Global Logistics Management

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CRC Press
Taylor & Francis Group

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Daily Planning for Three-Echelon Logistics Associated with Inventory Management under Demand Deviation

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1.1 Introduction

Due to service innovation and pressures to improve agility and greenness, daily logistics optimization is becoming important in Japan, especially for small businesses like convenience stores and supermarkets. A recent review of articles published on supply chain management within the last decade has revealed a scarcity of models that capture dynamic aspects relevant to real-world applications and has underscored the need for extensive studies on this topic (Melo et al., 2009).

In view of these observations, in this chapter, we investigate three-echelon logistic network optimization and provide a practical hybrid metaheuristic method. The model supports decision making at the tactical level for daily planning and inventory management in the presence of demand deviation. To deal with this problem, we extend our strategic approach to include some decisions at the operational level. In particular, we consider the multivehicle routing problem (M-VRP) while taking into account inventory management issues.

By taking into account the dynamics of demand and warehouse inventory, we try to give a practical approach that can provide innovative resolutions to daily planning problems. Then, to examine some effects of demand deviation on inventory condition, we carried out a parametric study regarding ordering points. The final aim of this study is to develop an integrated information and decision support system (DSS) that can dynamically manage appropriate databases of resources and product demand (see Figure 1.1). Additional work must be undertaken to realize this goal, such as the deployment of variants of the basic idea and the use of parallel computation to increase the speed of finding solutions and to enhance information retrieval and the visualization of results on a real map. We also describe our efforts along these lines in this chapter.

1.2 Problem Statements

1.2.1 Background of the Study

Noticing the growing importance of logistics network optimization, as mentioned earlier, we have investigated specific problems and the overall framework for solving such problems by considering the

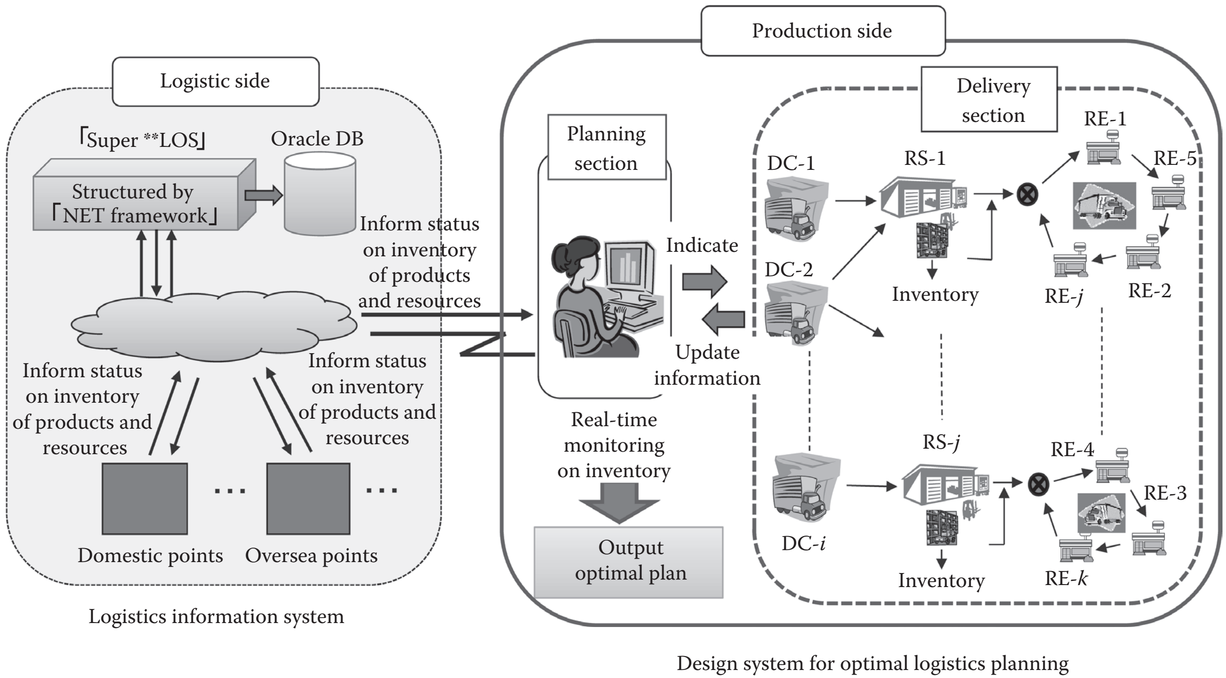

Figure 1.1 Global overview of a DSS for logistics planning.

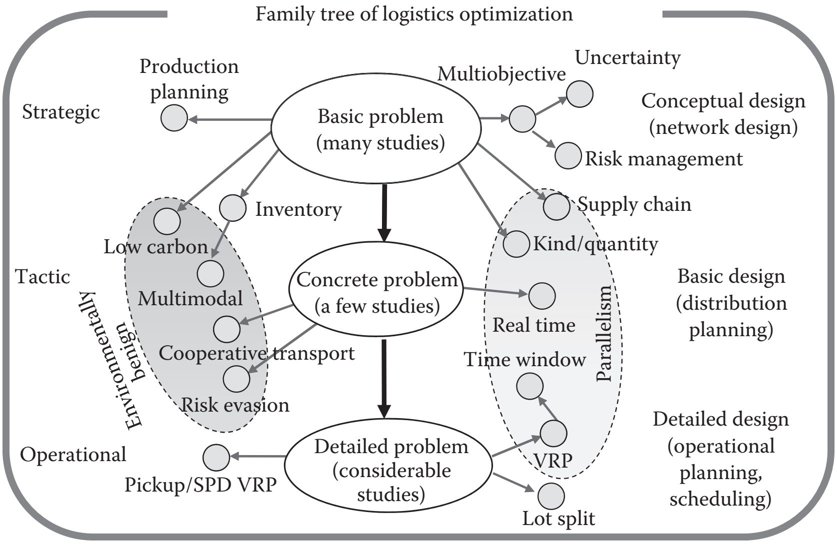

Figure 1.2 Family tree of logistics optimization problems.

similarity of problem classes in logistics systems and production planning (Shimizu, 2011a). We noticed that logistics optimization problems are broadly classified as strategic (network design), tactical (distribution planning), and operational (operational planning), just as production planning problems are. We also find a similarity to design tasks for artificial products, which are classified into three levels: conceptual, basic, and detailed designs. By using this classification, we should be able to define the system boundary adequately and to provide the required information, which can be different for each level. Eventually, we will have a suite of ideas that can be used at each level as well as across the levels. Figure 1.2 illustrates a sort of family tree of techniques that we are attempting to realize. It should be comprehensive but involve some cutting-edge aspects to meet real-world interests as well. It becomes essential, therefore, to develop a general and systematic approach so that we can cope with a variety of problems in a similar manner and reach the desired goals without expending extra effort.

