running an ACO algorithm for the VRPCRT consists of three steps. The first step involves construction of a solution such that the ants (vehicles) selects each node probabilistically and repeats this process until feasible solutions (routes) were generated. The second step requires local pheromone updating. Whenever ants constructed a feasible solution, local pheromone updating was performed to change the probability that the ants would choose each node. In the third step, the global pheromone updating is performed. It affected the probability that ants would select each node according to the best solution, which had been constructed in the first step.

The three steps of the proposed ACO algorithm were repeated as described to discover and improve feasible solutions

4.1 Construction of a solution

In this section, the process of construction of a solution is described. For the DARP, only the routes of the transportation vehicles are considered as the feasible solutions. Meanwhile, the model presented in this thesis takes into account both reconnaissance and transportation vehicles simultaneously, so the feasible solution refers to route pairs of reconnaissance and transportation vehicles that satisfy the constraints.

For the creation of a feasible solution for the VRPCRT, a reconnaissance vehicle route was made. Then, the transportation vehicle route was determined according to the reconnaissance vehicle route. Because the time window constraints of the transportation vehicle were affected by the reconnaissance vehicle route, the reconnaissance vehicle route must be fixed first to determine the transportation vehicle route.

In the ACO algorithm, vehicles are represented by ants. Therefore, for this study, reconnaissance and transportation ants represent reconnaissance and transportation vehicles, respectively. The reconnaissance route was made as follows: the number of ants (vehicles) was given as a parameter, and every reconnaissance ant was located at the depot. One of the ant is selected randomly. It selects one of the feasible nodes that can visit from its current node through transition rule and adds the feasible node to its route. The next ant, also selected randomly, moves to a feasible node and creates a route, different from the first ant, by adding feasible nodes. This process was repeated until the reconnaissance ants (vehicles) visit all the destination nodes and satisfy all the constraints at the same time. The reconnaissance routes were thus created by the time the process was ended. After the reconnaissance routes were made, transportation routes were made in the same way.

Whenever it adds a feasible node to its route, the ant (vehicle) follows the transition rule for constructing a route [15]: The ant selects the node with the highest $[\tau_{ij}]^{\alpha} \cdot [\eta_{ij}]^{\beta}$ value with probability q_0. If the node with the highest $[\tau_{ij}]^{\alpha} \cdot [\eta_{ij}]^{\beta}$ value is not selected(with probability 1-q_0), then the ant selects another node *j* with probability P_{ij} as follows:

$$P_{ij} = \begin{cases} \dfrac{[\tau_{ij}]^{\alpha} \cdot [\eta_{ij}]^{\beta}}{\sum_{l \in N_i^k} [\tau_{il}]^{\alpha} \cdot [\eta_{il}]^{\beta}}, & if\ j \in N_i^k \\ 0 & \text{otherwise} \end{cases}$$

In this equation, N_i^krepresents the set of feasible nodes when ant *k* is positioned at node *i*. The term τ_{ij} stands for a pheromone between node *i* and *j*. The η_{ij} value is a heuristic reciprocal of the time value for travel between node *i* and *j*. The parameters are q_0, *α*, and β. In addition, several feasible solutions were generated by repeating the first step in each iteration of the ACO algorithm.

4.2 Pheromone updating

The pheromone affects how ants move in the natural world. Therefore, for the ACO algorithm, the pheromone affects the node selection of ants (vehicles). Because the probability of node selection in construction of a solution depends on the pheromone, the probability of node selection changes as the pheromone updating progresses. For the VRPCRT, τ_{ij}^r and τ_{ij}^t refer to the respective pheromones between node *i* and *j* for the reconnaissance and transportation ants. The pheromones are distinguished in the ACO algorithm to create various feasible solutions in the first step. Pheromones for reconnaissance and transportation ants are updated, independently. Two types of pheromone updating were used for the ACO algorithm: local and global.

