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科目名稱：文獻評論

壹·文獻評論：A heuristic algorithm for the truckload and less-than-truckload problem

一、試述 A heuristic algorithm for the truckload and less-than-truckload problem 這

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Discrete Optimization

A heuristic algorithm for the truckload and less-than-truckload problem

Abstract

The delivery of goods from a warehouse to local customers is an important and practical problem of a logistics manager. In reality, we are facing the fluctuation of demand. When the total demand is greater than the whole capacity of owned trucks, the logistics managers may consider using an outsider carrier.

Logistics managers can make a selection between a truckload (a private truck) and a less-than-truckload carrier (an outsider carrier). Selecting the right mode to transport a shipment may bring significant cost savings to the company.

In this paper, we address the problem of routing a fixed number of trucks with limited capacity from a central warehouse to customers with known demand. The objective of this paper is developing a heuristic algorithm to route the private trucks and to make a selection of less-than-truckload carriers by minimizing a total cost function. Both the mathematical model and the heuristic algorithm are developed. Finally, some computational results and suggestions for future research are presented.

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Keywords: Vehicle routing; Heuristics; 0–1 integer programming; Logistics

1. Introduction

The delivery of goods from a warehouse to local customers is an important and practical problem of a logistics manager. In many sectors of the economy, transportation costs amount for a fifth or even a quarter (lumber, wood, petroleum, stone, clay, and glass products) of the average sales dollars [1].

Logistics managers can make a selection between a truckload (a private truck) and a less-than-truckload carrier (an outsider carrier). A private truck allows a company to consolidate several shipments, going to different destinations, in a single truck. A less-than-truckload carrier usually assumes the responsibility for routing each shipment from origin to destination. The freight charged by a less-than-truckload carrier is usually much higher than the cost of a private truck. Selecting the right mode to transport a shipment may yield significant cost savings to the company.

Our motivation for this study stems from observations on a local logistics company. This

company owns different types of trucks and main business of this company is delivering foods and beverages to wholesalers. Since the business hours of the wholesalers are fixed, the delivery time window constraint is not major concern for this company. But, this company is facing the fluctuation of demand within a year. When the demands are greater than the whole capacity of owned trucks during the peak season, there are two ways to deal with this situation. One is asking truck drivers to work overtime; the other is using the outsider carriers. Since the overtime cost is much higher than that of using an outsider carrier, the logistics managers may consider using an outsider carrier.

In this paper, we address the problem of routing a fixed number of trucks with limited capacity from a central warehouse to customers with known demand. The objective of this paper is developing a heuristic algorithm to route the private trucks and to make a selection of less-than-truckload carriers by minimizing a total cost function.

The literature on vehicle routing problem has been concerned almost exclusively with heuristics. Several families of heuristics have been proposed for the VRP. These can be broadly classified into two main classes: classical heuristics developed mostly between 1960 and 1990, and meta-heuristics whose growth has occurred in the last decade [2]. In general, the classical heuristics are of four types: (i) tour building heuristics, (ii) tour improvement heuristics, (iii) two-phase method, (iv) incomplete optimization methods.

The most often mentioned tour building heuristics is the Clarke and Wright method [3]. There have been many modifications to the basic Clarke and Wright method. Gaskell [4] and Yellow [5] independently introduced the concept of a modified savings given by $S_{ij} - \theta C_{ij}$ where θ is a scalar parameter. One can change emphasis on the cost of travel between two nodes by varying θ .

The tour improvement heuristics are based on Lin [6] and Lin-Kernighan [7] heuristics for the traveling salesman problem. Christofides and Eilon [8] have modified this heuristic for vehicle routing problem. Two-phase methods include those of Gillett and Miller [9] and Christofides et al. [10]. The example of a heuristic based on

incomplete optimization is the tree-search method reported in [10].

The meta-heuristics presented below is restricted to tabu search methods since these have been proved the most successful meta-heuristic approach. Over the past decade, tabu search have been applied to the VRP by several authors. Osman [11], Taillard [12], Gendreau et al. [13], Rochat and Taillard [14], Xu and Kelly [15] and Rego and Roucairol [16] all obtained quite satisfactory results.

