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LARGE SCALE VEHICLE ROUTING PROBLEM: AN OVERVIEW OF ALGORITHMS AND AN INTELLIGENT PROCEDURE

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Abstract. *In this paper, we provide a taxonomic literature review of Large Scale Vehicle Routing Problem (Large Scale VRP, LSVRP) and present a new solution procedure integrating qualitative and quantitative processes for solving it. First of all, according to the principles of different heuristics that the metaheuristics derived from, 5 categories are classified. Then based on the analysis of the characteristics of the problem, a framework of the generalized procedure to solve LSVRP is given. The techniques of knowledge representation, state-space search theory, heuristics, and modeling optimization used in the procedure are elaborated. Finally, a comparison study is given to show the procedure's competitiveness. The new idea of incorporating the qualitative reasoning into quantitative approaches can strengthen the procedure's capability of dealing with empirical information. It is beneficial to greatly decreasing the number of possible routing schemes, and meanwhile, improving the practicability of the procedure.*
Keywords: Large scale vehicle routing problem (LSVRP), Qualitative reasoning, Quantitative computing, Distribution

1. **Introduction.** As it closely relates theoretical research to real-world practices, and is an NP-hard problem, the Vehicle Routing Problem (VRP) has attracted a great deal of research efforts in the areas of operations research, management science, and transportation science. Over the past 50 years, hundreds of models and algorithms have been developed to obtain either optimal or heuristic solutions for different versions of VRP. In their famous book titled "The Vehicle Routing Problem", Toth and Vigo [1] provide a comprehensive review of the state of the art of both exact and heuristic methods developed in the last decade for the VRP and some of their main variants.

According to the statistical analysis of the literatures, it shows that the majority of the current research has put emphasis on the problems within a limited size of 200 customers. Especially for the results by exact algorithms, most of them can only solve the instances with a size less than 100 customers within an acceptable computation time.

Compared with the traditional one, VRP under E-commerce environment is more complex and more difficult to solve. It reveals several new features, for example, with more delivery points, delivery points being scattered over broader area, small delivery volume, higher costs, with strict delivery time window. The features are reflected notably in the daily commodity industries, such as milk delivery, beverage distribution, and cigarette distribution. Furthermore, the complexity of the problems and their solution difficulties will increase due to some additional practical requirements (e.g., real-time order request processing and real-time scheduling). The classical methods, exact algorithms and traditional heuristic algorithms, have been difficult to solve large-scale application problems. Therefore, the research focuses are gradually turned to Large Scale VRP (LSVRP) in recent years. In [2], it has been defined that VRP with the number of customers scaling from 10^2 to 10^3 is classified as LSVRP.

LSVRP concerns complex management decision-making. A general way to solve complex management decision-making problems is firstly to simplify them before solving. For example, the solution process begins from their sub-problems. Here the sub-problem selection depends on the researcher's domain knowledge. In addition, some theoretical studies always start from several assumptions of the problems. Although there is a gap between the hypothesis and the reality [3], it is an effective dealing way of simplifying complex issues. Due to the gap, the solutions may have some limitations in the aspect of application. Since 90s in the 20th century, a new approach has emerged to solve complex decision-making problems, which is more scientific and effective. This thought puts emphasis on the description, formulation and solution process for the problem, synthesizes the human's intelligence and computer's efficiency, and achieves a comprehensive integration of the information, knowledge and intelligence. The two disciplines, Artificial Intelligence (AI) and Operations Research (OR) can approach this objective in fundamentally different but complementary ways [4]: AI problem solution techniques tend to be inferential and to rely on expert knowledge and heuristics; OR uses algorithmic, mathematically based approaches. That is, AI emphasizes qualitative aspects of problems; OR emphasizes the quantitative. A careful integration of these two approaches to problem solution shows significant promise for improving the efficiency and, notably, the acceptability of problem solving systems. Knowledge Representation in AI realizes the utilization of empirical information in computer, which helps reduce the computational complexity. [5] applied the idea to deal with disruption events in the distribution industry. [6] proposed a methodology for analyzing and solving complex problems in the social economic system by the integration and the conformity of multiple disciplines which led to the formation of a comprehensive integration of the qualitative and the quantitative, the computational and the experimental, and the virtual and the actual.

In the paper, we attempt to introduce the above thought into solving LSVRP and present a procedure that integrates qualitative reasoning and quantitative computing to support effective LSVRP solving and decision-making. We also will specifically elaborate how we can integrate the qualitative reasoning and quantitative computing in the solution process. In Section 2, we review the algorithms that have been used to solve LSVRP. In Section 3, we present a framework of the procedure integrating qualitative and quantitative processes for LSVRP. A comparative study is given in Section 4. Finally, concluding remarks and future research directions are summarized in Section 5.