Local pheromone updating was performed whenever a feasible solution was generated in the first step. When the reconnaissance and transportation ants visit node *j* from node *i* along the feasible solution (route), local pheromone updating was performed as follows [15]:

$$\tau_{ij}^{r} \leftarrow (1-\rho_l)\cdot\tau_{ij}^{r} + \rho_l\cdot\tau_0^{r}$$

$$\tau_{ij}^{t} \leftarrow (1-\rho_l)\cdot\tau_{ij}^{t} + \rho_l\cdot\tau_0^{t}$$

The initial pheromone for the reconnaissance and transportation ant (vehicle) is τ_0^r and τ_0^t, respectively, and ρ_l is a parameter to control the evaporation rate during local pheromone updating. The first step and local pheromone updating were repeated several times for each iteration. When first step and local pheromone updating finished in an iteration, the global pheromone updating was performed. When global pheromone updating is processed, only the best solution is required. The best solution is the feasible solution which has the minimum objective value among the feasible solutions generated from the iteration.

Therefore, global pheromone updating was executed only once for each iteration. When the reconnaissance and transportation ant (vehicle) visits node *j* from node *i* using the best solution (the best route), global pheromone updating was performed as follows [15]:

$$\tau_{ij}^{r} \leftarrow \left(1-\rho_g\right)\cdot\tau_{ij}^{r} + Q/L_k$$

$$\tau_{ij}^{t} \leftarrow \left(1-\rho_g\right)\cdot\tau_{ij}^{t} + Q/L_k$$

Q is a parameter and L_k means the objective function value of the best route in the kth iteration.

Procedure of ACO Algorithm for the VRPCRT

Input parameters for ACO algorithm(ρ_g, ρ_l, Q, α, β, q_0)

τ_0^r, τ_0^t: initial pheromones

I: number of iterations that algorithm repeated

A: number of feasible solutions in each iteration

Output final_sol, final_value

begin algorithms
initialize final_sol, final_value, τ_0^r, τ_0^t
for $i = 1$ to I
    initialize L_i, best_sol, best_value
    for $j = 1$ to A // Construction of a solution
        while do // Construction of reconnaissance vehicle route
            Select one of reconnaissance ant k
            Move ant k to a feasible node with transition rule
        until $N_i^k = \{\}$ for all k $\in$ K
        while do // Construction of transportation vehicle route
            Select one of transportation ant s
            Move ant s to a feasible node with transition rule
        until $N_i^s = \{\}$ for all s $\in$ S
        Get feasible value and feasible solution //
        Local pheromone update // updating based on feasible solution
        If $L_i \geq$ feasible value **then**
            $L_i \longleftarrow$ feasible value
            best_sol $\longleftarrow$ feasible solution
    end for
    best_value $\longleftarrow L_i$
    Global pheromone update **//** updating based on best_sol
    If final_value $\geq$ best_value
        final_value $\longleftarrow$ best_value
        final_sol $\longleftarrow$ best_sol
end for
End algorithm

Chapter 5

Computational experiment

Table 6. Experiment 1 results with 13 nodes

In this section, the computational experiment for the model is presented. The discussion consists of two parts. First, a comparison is described for the performance between the proposed ACO algorithm and a MIP model. The MIP model was solved with Xpress-IVE Version 1.24, and the ACO algorithm was coded by JAVA Eclipse. Second, a sensitivity analysis on the changes in the number of vehicles is explained. All computational experiments were conducted by a computer featuring 8GB RAM and Intel(R) Core(TM) i5-3470 CPU with 3.20GHz.

5.1 Experiment 1

For the first part of the experiment, the performance of the proposed ACO algorithm was verified. Data sets for the computational experiment were randomly generated. Parameters of the ACO are presented in Table 5, and the results of the computational experiment are shown in Table 6, 7, and 8. Each experiment consisted of 10 instances. The ACO algorithm was run 10 times for each instance.

Table 5. Parameters of the ACO algorithm in experiment 1

α	β	Q	q_0	ρ_g	ρ_l	A	I
0.25	0.97	70	0.5	0.05	0.0003	250	400

	MIP (optimal)	ACO (best)	ACO (average)	Gap
13-1	211	211	211.0	0%
13-2	222	222	222.3	0%
13-3	199	199	199.0	0%
13-4	231	231	231.6	0%
13-5	226	226	226.3	0%
13-6	219	219	219.0	0%
13-7	219	221	221.3	0.91%
13-8	196	196	196.9	0%
13-9	230	230	230.4	0%
13-10	238	238	241.2	0%