1.2.2 Brief Review of Related Studies

The strategic problem class described in the previous section has been studied for a long time. Problems in this class are often formulated mathematically as mixed-integer programming problems that are nondeterministic polynomial time hard (NP-hard). Hence, the number of studies is still growing by virtue of the outstanding advancements in both computer software and computer hardware. Nevertheless, hybrid methods have an advantage over these techniques, because it is almost impossible to solve real-world problems by using commercial solvers. Moreover, we note that transportation cost accounting is reasonably described by a bilinear model of loading weight and travel distance (Ton–Kilo or Weber basis).

There are also many studies belonging to the operational level. A popular problem studied at this level is named vehicle routing problem (VRP; Yeun et al., 2008). VRP is an NP-hard combinatorial optimization problem on minimizing the total distance traveled by a fleet of vehicles under various constraints. This transportation of goods from depots to all customers must be considered under the constraint that each vehicle must take a circular route with the depot as its starting point and destination.

Recent studies of VRP can be roughly classified in the following ways. One type is an extension from generic customer demand satisfaction and vehicle payload limit conditions to include practical concerns, such as customer availability or time windows (Hashimoto et al., 2006; Mester et al., 2007), pickups (Gribkovskaia et al., 2007), and split and mixed deliveries (Mota et al., 2007). These extensions are considered both separately and in combination (Zhong and Cole, 2005). The second type is known as the multidepot problem, in which deliveries can originate from multiple depots (Wu et al., 2002; Chen et al., 2005; Crevier et al., 2007). The third type investigates multiobjective formulations of the single-depot and multidepot problems (Murata and Itai, 2005; Pasia et al., 2007; Jozefowiez et al., 2008; Geiger, 2010). Recently, many researchers have been interested in VRP with varying pickup and delivery configurations because this is the most practical and suitable way to consider reverse logistics (Min, 1989; Catay, 2010; Goksal et al., 2013). These studies can be classified into three categories (Nagy and Salhi, 2005): delivery first and pickup second, in which pickup happens only after delivery; mixed pickup and delivery (VRPMPD), in which delivery and pickup are permitted in any sequence along the routes; and simultaneous pickup and delivery (VRPSPD). The VRPSPD problem reduces to the VRPMPD problem if only either pickup or delivery is required at each customer. Instances of the VRPSPD problem are frequently encountered in the distribution system of bottled drinks, groceries, liquid propane gas tanks, hotel laundry services, etc. Due to the difficulty of solving such problems, only small instances of VRP are solved to validate the effectiveness of the approaches. Moreover, it should be noted that those studies consider only distance (Kilo basis) to derive the route. To solve VRP in terms of the Ton–Kilo basis, we developed a hybrid approach composed of a modified saving method and modified tabu search (Shimizu, 2011b,c).

Apart from those two classes of problem, there have been a few studies (Tuzun and Burke, 1999; Albareda-Sambola et al., 2005; Prins et al., 2006; Zhao et al., 2008) at the tactical level. At this level, it is necessary to consider connections to both the upper (strategic) level and the lower (operational) level. In such problems, decisions about allocations to the depot are considered in addition to VRP. Hence, we must take care to use consistent transport cost accounting. However, it is common to use the Ton–Kilo basis at the strategic level and the Kilo basis at the operational level. Moreover, each formulated problem is NP-hard. Thus, it becomes necessary to resolve the inconsistency in cost accounting while coping with the inherent hardness of the problem.

1.3 Problem Formulation

For a global logistics network composed of major distribution centers (DCs), sub-DCs (i.e., depots) (RSs), and customers (REs), we wish to determine the available depots, paths from DCs to depots, and circular routes from every depot to its client customers (refer to *Delivery section* in Figure 1.1). The goal of this problem is to minimize the total cost for daily logistics over planning horizon T. This problem is formulated as the following mixed-integer programming problem under some mild assumptions: round-trip transport between DC and depot, unimodal transport, averaged time-invariant unit costs and system parameters (except for demand and inventory), independence (separability) of decisions per planning period, and so forth.

$(p.1)$ Minimize for every $t\in T$

$$\sum_{i\in I}\sum_{j\in J}\left(C_{ij}d1_{ij}+Hp_i\right)f_{ij}(t)+\sum_{v\in V}\sum_{p\in P}\sum_{p\in P}c_v d2_{pp'}\left(g_{pp'v}(t)+q_v\right)z_{pp'v}(t)$$

$$+\sum_{j\in J}\left(Ho_j r_j(t)+Ha_j s_j(t)+Hs_j\left(s_j(t)+\sum_{i\in I}f_{ij}(t)\right)\right)+\sum_{v\in V}F_v y_v(t)$$

subject to the constraints

$$\sum_{p\in P}z_{kpv}(t)\le 1,\quad \forall k\in K;\forall v\in V,\ \exists t\in T \tag{1.1}$$

$$\sum_{p\in P}z_{pp'v}(t)-\sum_{p\in P}z_{p'pv}(t)=0,\quad \forall p\in P;\forall v\in V,\ \exists t\in T \tag{1.2}$$

$$\sum_{j\in J}z_{jj'v}(t)=0,\quad \forall j\in J,\forall v\in V,\ \exists t\in T \tag{1.3}$$

$$s_j(t)+\sum_{i\in I}f_{ij}(t)=\sum_{v\in V}\sum_{k\in K}g_{jkv}(t),\quad \forall j\in J,\ \exists t\in T \tag{1.4}$$

$$r_j(t)+s_j(t)+\sum_{i\in I}f_{ij}(t)\le Q_j x_j(t),\quad \forall j\in J,\ \exists t\in T \tag{1.5}$$

$$g_{pp'v}(t)\le W_v z_{pp'v}(t),\quad \forall p\in P;\forall p'\in P;\forall v\in V,\ \exists t\in T \tag{1.6}$$

$$\sum_{p\in P}\sum_{p\in P}z_{pp'v}(t)\le M y_v(t),\quad \forall v\in V,\ \exists t\in T \tag{1.7}$$

$$\sum_{k\in K}g_{kjv}(t)=0,\quad \forall j\in J;\forall v\in V,\ \exists t\in T \tag{1.8}$$

$$\sum_{v\in V}\sum_{p\in P}g_{pkv}(t)-\sum_{v\in V}\sum_{p\in P}g_{kpv}(t)=D_k(t),\quad \forall k\in K,\ \exists t\in T \tag{1.9}$$

$$\sum_{p\in P}\left(g_{pkv}(t)-D_k(t)z_{pkv}(t)\right)=\sum_{p\in P}g_{kpv}(t),\quad \forall k\in K,\forall v\in V,\exists t\in T \tag{1.10}$$

$$\sum_{j\in J}\sum_{k\in K} z_{jkv}(t) = y_v(t), \quad \forall v\in V, \ \exists t\in T \tag{1.11}$$

$$\sum_{j\in J}\sum_{k\in K} z_{kjv}(t) = y_v(t), \quad \forall v\in V, \ \exists t\in T \tag{1.12}$$

$$\sum_{p\in\Omega}\sum_{p\in\Omega} z_{pp'v}(t) \le |\Omega| - 1, \forall\Omega \subseteq P\setminus\{1\}, |\Omega| \ge 2, \forall v\in V, \exists t\in T \tag{1.13}$$