Very little research has examined the problem of selecting between a less-than-truckload and truckload carrier. Ball et al. [17] consider a fleet planning problem for long-haul deliveries with fixed delivery locations and an option to use an outside carrier. Agarwal [18] considers the static problem with a fixed fleet size and an option to use an outside carrier. Klinkewicz et al. [19] develop a methodology to address the fleet size planning and to route limited trucks from a central warehouse to customers with random daily demands.

In general, our research described here differs from previous fleet planning or vehicle routing in that it modifies the Clarke and Wright method by shifting from distance to cost and also incorporates the fixed cost of different types of trucks into the model; it allows the permutations of the three improvement procedures that will result in best results; it simultaneously considers the determination of routing a heterogeneous fleet vehicles and the selection of less-than-truckload carriers; it also presents a mathematical model for solving the problem.

This paper is organized as follows. Next section formulates the mathematical model for our problem. Section 3 presents the heuristic algorithm. Some computational results are reported in Section 4. Finally some concluding remarks and suggestions for future research are provided in Section 5.

2. Mathematical model

To simplify the analysis, we formulate our mathematical model based on the following assumptions:

1. We consider one warehouse system; all trucks start at the warehouse and return back to the warehouse.
2. The requirements of all the customers are known; the requirement of each customer cannot exceed the truck capacity;
3. Each customer is served by one truck (either by the private truck or the less-than-truckload carrier); the requirements of all the customers must be met.
4. We restrict ourselves to delivery only.
5. The cost of operating the truck fleet consists of fixed cost and variable cost. Principal cost items in fixed cost include personnel, insurance, and truck depreciation. The main item of variable cost is fuel. It is usually proportional to the distance of truck traveled.

In the following we present an integer programming model and relevant notations:

$$\min z = \sum_k^m FC_k + \sum_i^n \sum_j^n \sum_k^m C_{ijk} X_{ijk} + \sum_i^n CL_i L_i$$

subject to

$$\sum_k^m Y_{ok} = m \quad (k = 1, \dots, m), \quad (1)$$

$$\sum_k^m Y_{ik} + L_i = 1 \quad (i = 1, \dots, n), \quad (2)$$

$$\sum_i^n q_i Y_{ik} \leq Q_k \quad (i = 1, \dots, n; k = 1, \dots, m), \quad (3)$$

$$\sum_j^n X_{ijk} = Y_{ik} \quad (i = 1, \dots, n; k = 1, \dots, m), \quad (4)$$

$$\sum_j^n X_{jik} = Y_{ik} \quad (i = 1, \dots, n; k = 1, \dots, m), \quad (5)$$

$$\sum_{ij \in S} X_{ijk} \leq |S| - 1 \text{ for all} \quad (6)$$

$$S \subseteq \{2, \dots, n\} \quad (k = 1, \dots, m),$$

$$X_{ijk} \in \{0, 1\}; \quad Y_{ik} \in \{0, 1\}; \quad L_i \in \{0, 1\}$$

$$(i = 0, \dots, n; j = 0, \dots, n; k = 1, \dots, m),$$

$i: \{i = 0, \dots, n\}$, the index set of customers (let the index 0 denote the warehouse);

$j: \{j = 0, \dots, n\}$, the index set of customers;

$k: \{k = 1, \dots, m\}$, the index set of trucks;

n : the number of customers;

m : the number of trucks;

$$X_{ijk} = \begin{cases} 1 & \text{if truck } k \text{ travels from customer } i \\ & \text{to customer } j, \\ 0 & \text{otherwise.} \end{cases}$$

$$L_i = \begin{cases} 1 & \text{if the demand of customer } i \text{ is} \\ & \text{satisfied by the} \\ & \text{less-than-truckload carrier,} \\ 0 & \text{otherwise.} \end{cases}$$

$$Y_{ik} = \begin{cases} 1 & \text{if the demand of customer } i \text{ is} \\ & \text{satisfied by the private vehicle } k, \\ 0 & \text{otherwise.} \end{cases}$$

FC_k : fixed cost of private truck k ;

C_{ijk} : the cost of truck k traveling from customer i to customer j ;

CL_i : the cost charged by the less-than-truckload carrier for serving customer i ;

q_i : the demand of customer i ;

Q_k : the capacity of private truck k .

The objective is to route the private trucks and to make a selection of less-than-truckload carriers by minimizing a total cost function.

Constraint (1) ensure that all trucks have been assigned to customers.

Constraint (2) ensure that each customer is served either by the private truck or the less-than-truckload carrier.