Table 7. Experiment 1 results with 15 nodes

	MIP (optimal)	MIP (feasible)	Time (seconds)	ACO (best)	ACO (average)	Gap
15-1	253	-	483	265	268.6	4.74%
15-2	-	312	7200	255	268.6	-
15-3	258	-	927	260	272.6	0.78%
15-4	-	265	7200	265	269.8	-
15-5	253	-	369	254	255.3	0.40%
15-6	230	-	2452	230	239.0	0%
15-7	262	-	5459	269	275.5	2.67%
15-8	-	229	7200	203	203.0	-
15-9	280	-	5820	282	288.2	0.71%
15-10	217	-	249	217	225.7	0%

Table 8. Experiment 1 results with 17 nodes

	MIP (optimal)	MIP (feasible)	Time (seconds)	ACO (best)	ACO (average)	Gap

17-1	-	228	7200	227	232.0	-
17-2	-	321	7200	295	303.1	-
17-3	216		3185	216	221.4	0%
17-4	-	313	7200	298	308.6	-
17-5	-	287	7200	288	290.1	-
17-6	-	261	7200	245	255.0	-
17-7	-	255	7200	250	256.9	-
17-8	-	252	7200	255	274.0	-
17-9	-	246	7200	231	245.5	-
17-10	-	239	7200	225	239.4	-

As shown in Table 6, the optimal value of each instance was found by the MIP Model through Xpress-IVE. The optimal solution was acquired within 30 seconds, and the ACO algorithm solution was found immediately. The gap between the optimal value and the value found by the ACO was within 1%.

For the case of 15 nodes, the computational experiment time was limited to 7,200 seconds per instance, and the optimal solution was obtained for 7 of 10 instances. The optimal value and experiment time for the MIP, conducted through Xpress-IVE, are presented in Table 7. The ACO algorithm found a feasible solution within 20 seconds for all instances and the gap was within 5% for the instance in which the optimal solution was obtained. The ACO algorithm found better solutions than the feasible solutions obtained by the MIP model using Xpress-IVE within 7,200 seconds for the instances that did not reach an optimal solution (instance 15-2, 8)

The computational experiment time also was limited to 7,200 seconds for the case of 17 nodes. The results are presented in Table 8. The optimal solution was obtained for only 1 of 10 instances (instance 17-3), and feasible solutions were found for the other instances. The ACO algorithm found the solution within 60 seconds and found the optimal solution in instance 17-3. In some instances (17-1, 2, 4, 6, 7, 9, 10), ACO algorithm found better feasible solutions than the MIP model that was conducted using Xpress-IVE.

5.2 Experiment 2

The second experiment was a sensitivity analysis related to the changing number of vehicles. The change in the number of vehicles can be divided into three cases: 1) the number of reconnaissance vehicles remained constant and the number of transportation vehicles changed 2) the number of transportation vehicles remained constant and the number of reconnaissance vehicles changed, and 3) the total number of vehicles remained constant and the ratio of reconnaissance to transportation vehicles changed. The ACO algorithm was used for sensitivity analysis. Data sets and parameters for this experiment were randomly generated. Cases 1 and 2 each featured 21 nodes, and the Case 3 featured 51 nodes. The parameters for the ACO are presented in Table 9. The computational experiments for the sensitivity analysis were limited to 300 seconds.

Table 9. Parameters for the ACO algorithm for experiment 2

α	β	Q	q_0	ρ_g	ρ_l	A	I
0.25	0.97	70	0.5	0.05	0.0003	100	200

Table 10 shows the results of the sensitivity analysis for Case 1 and Figure 5 presents graphs showing the average results of Case 1: As the number of transportation vehicles increased, the completion time for troop movements also decreased. Also, the rate of change of the completion time for the troop movement decreased as the number of transportation vehicles increased.

Table 10. Sensitivity analysis results for Case 1

Number of transportation Vehicles	ACO(Instance 1) Number of reconnaissance vehicles			ACO(Instance 2) Number of reconnaissance vehicles			ACO(Instance 3) Number of reconnaissance vehicles		
	1	3	5	1	3	5	1	3	5

1	637	603	591	556	519	490	663	639	604
2	406	367	353	327	287	281	434	341	341
3	340	312	295	252	225	230	319	261	259
4	312	269	256	241	200	198	313	233	226
5	312	236	214	226	172	175	295	215	212