$$P_i^{min} \le \sum_{j\in J} f_{ij}(t) \le P_i^{max}, \quad \forall i\in I, \ \exists t\in T \tag{1.14}$$

$$r_j(t) + s_j(t) \leqq S_j x_j(t), \quad \forall j\in J, \ \exists t\in T \tag{1.15}$$

$$x_j(t)\in\{0,1\}, \quad \forall j\in J, \forall t\in T; \quad y_v(t)\in\{0,1\}, \quad \forall v\in V, \forall t\in T$$

$$s_j(t)\ge 0, \quad \forall j\in J, \forall t\in T; \quad r_j(t)\ge 0, \quad \forall j\in J, \forall t\in T$$

$$z_{pp'v}(t)\in\{0,1\}, \quad \forall p\in P; \forall p'\in P; \forall v\in V, \quad \forall t\in T$$

$$f_{ij}(t)\ge 0, \quad \forall i\in I; \forall j\in J, \forall t\in T;$$

$$g_{pp'v}(t)\ge 0, \forall p\in P; \forall p'\in P; \forall v\in V, \forall t\in T$$

Variables

$f_{ij}(t)$: Load from DC i to depot j at time t

$g_{pp'v}(t)$: Load of vehicle v on the path from $p \in P$ to $p' \in P$ at time t

$r_j(t)$: Takeover inventory at depot j at time t

$s_j(t)$: Consumption quantity from inventory at depot j at time t

$x_j(t) = 1$ if depot j is open at time t; otherwise 0

$y_v(t) = 1$ if vehicle v is used at time t; otherwise 0

$z_{pp'v}(t) = 1$ if vehicle v travels on the path from $p \in P$ to $p' \in P$ at time t; otherwise 0

Parameters

C_{ij}: Transportation cost per unit load per unit distance from DC i to depot j

c_v: Transportation cost per unit load per unit distance of vehicle v

$D_k(t)$: Demand of customer k at time t

$d1_{ij}$: Path distance between $i \in I$ and $j \in J$
$d2_{pp'}$: Path distance between $p \in P$ and $p' \in P$
F_v: Fixed cost for the working vehicle v
Ha_j: Handling cost per unit load at depot j
Ho_j: Holding cost per unit load at depot j
Hp_i: Shipping cost per unit load from DC i
Hs_j: Shipping cost per unit load from depot j
M: Auxiliary constant (a large integer)
P_i^{max}: Maximum load available at DC i
P_i^{min}: Minimum load required to ship from DC i
q_v: Unladen weight of vehicle v
Q_j: Maximum capacity at depot j
S_j: Maximum inventory at depot j
W_v: Maximum capacity of vehicle v

Index set
I: DC
J: Depot
K: Customer
V: Vehicle
$P = J \cup K$
T: Planning horizon
Ω: Subtour candidate

In (p.1), the objective function is composed of round-trip transportation costs between each DC and the opening depot (hereinafter just *the depot*); circular transportation costs for traveling to every customer; shipping costs at each DC; holding, handling, and shipping costs at each depot; and fixed costs for the working vehicles. Several constraints are applied: vehicles cannot visit a customer twice (Equation 1.1), a vehicle visiting a certain depot or customer must leave it (Equation 1.2), no direct travel between DCs (Equation 1.3), material balance (Equation 1.4), upper-bound capacity at depot (Equation 1.5), upper-bound load capacity for a vehicle (Equation 1.6), each vehicle must travel on a certain path (Equation 1.7), vehicles return to the depot empty (Equation 1.8), customer demand is satisfied by a certain vehicle (Equation 1.9), the sum of incoming goods must be greater than the outgoing goods due to demand (Equation 1.10), each vehicle leaves only one depot and returns there (Equations 1.11 and 1.12), subtour elimination constraint (Equation 1.13), the amount of goods available from DC is bounded (Equation 1.14), and the amount of inventory is bounded above (Equation 1.15). We also assume the following inventory control policy:

$$r_j(t) = \begin{cases} (1-\zeta)r_j(t-1) & \text{if } (1-\zeta)r_j(t-1) \geq R_j \\ S_j - (1-\zeta)r_j(t-1) & \text{if } (1-\zeta)r_j(t-1) < R_j, \end{cases} \quad \forall j \in J, \forall t \in T \tag{1.16}$$

Here, ζ (<1) and R_j are the fouling rate of unsold goods and the ordering point at depot j, respectively.

We know that it is almost impossible to solve this problem under realistic sizes using any currently available commercial software. Hence, we try to solve the problem in a hybrid manner that divides it into subproblems and applies a suitable method to each. Previously, we have combined tabu search (Glover, 1989) for the location subproblem and a graph algorithm for the allocation subproblem to develop a method called hybrid tabu search (HybTS) (Shimizu and Wada, 2004; Wada and Shimizu, 2006), and we have successfully used this approach to solve complicated logistics optimization problems arising from a variety of real-world situations. HybTS is a two-level solution method in which the upper-level subproblem optimizes the selection of available depots while the lower-level subproblem optimizes the paths from DCs to customers via depots in a way that minimizes the total cost. It is not only a practical and powerful method, but also flexible and suitable for dealing with a variety of extensions, as shown in Figure 1.2. Hence, we use a similar idea here to solve this problem in a way that is computationally effective (Shimizu and Fatrias, 2013).

1.4 Daily Decision Associated with Inventory Conditions

1.4.1 Multilevel Approach Incorporating Vehicle-Routing Problem

For daily logistics optimization, it is meaningful to take into account the inventory control at each depot. To make the hierarchical approach suitable for the present case, we have developed two new ideas and integrated them into the framework of our hybrid method. To the best of our knowledge, such a global approach has not been reported elsewhere.

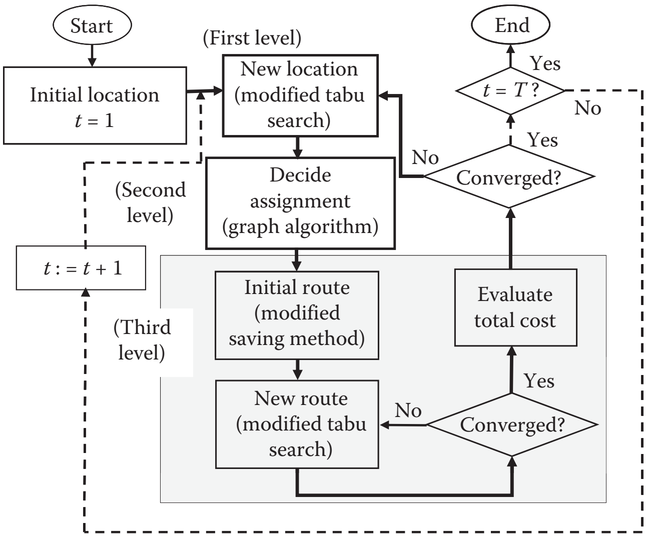

Figure 1.3 Flow chart of the solution procedure.