Constraint (3) are the truck capacity constraints.

Constraints (4) and (5) ensure that a truck arrives at a customer and also leaves that location.

Constraint (6) serve as subtour-breaking constraints.

3. Heuristic algorithm

In this section we describe an algorithm, called TL-LTL, for solving the vehicle routing and the selection of less-than-truckload carriers problem. The heuristic algorithm can be decomposed into three main steps. In the following we describe algorithm TL-LTL by examining its main steps separately.

3.1. Selection step

The first step of algorithm TL-LTL requires the selection of a group of customers, who will be served by the less-than-truckload carriers. In this step, we will check if the total demand is greater than the whole capacity of owned trucks. If the answer is not, we will skip this step and implement next step directly.

In order to minimize the total cost, we have to design a procedure that can achieve this goal. In reality, the freight charged by the less-than-truckload carrier is usually higher than the cost handled by a private truck. It is obvious that we should order the customers in ascending order based on the freight charged by the less-than-truckload carrier and choose the customers with the lowest cost.

The detail for selecting the customers is described as follows:

- (1) Calculate the total demand for all customers.
- (2) Calculate the whole capacity of owned trucks.
- (3) If the total demand for all customers is greater than the whole capacity of owned trucks, go to step (4) otherwise skip this procedure.
- (4) Subtract the whole capacity of own trucks from the total demand for all customers, which is the unsatisfied truck capacity.
- (5) Order the customers in ascending order based on the freight charged by the less-than-truckload carrier. Starting at top of the list, do the following.
- (6) Sum up the demand of each customer until the total demand is greater than the unsatisfied truck capacity. The corresponding customers will be served by the less-than-truckload carrier: the remaining customers in the list will

be served by private trucks and will be used for constructing initial solution.

3.2. Initial solution construction

The Clarke and Wright's savings algorithm is used to solve this problem by making two modifications. The first modification to the algorithm is a shift in criterion from distance to cost. The second modification of the Clarke and Wright formulation is a change in the savings calculation.

The mathematical relationship of the savings of linking two customers is a function of the mix of a less-than-truckload carrier and a private truck that serve customers. There are three possible mixes serving a pair of customers: (1) two less-than-truckload carriers; (2) a private truck and a less-than-truckload carrier; (3) two private trucks.

Before explaining the revised savings calculation, we list the relevant notations as follows:

S_{ij} = savings from consolidating shipments to customer i and j into the same truck.

LTL_i = the total cost charged by the less-than-truckload carrier for serving customer i .

TL_{ij} = the total cost of a private truck that travels from warehouse to customer i , then from customer i to customer j and finally returns back to warehouse.

$FC(Z)$ = the fixed cost of the smallest truck that can serve a demand of Z .

d_{ij} = the distance from customer i to customer j .

v = the cost of traveling a mile for private truck (\$/per mile).

Fig. 1 illustrates the revised savings calculation from linking two customers under each of the three possible mixes.

The detail for constructing the initial solution is described as follows:

- (1) Calculate the savings for all pairs customers based on revised savings scenario 1 in Fig. 1.
- (2) Order the savings in descending order. Starting at top of the list, do the following.
- (3) Find the feasible link in the list which can be used to extend one of the two ends of the currently constructed route.