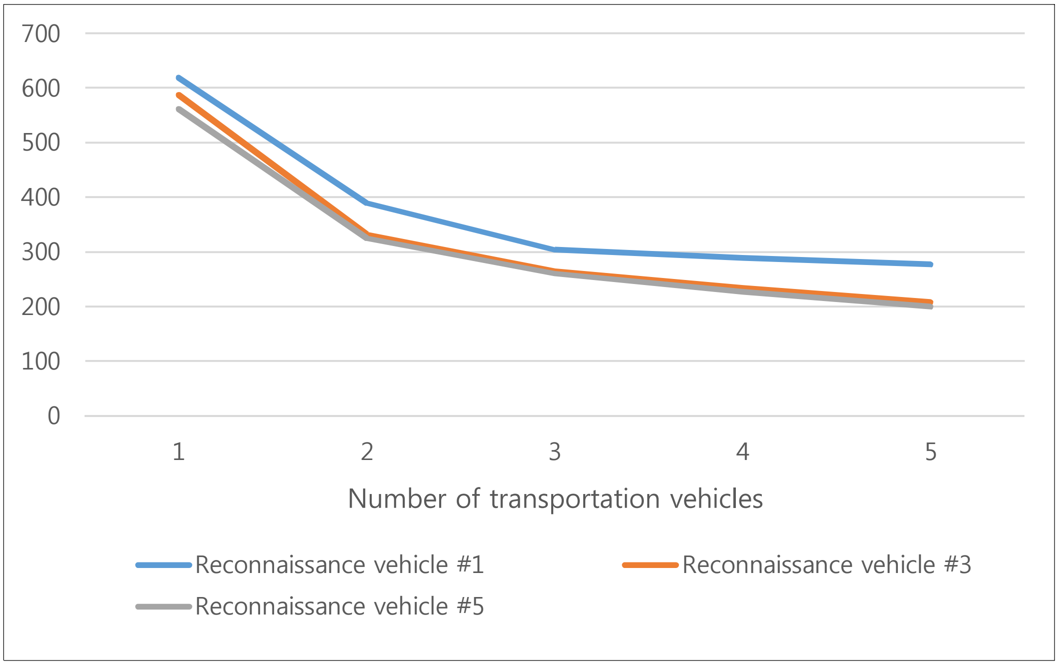

Figure 5. Sensitivity analysis results for Case 1

Table 11 shows the sensitivity analysis results for Case 2, and Figure 6 features graphs showing the average results of Case 2: As the number of reconnaissance vehicles increased, the completion time for troop movement also decreased. However, the rate of change of completion time for the troop movement did not change significantly when the number of reconnaissance vehicles was increased.

Table 11. Sensitivity analysis results for Case 2

Number of reconnaissanc e vehicles	ACO(Instance 1) Number of transportation vehicles			ACO(Instance 2) Number of transportation vehicles			ACO(Instance 3) Number of transportation vehicles		
	1	3	5	1	3	5	1	3	5
1	637	340	312	556	252	226	663	319	295

2	633	313	264	535	239	183	624	310	231
3	603	312	236	519	225	172	639	261	215
4	597	299	226	511	222	172	616	264	215
5	591	295	214	490	230	175	604	259	212