In the first level, we choose the available depots by a modified tabu search. Then, in the second level, we obtain tentative round-trip paths from DCs to customers via depots by a graph algorithm for solving the minimum cost flow (MCF) problem. Using the customers thus allocated as the clients for each depot, we derive vehicle routes for every depot by using the modified savings method and modified tabu search. The obtained result is fed back to the first level to evaluate another candidate set of available depots. This procedure is repeated until a given convergence condition has been satisfied. The algorithm is illustrated in Figure 1.3.

In developing this algorithm, we need to obtain the MCF graph that takes into account the inventory at each depot. For example, the case where $|I| = |J| = |K| = 2$ is illustrated in Figure 1.4. In Table 1.1, we summarize the information required for the edges and nodes in the graph. In terms of the MCF graph thus derived, we can solve the original allocation problem extremely quickly by a graph algorithm such as RELAX4 (http://mit.edu/dimitrib/www/home.html) together with its sensitivity analysis. The sensitivity analysis allows the problem to be repeatedly solved with slightly different parameters. At the end of this procedure, we can efficiently allocate

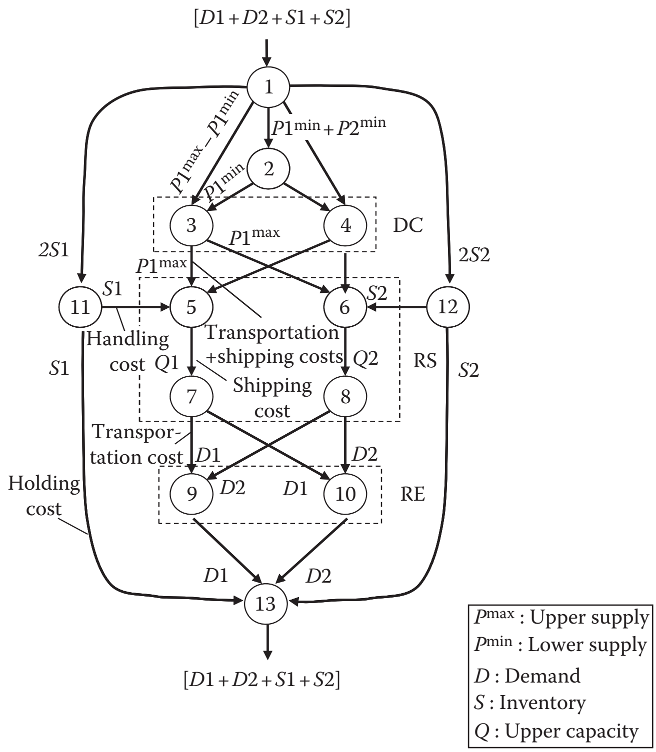

Figure 1.4 Example of an MCF graph. *Note:* Each digit refers to suffix in Table 1.1.

Table 1.1 Labeling on the Edges of an MCF Graph

EDGE (FROM–TO)	COST	CAPACITY	CASE IN FIGURE 1.4
Source–∑(Dummy node)	$-M$	$\sum_{i\in I} P_i^{\min}$	#1–#2
Source–DC i	0	$P_i^{\max} - P_i^{\min}$	#1–#3, #1–#4
∑–DC i	0	$P_i^{\min}$	#2–#3, #2–#4
DC i–RS j	$C_{ij}d1_{ij} + Hp_i$	$P_i^{\max}$	#3–#5, #3–#6, etc.
Between double nodes of RS j	Hs_j	Q_j	#5–#7, #6–#8
Stock–RS j	Ha_j	S_j	#11–#5, #12–#6
Source–Stock j	0	$2S_j$	#1–#11, #1–#12
Stock j–Sink	Ho_j	S_j	#11–#13, #12–#13
RS j–Customer k	$c_v d2_{jk}$	D_k	#7–#9, #7–#10, etc.
Customer k–Sink	0	D_k	#9–#13, #10–#13

the client customers to each depot on the Ton–Kilo basis. In other words, the original M-VRP has now been turned into multiple ordinary VRPs.

To derive the initial solution of each VRP with consistent transport cost accounting, we apply the modified savings method whose algorithm is outlined as follows:

Step 1: Create round-trip routes from the depot to all customers. Compute the savings value $s_{ij} = (d_{0j} - d_{0i} - d_{ij})D_j + (d_{0j} + d_{i0} - d_{ij})q_v$, where D_j, q_v, and d_{ij} denote the demand at location j, the unladen weight of the vehicle v, and the distance between locations i and j, respectively (refer to Figure 1.5).

Step 2: Order these pairs in descending order of savings value.

Step 3: Merge the path, following the order obtained from Step 2 as long as it is feasible and the savings value is greater than $-F_v/c_v$, where F_v denotes the fixed operational cost of vehicle v. Here, we note that the inclusion of fixed operational costs for the working vehicles in practical economic evaluations is a new idea.

However, since the modified savings method derives only an approximate solution, we apply the modified tabu search to update such a solution. The modified tabu search is a variant that probabilistically accepts even a degraded candidate in its local search, where a neighboring solution is generated from a randomly selected insert, swap, or two-opt operation. For this purpose, we applied the Maxwell–Boltzmann

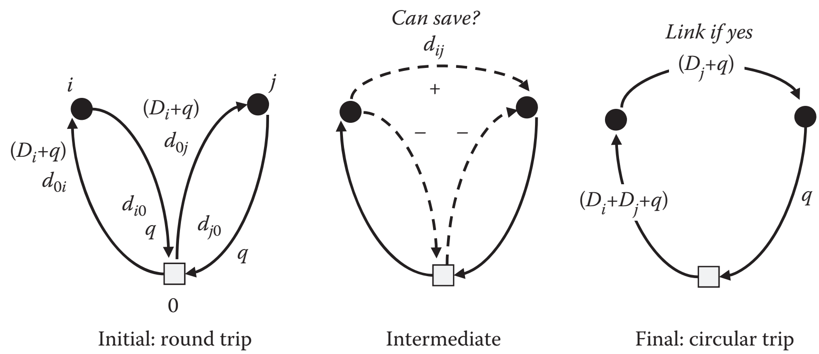

Figure 1.5 Illustrative steps to derive savings value.

probability function used in simulated annealing (Kirkpatrick et al., 1983). Here, we emphasize that the advantage of this approach is that transport cost accounting is on the same Ton–Kilo basis for the procedures at the upper levels (first and second) and the lower level (third) in Figure 1.3.

1.4.2 Analysis of Inventory Level on Demand Variation

It is commonly known that too much inventory lowers economic efficiency while the stock-out condition or opportunity loss will happen in the opposite case. For daily logistics, therefore, it is of special importance to correctly estimate the demand and properly manage the inventory. Generally speaking, although estimating demand correctly is almost impossible in many cases, it is possible to give a rough estimate of the variability from prior experience.

Under such circumstances, it is relevant and practical to try to discern the relation between demand variability and inventory level by a parametric approach. Through such analyses, we can set up a reliable inventory level to maintain economically efficient logistics while avoiding the stock-out state. Though such considerations are able to reveal many prospects for robust and reliable logistic systems, it has not been used much until now in the network optimization of logistics due to computational difficulties.