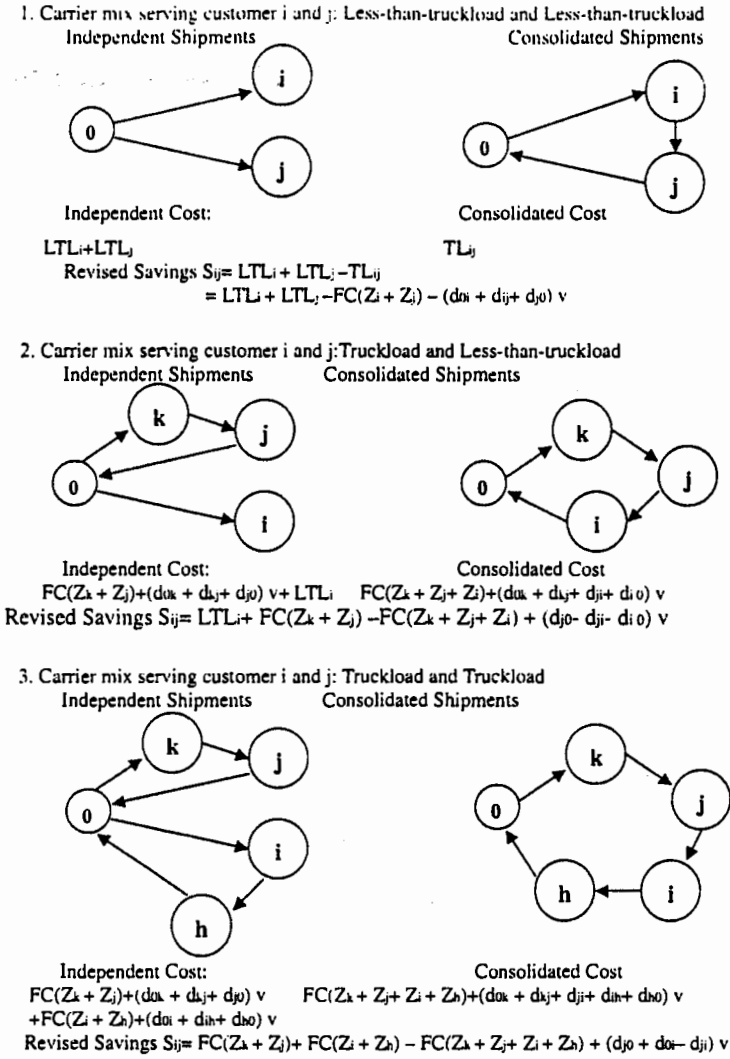


Fig. 1. Savings calculation from consolidating two customers.

- (4) If the route cannot be expanded further, terminate the route. Choose the first feasible link in the list to start a new route.
- (5) Repeat Steps (3) and (4) until no more links can be chosen.
- (6) Output all the temporary single-customer routes (served by the less-than-truckload carriers) and multi-customer routes.
- (7) Calculate the savings for single-customer routes based on revised savings scenario 2 in Fig. 1.
- (8) Order the savings in descending order. Starting at top of the list, do the following.
- (9) Find the feasible link in the current multi-customer routes which can be used to extend the route.
- (10) If the route cannot be expanded further, terminate the route.
- (11) Repeat Steps (9) and (10) until no more links can be chosen.
- (12) Output all the routes.

3.3. Refining procedure

A refining procedure is applied to the solution obtained through the initial solution step. This procedure is composed of a succession of intra-route and inter-route arc exchanges.

3.3.1. Intra-route improvement

Each route is improved by applying a refining procedure which considers all the feasible exchanges of two arcs belong to the route (the so-called intra-route two-exchanges [20]). The procedure is similar to those described in Christofides and Eilon [8] and Kindervater and Savelsbergh [21]. Given a route, a two-exchange is obtained by replacing arcs (m, n) and (p, q) with arcs (m, p) and (n, q) , as illustrated in Fig. 2.

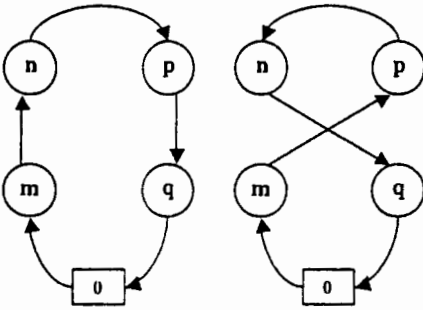


Fig. 2. Example of intra-route two-exchanges.

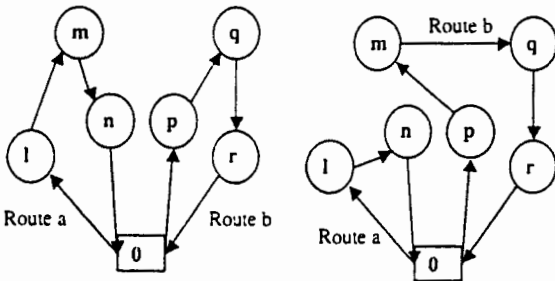


Fig. 3. Example of inter-route one-exchange.