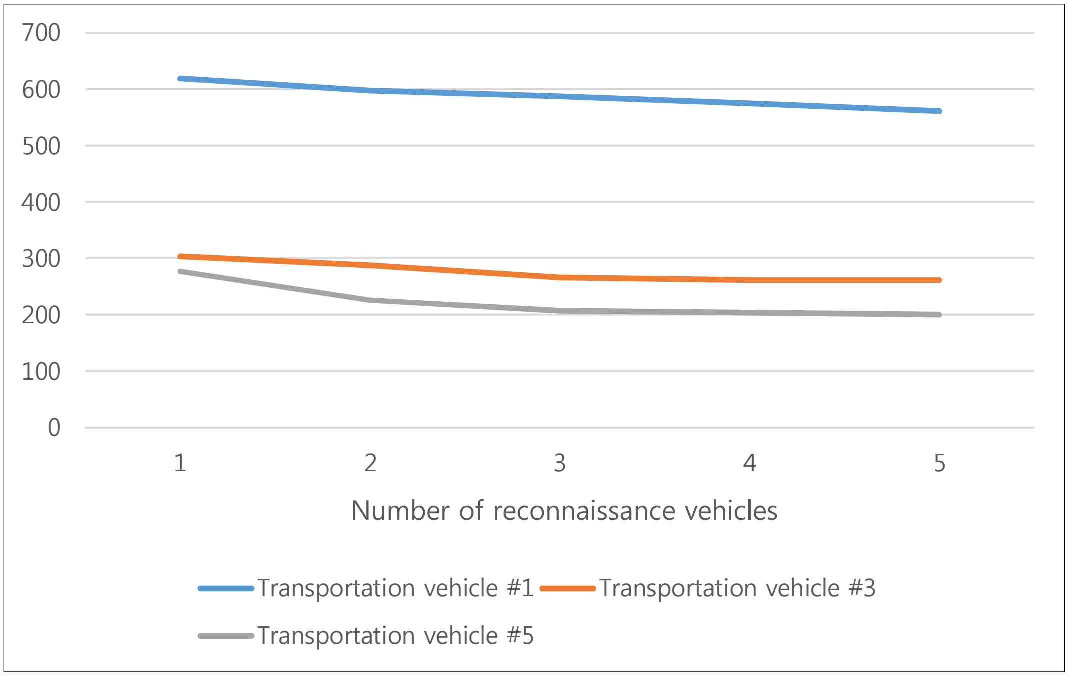

Figure 6. Sensitivity analysis results for Case 2

Table 12 and Figure 7 present the sensitivity analysis results for Case 3. As shown in Figure 7, the experimental results of Case 3 generally took a convex shape. The proportion of the transportation vehicle was confirmed as necessarily greater than the reconnaissance vehicle proportion to minimize the completion time for troop movement when the total number of vehicles remained constant. The completion time for troop movement increased as the number of transportation vehicles decreased when the proportion of the reconnaissance vehicles was greater than the proportion of transportation vehicles. According to the sensitivity analysis results, the completion time for troop movement decreased as the total number of vehicles increased, and the number of transportation vehicles was found to have exerted greater influence on the completion time of troop movement than did the number of reconnaissance vehicles.

Table 12. Sensitivity analysis results for Case 3

Number of reconnaissance vehicles	Number of transportation vehicles	ACO			
		Instance 1	Instance 2	Instance 3	average
1	9	596	608	596	600
2	8	392	478	439	436
3	7	452	437	451	447
4	6	460	426	440	442
5	5	486	456	435	459
6	4	556	543	509	536
7	3	690	649	656	665
8	2	995	892	857	915
9	1	1593	1563	1699	1618