1.5 Numerical Experiments

1.5.1 Setup of Test Problem

To examine the performance of the proposed method, we considered several benchmark problems of different problem sizes (i.e., different specifications of $\{|I|, |J|, |K|\}$). Every system parameter is set randomly within a prescribed interval, as summarized in Table 1.2. The location of every member is also generated randomly, and distances between them are given by the Euclidian distance.

1.5.2 Results for the Reference Conditions

We randomly changed the demand to an amount within $(100 \pm \rho)\%$ of the demand on the previous day. Unsold goods at each depot are

Table 1.2 Notes on Parameter Setup

MEMBER	ITEM	RANGE	REMARKS
DC	*Hp*: Shipping cost	$100 \times [0.2, 0.8]$	<3>
	P^{max}: Available (max)	$1000 \times [0, 1] + P^{min}$	<5>, Total P^{max} > Total capacity of RS
	P^{min}: Available (min)	$1000 \times [0.2, 0.8]$	<5>, Total P^{min} > Total demand
RS	*Hs*: Shipping cost	$100 \times [0.2, 0.8]$	<3>
	Ha: Handling cost	$50 \times [0.2, 0.8]$	<3>
	Ho: Holding cost	$100 \times [0.2, 0.8]$	<5>
	Q: Capacity	$p \times [0.2, 0.8]$	<5>, $p = 100 \times \|K\|/\|J\|$
	S: Allowable inventory	$x \times [0.5, 0.7]$	<3>, Varying at each time
RE	*D*: Demand	$100 \times [0.2, 0.8]$	<3>, Total demand < Total capacity of RS[a]

Note: $C_{ij} = 3$, $c_v = 1$, $W_v = 500$, $F_v = 50{,}000$, and $q_v = 10$; <*n*> multiple of n.
[a] Under this condition, the stock-out status will not occur.

stored as inventory, and it is possible to use them in the following days. However, it is assumed that up to the rate (ζ) of the goods are spoiled at random and that goods are restocked to the upper limit when the inventory level falls below the prescribed safety level ($R_j = \sigma S_j$), which is equivalent to adopting a fixed-order-quantity policy.

First, we solved smaller problems, such as those characterized by $|I| = 3$, $|J| = 10$, and $|K| = 100$ over 30 days and $|I| = 5$, $|J| = 20$, and $|K| = 200$ over 10 days. Parameters ρ, σ, and ζ are set at 0.3, 0.5, and 0.1, respectively. Figures 1.6 and 1.7 illustrate the changes in demand and inventory during the planning horizon. Under these conditions, we derive the optimal cost, which broadly changes in accord with demand fluctuation, as shown in Figure 1.8. In Figure 1.9, we can see that the change in the number of active depots is moderated and kept nearly constant (around 60%). However, the activity rates of

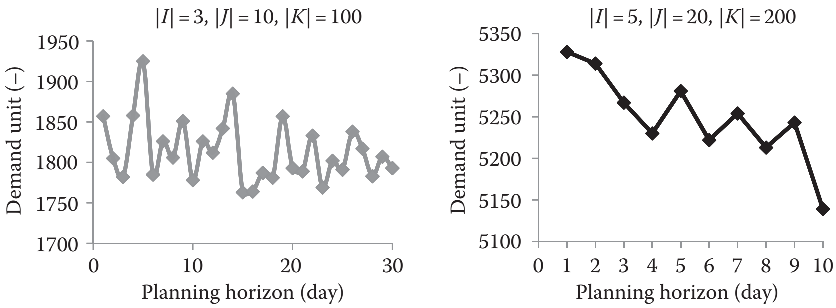

Figure 1.6 Variation of demand.

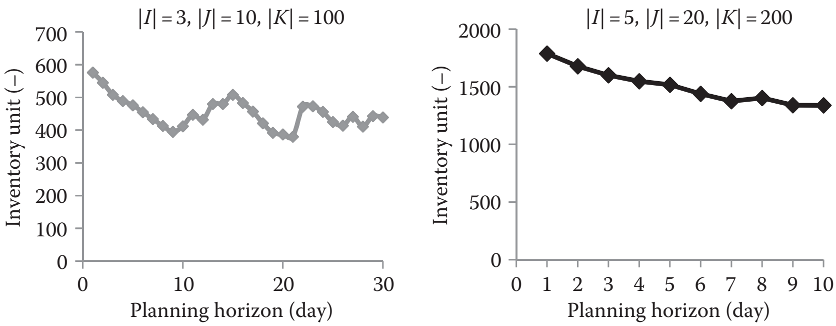

Figure 1.7 Variation of inventory.

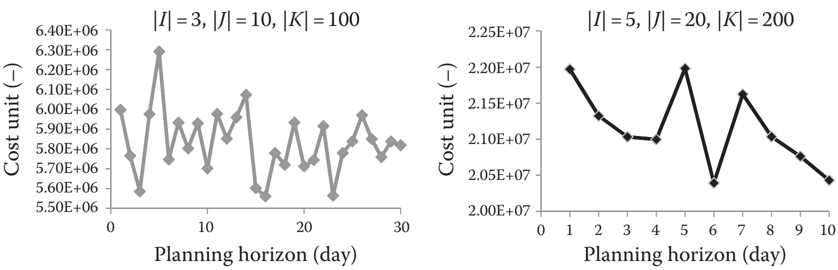

Figure 1.8 Trend of optimal cost.

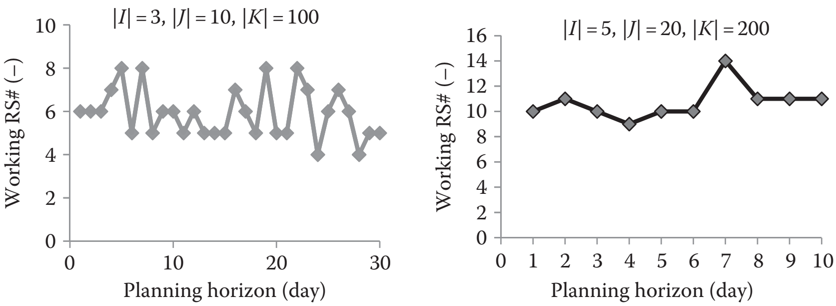

Figure 1.9 Variation of the number of active depots.

each depot differ greatly, as shown in Figure 1.10. At the next stage of logistical restructuring, the depots that have a low activity rate may be merged with those that have higher rates.

We solved some larger problems to examine the necessary computation time. Fixing the planning horizon at 1, and fixing $|I| = 10$ and $|J| = 30$, we solved the problems given by $|K| = \{250, 500,$

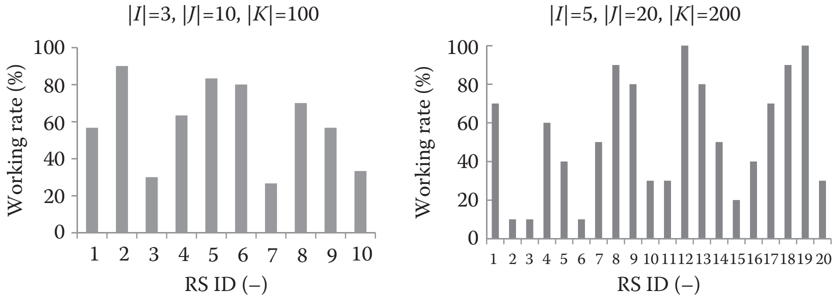

Figure 1.10 Activity rate of each RS.