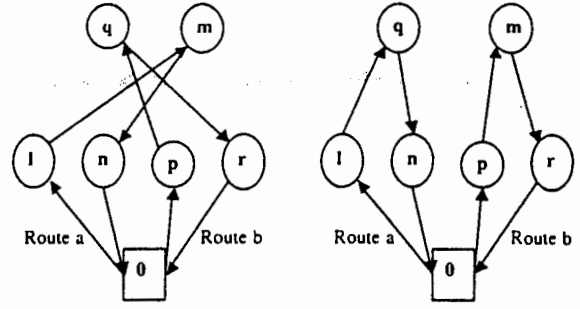


Fig. 4. Example of inter-route two-exchanges.

3.3.2. Inter-route improvement

In this step, a set of routes is obtained by using further local search procedures. These procedures are based on the so-called inter-route one-exchange and two-exchanges, illustrated in Figs. 3 and 4, respectively.

For each node m , belonging to route a , the one-exchange corresponding to its insertion after node p , belonging to route b , is obtained by removing arcs (l, m) , (m, n) and (p, q) , and replacing them with arcs (l, n) , (p, m) and (m, q) , as illustrated in Fig. 3.

For each node m , belonging to route a , the two-exchange corresponding to its exchange with node q , belonging to route b , is obtained by removing arcs (l, m) , (m, n) , (p, q) and (q, r) , and replacing them with arcs (l, q) , (q, n) , (p, m) and (m, r) , as illustrated in Fig. 4.

3.3.3. Search procedure

A search procedure is designed in searching for a better solution. From the results of extensive experiments which are not shown here, we know that the implementation sequence of intra-route and inter-route improvement procedure might have impacts on the quality of solution.

The improvement procedures mentioned above include intra-route two-exchanges, inter-route one-exchange and two-exchanges. The possible permutations of three different improvement procedures are only six, so a loop procedure consisting of arranging the possible sequences of intra-route and inter-route improvement is applied on the solution obtained in the initial solution construction phase. The purpose of this loop proce-

Table 1
Results for five test problems

Test problem	Routes	Total cost	CPU* time	% larger than the best solution
1	Heuristic algorithm	387.5	3.14	0
	1-3-5-4-1 1-6-1 Customer 2 is served by LTL			
	Mathematical model	387.5	1.1	
	1-3-5-4-1 1-6-1 Customer 2 is served by LTL			
2	Heuristic algorithm	631	4.58	7.67
	1-9-8-7-5-11-1 1-2-4-3-10-1 Customer 6 is served by LTL			
	Mathematical model	586	34.5	
	1-4-3-10-11-5-1 1-2-9-8-7-1 Customer 6 is served by LTL			
3	Heuristic algorithm	900	5.88	0
	1-3-2-4-11-10-1 1-12-15-8-13-1 1-16-6-14-9-7-1 Customer 5 is served by LTL			
	Mathematical model	900	578	
	1-8-12-4-2-3-1 1-7-13-10-11-1 1-9-15-14-16-6-1 Customer 5 is served by LTL			
4	Heuristic algorithm	1681.5	8.42	1.81
	1-17-16-4-3-2-7-14-10-6-5-9-1 1-22-20-19-21-15-18-23-12-8-13-1 Customer 11 is served by LTL			
	Mathematical model	1651.5	830	
	1-20-23-21-19-15-18-16-17-4-3-2-8-10-13-1 1-7-14-12-6-5-9-22-1 Customer 11 is served by LTL			
5	Heuristic algorithm	1917	11.06	0.86
	1-19-24-9-15-30-28-27-29-1 1-11-12-13-10-18-8-14-17-16-1 1-20-21-23-7-26-25-2-6-5-4-1 Customers 3 and 22 are served by LTL			
	Mathematical model	1900.5	2406	
	1-3-5-2-1 1-22-18-17-27-29-28-26-25-23-21-1 1-4-6-7-30-16-14-8-10-15-9-13-12-11-1 Customers 19, 20 and 24 are served by LTL			

* All times are in seconds; the results were obtained on a PC running at 2000 MHz.

cedure is in a sense similar to the tabu search method to escape from a local minimum. Once a better solution is found after finishing improvement phase, the best solution record is updated. We repeat the above improvement processes until all possible permutations of three different improvement procedures have been implemented.

4. Computational results

In this section, we summarize our computational results on five test problems. The detailed data associated with five examples are given in Appendix A. The solutions produced by the heuristic algorithm are compared with the optimal results from the mathematical model. The heuristic algorithm was written in FORTRAN language and the mathematical model was solved using the software LINDO version 6.1. Both of them were implemented on a PC with a 2000 MHz processor. Computational results on five test problems are reported in Table 1.