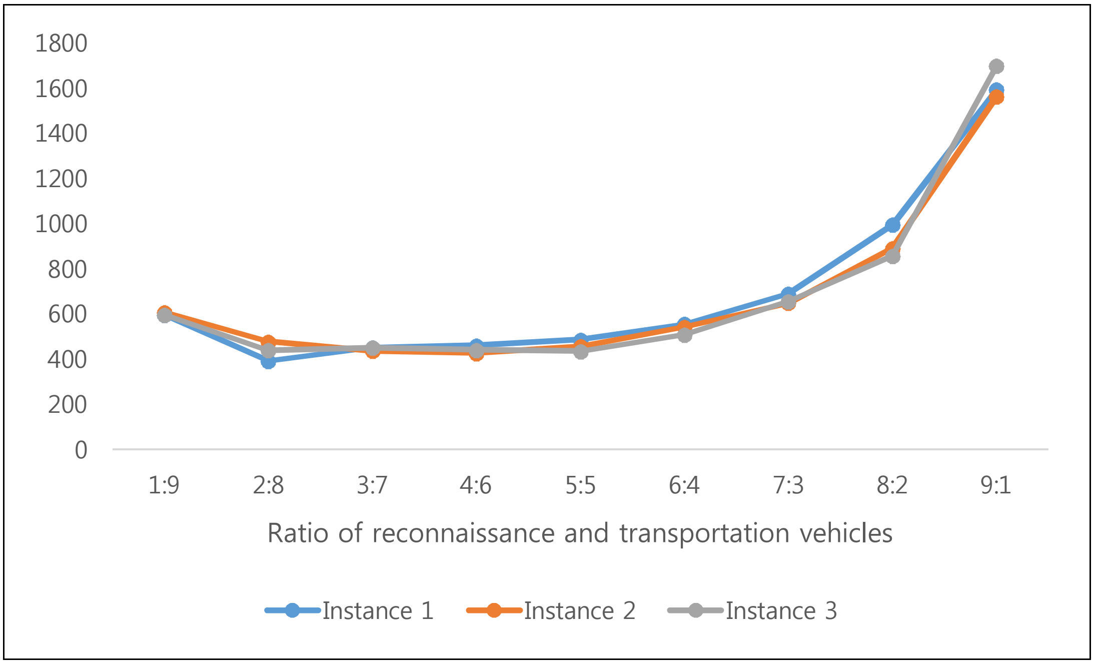

Figure 7. Sensitivity analysis results for Case 3

Chapter 6

Conclusion

In a major contribution from this study, the new model for troop movement in wartime was developed by extending the DARP. The following differences characterize the DARP and VRPCRT: In the DARP, only transportation vehicles are considered, and the transportation vehicle routes are determined using various constraints. Time windows for transportation vehicles at each node are deterministic as parameters in DARP. In VRPCRT, as proposed in this study, reconnaissance and transportation vehicles were considered, and both vehicle routes were determined simultaneously. In the VRPCRT, the earliest time that a transportation vehicle arrives at destination node was determined according to the arrival time of the reconnaissance vehicle.

6.1 Findings

In this study, VRPCRT which is the mathematical model for determining tactical troop movements and the ACO algorithm were developed. The performance of the ACO algorithm was tested through computational experiments and was shown to yield excellent results even for the real-sized problem. The sensitivity analysis on the number of vehicles was performed using the ACO algorithm developed for the model, and troop movement in wartime was shown to be sensitive to the number of transportation vehicles.

6.2 Future direction

In this thesis, the performance of the ACO algorithm was tested and confirmed through computational experiments. The performance of the ACO algorithm was influenced greatly by the chosen parameters. Although the ACO algorithm performed well in the computational experiment, the best parameters must be found through the sensitivity analysis and used to improve the ACO algorithm.

In this study, a sensitivity analysis related to the number of vehicles was performed, and it confirmed that the transportation vehicles affected troop movement more than the reconnaissance vehicles did. If the size of the input data for computational experiments is increased or the maximum running time for solving the problem is extended, it could be thought that a better insight may be derived. Also the sensitivity of various parameters must be analyzed to obtain insights that can help a commander move troops. The mathematical model proposed in this study focused on the movement of ground troops. Also, aircraft and ships are used to carry people and goods in wartime. Therefore, it is necessary to develop a new model considering not only vehicles but also aircrafts and ships for troop movement in wartime

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국문초록

전시 부대 이동이란 전시에 모든 가용 수단을 이용해 지휘관이 원하는 시간과 장소에 부대를 이동시키는 것을 의미한다. 전시 부대이동 시, 적의 위협으로부터 피해를 최소화하기 위해, 정찰 부대가 중요 지형지물 및 부대의 목적지에 대한 정찰을 실시한 이후, 수송 부대에 의해 병력들이 수송된다.

본 연구에서는 전시 부대 이동 완료 시간을 최소화하는 혼합정수계획법(MIP) 모형 기반의 '정찰 및 수송차량 경로 결정 문제'을 제시한다. 또한 MIP모형의 단점인 높은 계산 복잡도를 극복하기 위해 합리적인 시간 안에 근사 최적해를

제공하는 개미 군집 알고리즘을 개발하였다. 본 논문에서는 개미 군집 알고리즘의 성능 비교를 위한 수치 예제 실험을 진행하였으며, 정찰 및 수송차량 수에 대한 민감도 분석을 통해 각 정찰 및 수송차량이 부대 이동에 미치는 영향을 분석하였다.

주요어: 개미 군집 알고리즘, 차량경로문제, 전시 물류

학번: 2017-23130

감사의 글

2017 년 2 월에 서울대 산업공학과를 입학한 이후 끊임없는 열정으로 저를 지도해주신 문일경 교수님께 감사의 인사 드립니다. 또한 SCM 연구실에서 2 년 동안 동거 동락한 연구원(영수, 윤제, 광, 동욱, 상윤, 영준, 영철, 영빈, 현우, 종민, 민정, 성우, 기현, 서현) 모두에게 고맙습니다. 문일경 교수님과 SCM 연구실 연구원과 함께 할 수 있어서 정말 즐거웠습니다. 그리고 서울대 위탁장교들이 학업에 전념할 수 있도록 성심 성의껏 지원 해준 학군단 간부

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