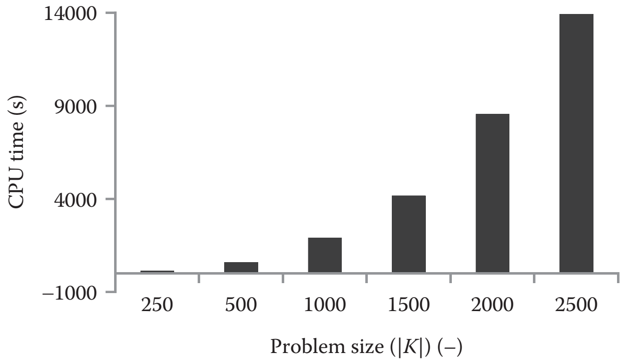

Figure 1.11 Profile of CPU time by problem size.

1000, 1500, 2000, 2500}. As expected a priori, the required CPU time increases exponentially with the size, as shown in Figure 1.11. Even for these larger problems, however, we can obtain the result within a reasonable time of around several hours.

From the convergence profile for the largest problem, shown in Figure 1.12, we can confirm that sufficient convergence is obtained. From all of these results, we can claim that the proposed method is significant and computationally effective.

1.5.3 Results over a Wide Range of Deviations

To analyze the effect of demand variation on the inventory condition, we carried out a parametric study varying the ordering points in a small model such as $|I| = 2$, $|J| = 5$, and $|K| = 100$ over 30 days. We solved every problem for each pairing of five different ordering

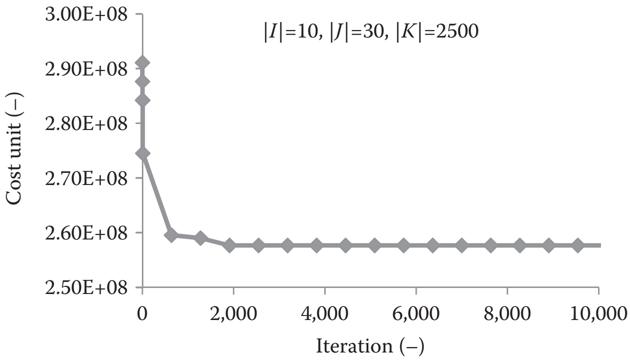

Figure 1.12 Profile of convergence.

points ($\sigma = \{0.1, 0.2, 0.3, 0.4, 0.5\}$) and four different ranges of demand variation ($\rho = \{0.2, 0.3, 0.4, 0.5\}$). In all, 600 optimization problems were solved under the same conditions as before. The results are shown in Figures 1.13 and 1.14.

Figure 1.13 shows the total cost for ranges of demand deviation and ordering point. Due to the nondeterministic parameter setting, a complicated profile is found. However, the overall shape is plausible since the region of minimum cost moves to a higher ordering point as the deviation increases. This suggests that, in terms of cost management, it is important to control the ordering point or inventory level according to the demand variation. When we separate the inventory cost from the total cost, its changes are rather simple, as shown in Figure 1.14. Since a higher stock level incurs a greater holding cost, the cost increases proportionally with the ordering point regardless of the variability of demand.

Finally, from these parametric studies, we claim that the applied model behind the mathematical formulation is adequate. The plausibility of the results supports the viability of the approach if it were used in a real-world optimization with actual parameters.

1.6 Prospects for Further Applications

1.6.1 Variants of the Modified Savings Method

We can generalize the foregoing Weber basis by introducing the power model of weight and distance. For this generalized Weber basis, the savings value for delivery is given by

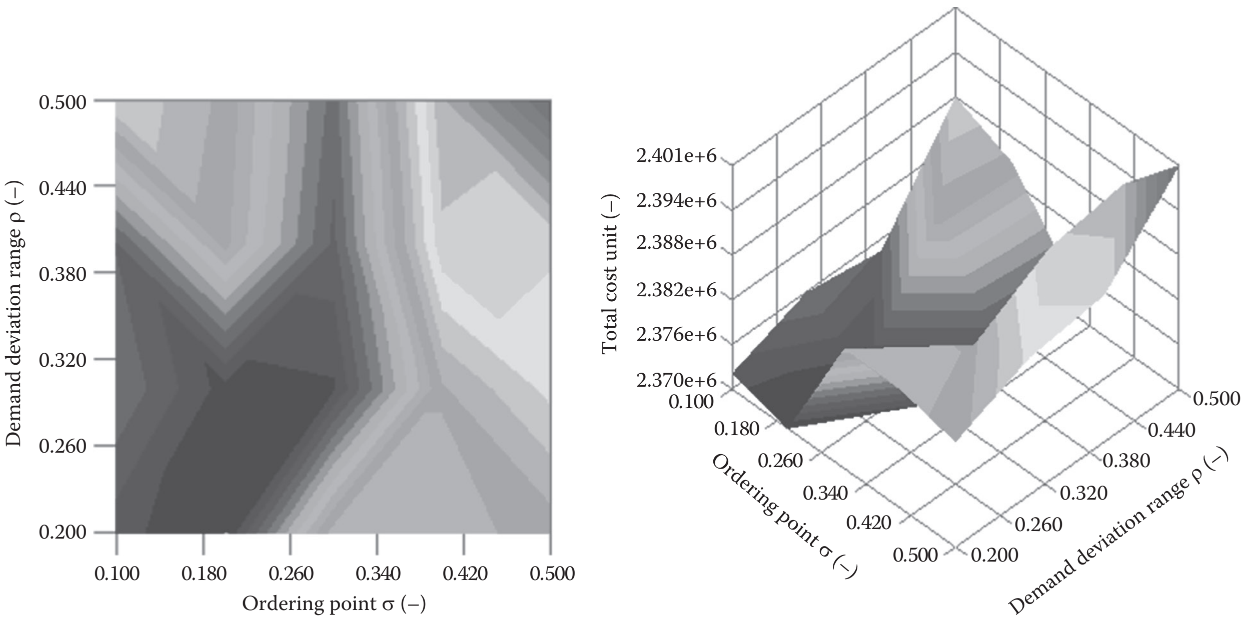

Figure 1.13 Total cost for various demand deviations and ordering points.