For the first and the third test problems, our heuristic algorithm obtains the optimal solution. As shown in Table 1, both the mathematical model and the heuristic algorithm yield the same total cost \$387.5 and \$900, respectively. The only difference between two approaches in the third test problem is in that each approach arranges customers in different routes and in different sequences.

Computationally, exact algorithm for the VRP is restricted to solving problems of only up to about 25 customers. For five test problems, the solution time of mathematical model increased quickly with problem size. On the other side, our heuristic algorithm required very little time to solve the problem. Every problem took only a few seconds. The CPU time of test problems is not very sensitive to problem size.

In order to test whether the solution time of our algorithm is not sensitive to larger size of problem, we have solved additional three test problems with the customer size of 51, 76 and 101, respectively. Because the VRP is very difficult to solve with mathematical model even for relatively small size

Table 2
Results for larger size of test problems

Test problem ^a	CPU ^b time
1 [E-n51-K5]	27.84
2 [E-n76-K7]	84.48
3 [E-n101-K8]	192.48

^a Test problem 1 and 3 can be found in Christofides and Eilon [8]; test problem 2 can be found in Gillett and Miller [9].

^b All times are in seconds; the results were obtained on a PC running at 2000 MHz.

instances, only the average computation times to run the heuristic are reported. These results are presented in Table 2. Though the solution's time increased with problem size, it is obvious that the solution's time increase gradually without rapid growth.

5. Conclusions

The delivery of goods from a warehouse to local customers is an important and practical problem of a logistics manager. In this paper, we develop both the mathematical model and the heuristic algorithm for solving the less-than-truckload and truckload problem. Some computational results are presented. Our heuristic algorithm obtains the optimal or near-optimal solutions in an efficient way in terms of time and accuracy.

As for further research, a wide range of test problems should be performed. It would be interesting to see if other intelligent optimization techniques, such as tabu search, genetic algorithms, simulated annealing and neural networks, can be modified to solve this problem and even provide better results.

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Integrating theories of work motivation is an awesome task. At this stage of development, it is probably impossible. We can step back and view these theories from a broad perspective, highlighting major points of divergence and convergence. Landy and Trumbo (1980) astutely observed that work-motivation theories are often more complex than the behavior they try to explain. The preceding sections dealt with each of these complex theories in detail; we will now attempt to simplify the perspectives.

The seven theories discussed roughly reflect three different views of motivation. Need theories and the theory of intrinsic motivation presume that people are motivated by internal factors, either innate needs causing us to seek fulfillment or feelings of pleasure and self-control from performing tasks we find enjoyable. Expectancy theory and goal-setting theory presume that people are rational. After carefully considering our wants and the relationship between behavior and attaining desired outcomes or goals, we try to maximize the chances of obtaining what we want. Equity theory and reinforcement theory presume we are motivated by external factors. According to equity theory, our perceptions of what others are giving and getting are involved. With reinforcement theory, motivation is a product of a schedule of rewards. We are left with diverse theoretical perspectives: motivation springs from within us due to subconscious forces; it is a product of rationally calculating what we must do to get what we want; or it is a result of things that are "done" to us.

Which perspective is most defensible? There is some research support for all of them, but some theories have received more confirmation than others. This is, in part, what makes motivation so intriguing. No theories are absolutely "wrong." But no theory to date has received so much support that it can be declared *the* theory of motivation. Even those receiving most of the research support make different predictions. Probably the two best theories of work motivation are expectancy theory and goal-setting theory. Expectancy theory advocates setting easy goals to maximize motivation; the probability of effort resulting in attainment is very high. Goal setting advocates the opposite: setting difficult goals. Perhaps the theories differ on this point only with regard to time. Easier goals should first be set so people can build up confidence (expectancy) that effort will result in performance, which will lead to outcome attainment. As expectancy grows, progressively harder goals could be set, leading to even greater attainment. Goal-setting theory stresses the difficulty of the goal; expectancy theory stresses the perceived relationship among effort, performance, and outcome attainment. Thus, predictions made by each theory need not be contradictory.