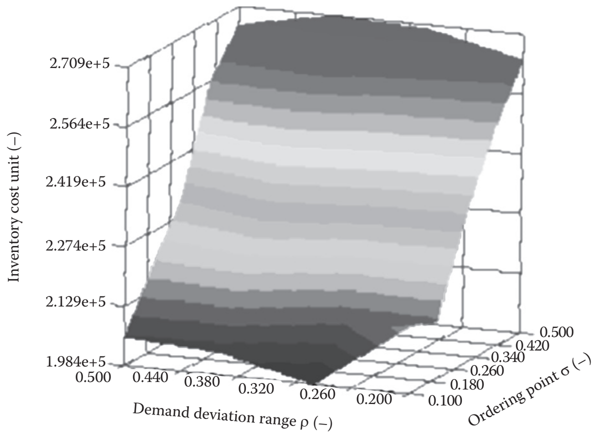

Figure 1.14 Inventory cost for various demand deviations and ordering points.

$$\frac{S_{ij}}{(\gamma C_v)} = (q_v + D_i)^{\alpha} d_{0i}^{\beta} + q_v^{\alpha} d_{i0}^{\beta} + (q_v + D_j)^{\alpha} d_{0j}^{\beta} - (q_v + D_i + D_j)^{\alpha} d_{0i}^{\beta} - (q_v + D_j)^{\alpha} d_{ij}^{\beta} \quad (1.17)$$

where

α and β denote the elastic coefficients for weight and distance, respectively

γ is a constant

When $\alpha = \beta = \gamma = 1$, this expression refers to the ordinary Weber basis.

Moreover, it is common to consider pickup problems instead of delivery ones in reverse logistics. Here, every vehicle visits the pickup points and returns to the depot directly. Letting *Pd* be pickup demand, we can derive the savings value as follows (refer to Figure 1.15):

$$\frac{S_{ij}}{(\gamma C_v)} = q_v^{\alpha} d_{0j}^{\beta} + (q_v + Pd_i)^{\alpha} d_{i0}^{\beta} + (q_v + Pd_j)^{\alpha} d_{j0}^{\beta} - (q_v + Pd_i)^{\alpha} d_{ij}^{\beta} - (q_v + Pd_i + Pd_j)^{\alpha} d_{j0}^{\beta} \quad (1.18)$$

The previous idea can be extended to the case where vehicles stop at an intermediate destination before returning to the depot. This is the case, for example, when a vehicle visits a disposal site to dump waste

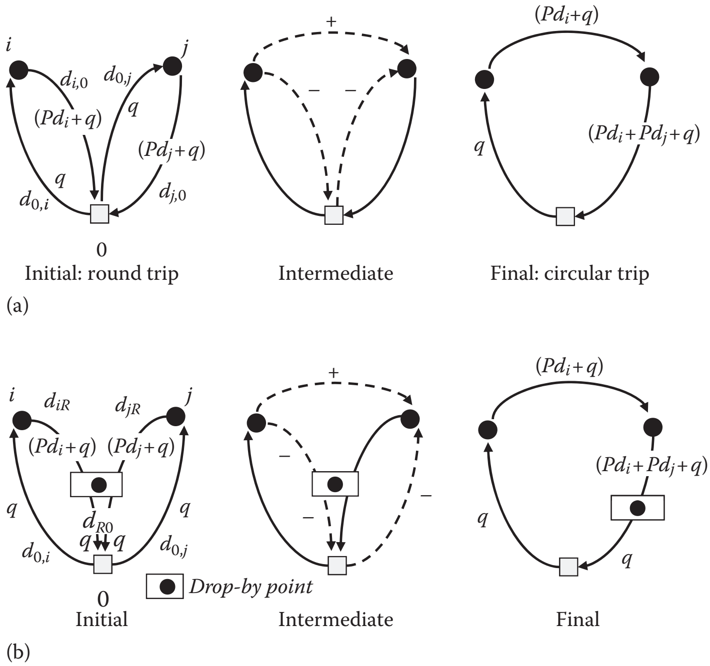

Figure 1.15 Scheme to derive savings value for pickup VRP for either (a) direct or (b) drop-by pickup.

or a remanufacturing facility to deliver used products. In this case, we can modify this equation as follows:

$$\frac{S_{ij}}{(\gamma C_V)} = (q_V + Pd_i)^\alpha d_{iR}^\beta + q_V^\alpha d_{R0}^\beta + q_V^\alpha d_{0j}^\beta + (q_V + Pd_j)^\alpha d_{jR}^\beta - (q_V + Pd_i)^\alpha d_{ij}^\beta - (q_V + Pd_i + Pd_j)^\alpha d_{jR}^\beta \qquad (1.19)$$

where the subscript R denotes the intermediate destination.

Similarly, we have the following expression in the case of VRPSPD (refer to Figure 1.16):

$$\frac{S_{ij}}{(\gamma C_V)} = (D_i + q_V)^\alpha d_{0i}^\beta + (Pd_i + q_V)^\alpha d_{i0}^\beta + (D_j + q_V)^\alpha d_{0j}^\beta + (Pd_j + q_V)^\alpha d_{j0}^\beta - (D_i + D_j + q_V)^\alpha d_{0i}^\beta - (Pd_i + D_j + q_V)^\alpha d_{ij}^\beta - (Pd_i + Pd_j + q_V)^\alpha d_{j0}^\beta \qquad (1.20)$$

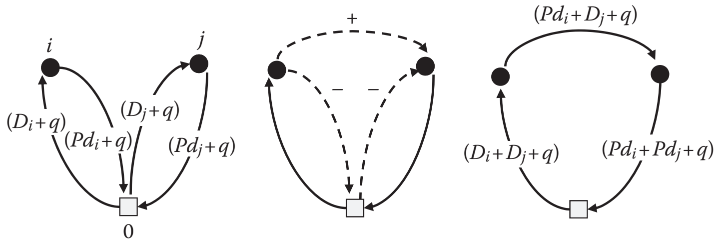

Figure 1.16 Scheme to derive savings value for VRPSPD.

Just by applying these formulas to derive the initial solution of the respective VRP, we can simply follow the overall procedure described earlier to obtain the respective final solutions.

1.6.2 Application of Parallel Computing Techniques

Unlike conventional studies, our method can cope with large-scale problems in a practical and flexible manner. However, there still exists a great need for solving problems more quickly and efficiently in order to make responsive decisions in global markets. For such requirements, it is natural to develop a parallel implementation for logistics optimization. In a special issue of *Parallel Computing*, Laporte and Musmanno (2003) emphasized the importance of parallel computing in logistics not only due to the large scale of these problems but also because of real-time applications arising in the delivery of emergency services and in courier or dial-a-ride services.

To make our hybrid approach suitable for parallel optimization, we developed a binary particle swarm optimizer (PSO) and substituted it for the modified tabu search used in the previous procedure. Compared with an individual search such as tabu search, the population-based PSO algorithm is well suited to implementing a parallel computation (Shimizu and Ikeda, 2010). The first application considered a rather simplified formulation for strategic problems using master–worker parallelism, as illustrated in Figure 1.17. Then, more complicated configurations were examined. For these, a novel parallel procedure similar to the island model used in genetic algorithms was developed, employing multithreading techniques so that the idle time for the parallel computation becomes very small. Moreover, the effect of the topology of subpopulations (Figure 1.18) and the manner

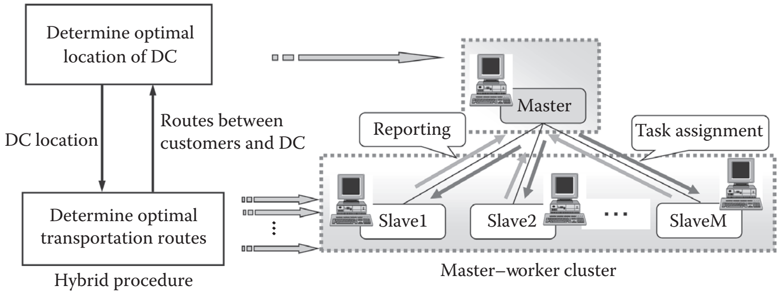

Figure 1.17 Scheme under master–worker parallelism.

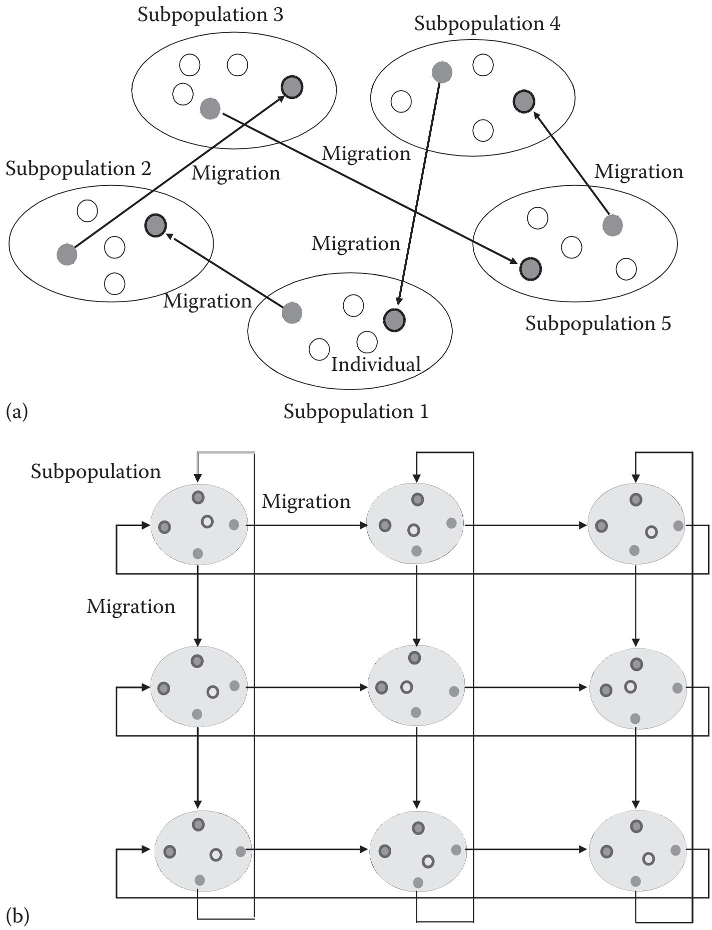

Figure 1.18 Topology for island model parallelism: (a) random ring (RR) or (b) two-node torus ring (2nR).

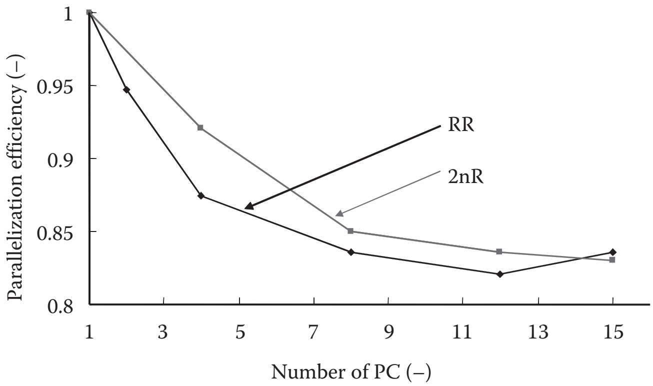

Figure 1.19 Efficiency of parallelization against the number of processors.

of information exchange between subpopulations were analyzed. Finally, we showed that such an approach can solve huge problems with more than 20,000 customers while maintaining high efficiency of the parallelization, as shown in Figure 1.19.

1.6.3 Enhancement for Practical Use

To realize the planning system illustrated in Figure 1.1, it is essential to provide a user-friendly interface to manage the system. In the planning section on the production side, this goal is closely related to data handling and visualization of the circumstances at hand. For this, we can effectively utilize some software developed for the Google Maps application programming interface (API). We have developed the following stepwise procedure by using JavaScript and appropriate free software:

Step 1: Collect the addresses of locations in an Excel spread sheet or text file.
Step 2: Add longitude and latitude information for every location in the sheet.
Step 3: Calculate the distance between every pair of locations by using the Google geocoding API.
Step 4: Solve the optimization problem by the proposed method.
Step 5: Display the routes obtained from Step 4 in Google Maps.

Figure 1.20 shows some results for an illustrative problem, in which every depot has a single route, $|I| = 1$, $|J| = 3$, and $|K| = 17$. In this figure,

Figure 1.20 A part of the display of a result (Route from depot 1 [marked as A]).

for simplicity, the routing paths from only depot 1 are shown. Marks for locations (A–B–···–K–A) and dotted arrows are superimposed to help visualize the actual circular route. We can see that this kind of visual information is very helpful for some tasks at an operational level. However, there still remain many possibilities to add more and valuable service information from geographical information system (GIS) applications and the Google Maps API.

1.7 Conclusion

We have described a hierarchical approach to optimize daily logistics including inventory control at depots and vehicle routing for customer delivery. For this purpose, we have extended our existing two-level method, using the modified savings method and the modified HybTS together with a graph algorithm that solves the MCF problem. Through this approach, we can evaluate transportation costs both practically and consistently in terms of the Ton–Kilo basis.

By means of numerical experiments, we have shown that the proposed method can solve complicated and varied problems that have not been previously solvable within a reasonable computation time. In addition, it is straightforward to apply the method to variants of VRP just by replacing the savings value in the procedure. To enhance the solution speed for larger problems, we can apply parallel computing techniques. It is also possible to use the Google Maps API to enhance practical usability.

Future studies should be devoted to relaxing the conditions assumed here. Multiobjective optimization could also be integrated into the system development, as illustrated in Figure 1.1. Eventually, we aim to establish a complete DSS for daily optimization associated with low-carbon logistics.

Abbreviations

API	Application programming interface
CPU	Central processing unit
DC	Distribution center
DSS	Decision support system
GIS	Geographical information system
HybTS	Hybrid tabu search
MCF	Minimum cost flow
M-VRP	Multivehicle routing problem
NP-hard	Nondeterministic polynomial time hard
PSO	Particle swarm optimization
RS	Relay station of DC, or depot
RE	Retailer, or customer
RELAX4	Software name for MCF problem
VRP	Vehicle routing problem
VRPSPD	VRP with simultaneous pickup and delivery
VRPMPD	VRP with mixed pickup and delivery

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