If we could distill the best of each of the seven theories, we would arrive at the following conclusions. Need theory reminds us that individual differences are important and that our efforts will always be channeled toward survival before social fulfillment. Different people have different needs and desires; any good theory of motivation must allow for this. Equity theory emphasizes that what we do is in part a product of what people around us do. We are social creatures; we do not exist in a vacuum. What we eat, how we dress, and how hard we work are all determined to some degree by other people in our environment. Expectancy theory raises motivation to a level of conscious choice. We deliberately choose how hard to work based on the gains we expect to receive from our efforts. If we do not see any benefit to be gained from our efforts, we will not be motivated. Goal-setting theory stresses that motivation is maximized by setting specific target objectives; such goals can prevent an ineffective diffusion of effort. Reinforcement theory states that when people are rewarded on units of performance as opposed to units of time, their motivation is greater. Finally, intrinsic-motivation theory suggests that people prefer to expend effort on tasks that enhance feelings of personal control and competence. A composite theory of motivation, drawing on the strengths of existing theories, would ideally include these findings as established by research. A general summary of all the motivation theories is presented in Table 10-3.

Mitchell (1982) feels that we must strive to integrate our existing theories of motivation. We don't need more theories of motivation; rather, we need to consolidate those that we already have. Some researchers have attempted to do just that. For example, Garland (1984) combined elements from the expectancy and goal-setting theories. He found that both goal levels and expectancy made independent contributions to variance in performance. Furthermore, Perry and Porter (1982) observed that most of what we know about motivation comes from

Summary and evaluation of work-motivation theories

<i>Theory</i>	<i>Source of Motivation</i>	<i>Empirical Support</i>	<i>Industrial Applicability</i>
Need theory	Unconscious, innate needs	<i>Weak:</i> Little support for proposed relationships among needs.	<i>Very limited:</i> Theory lacks sufficient specificity to guide behavior.
Equity theory	Drive to reduce feelings of tension caused by perceived inequity	<i>Mixed:</i> Good support for underpayment inequity, weak support for overpayment inequity.	<i>Limited:</i> Social comparisons are made, but feelings of inequity can be reduced through means other than increased motivation.
Expectancy theory	Relationship among desired outcomes, performance-reward, and effort-performance variables	<i>Moderate-strong:</i> More strongly supported in within-subject than across-subject experiments.	<i>Strong:</i> Theory provides a rational basis for why people expend effort, although not all behavior is as consciously determined as postulated.
Reinforcement theory	Schedule of reinforcement used to reward people for their performance	<i>Moderate:</i> Ratio reinforcement schedules evoke superior performance compared to interval schedules, but little difference exists among various ratio schedules.	<i>Moderate:</i> Contingent payment for performance is possible in some jobs, although ethical problems can be present in an organization's attempt to shape employee behavior.
Goal-setting theory	Intention to direct behavior in pursuit of acceptable goals	<i>Moderate-strong:</i> Performance under goal-setting conditions usually superior to conditions under which no goals are set.	<i>Strong:</i> Ability to set goals is not restricted to certain types of people or jobs.
Intrinsic-motivation theory	Feelings of competence and self-control that come from performing enjoyable tasks	<i>Mixed:</i> Extrinsic and intrinsic rewards do not seem to be purely additive, but extrinsic rewards do not always decrease intrinsic motivation.	<i>Very limited:</i> Little evidence that intrinsically motivating tasks remain intrinsically motivating for long periods.

private-sector (business and industry) employees, and we need to expand our theories to include public organizations.

Katzell and Thompson (1990) analyzed the vast body of research and theory on motivation, and identified seven practices that can raise the level of motivation of people in work organizations.

1. Ensure that workers' motives and values are appropriate for the jobs on which they are placed.
2. Make jobs attractive and consistent with workers' motives and values.
3. Define work goals that are clear, challenging, attractive, and attainable.
4. Provide workers with the personnel and material resources that facilitate their effectiveness.
5. Create supportive social environments.
6. Reinforce performance.
7. Harmonize all these elements into a consistent socio-technical system.

As can be gathered from the theories of work motivation presented in this chapter, no one theory embraces all seven of these practices. Furthermore, some theorists believe there is an inherent association between motivation and satisfaction, in the sense that people are motivated by the anticipation of satisfaction. As such, future theories of motivation may formally and directly incorporate many of the research findings on job satisfaction discussed in Chapter 9. Rather than treating constructs such as motivation, job satisfaction, and leadership as segmented or discrete, more comprehensive theories attempt to explain their interrelationships. We will witness some of these theories in the next chapter.