2. A Review of Related Literature.

In the last ten years, a variety of algorithms have been developed to solve the LSVRP. Most of them apply the principles of tabu search, evolutionary algorithm (including genetic algorithm) and simulated annealing, and then improve them. All the algorithms fall into the category of metaheuristics. Metaheuristics provide much better solutions, especially on large scale problems. One excellent survey for this active research area is provided in the work of [7]. It showed that the best metaheuristics for the VRP are powerful tabu search algorithms that easily outperform other metaheuristics like simulated annealing, genetic algorithms and ant algorithms. In this paper, we divide the related results for LSVRP into 5 categories: (1) Tabu search

(TS), (2) Evolutionary algorithm (EA), (3) Simulated annealing (SA), (4) Local search, and (5) Cluster first-route second.

(1) Tabu search (TS)

The principle of TS has been widely utilized to improve the algorithms' ability for solving LSVRP. We list the new algorithms derived from TS as follows.

• Network flow-based tabu search. Xu and Kelly [8] developed the local search approach based on a network flow model that is used to simultaneously evaluate several customer ejection and insertion moves. The capacity constraints are relaxed using penalty terms whose parameter values are adjusted according to time and search feedback. Tabu Search is incorporated into the procedure to overcome local optimality. More advanced issues such as intensification and diversification strategies are developed to provide effective enhancements to the basic tabu search algorithm.

• Adaptive memory-based tabu search. In 1996, Glover [9] presented the advances, applications, and challenges in tabu search and adaptive memory programming. Tarantilis and Kiranoudis [10] presented it in 2002. The main idea is to extract a sequence of points (called bones) from a set of solutions and generate a route using adaptive memory. If a large number of routes in the set of solutions contain a specific bone, then the authors argue that this bone should be included in a route that appears in a high-quality solution. The BoneRoute algorithm has two phases. In Phase I, a set of initial solutions is generated using weighted savings. The solutions are improved using a standard tabu search algorithm. In Phase II, promising bones are extracted, a solution is generated and improved using tabu search, and the set of solutions is updated.

• Granular tabu search (GTS). It was presented by Toth and Vigo in 1998 and then was published in INFORMS journal in 2003 [11]. They defined a granular neighborhood for VRP by considering short edges whose lengths are less than a threshold value and by typically not considering long edges. It will benefit decreasing the search space and achieving a better solution within a shorter computing time. However, as the quality of tabu search depends on the quality of initial solution and it only can process one solution, it is more necessary to get a better initial solution. Due to the advantage of GTS, it is applied to solve some variants of LSVRP. Chao [12] and Scheuerer [13] used it to solve truck and trailer routing problem; Brandao [14] solved an open VRP by it. Ho and Haugland [15] solved a VRP with time windows and split deliveries. Montané and Galvao [16] settled vehicle routing problem with simultaneous pick-up and delivery service.

• Others. Due to the high complexity of the problems, the work of [17] has presented an effective tabu search algorithm which applies dynamic oscillation and candidate list strategies, which are controlled by the success of the search as the solution progresses, to make best use of infeasible verses feasible space and promising verses the most promising neighbors' moves. The work of [18] proposed a hybrid heuristics, in which the whole area is split into several sub-areas by the sweep technology and the divisional tabu search algorithm is designed for the splitting of area, and the goods to be delivered in the adjacent areas is exchanged to improve the global search ability of the algorithm.

(2) Evolutionary algorithm (EA)

• Evolution strategy. D. Mester and O. Braysy present active-guided evolution strategies metaheuristic for the vehicle routing problem with time windows and for the capacitated vehicle routing problem in the works of [19,20] respectively. The metaheuristic combines the strengths of the guided local search and evolution strategies metaheuristics into an iterative two-stage procedure.

• Hybrid genetic algorithm. The work of [21] presents the first hybrid GA for the VRP able to compete with powerful TS algorithms in terms of average solution cost. On Christofides instances, this GA outperforms all metaheuristics published, except one. It becomes the best algorithm available for the large-scale instances generated by Golden et al. [7]. In this work, the very good results can be explained by some key-features. A possible premature convergence due to the local search is prevented by using small populations of distinct solutions. Three classical heuristics provide good starting points. The incremental population management and the partial replacement technique used in restarts accelerate the decrease of the objective function. However, one point needs improvement, that is, the GA is still slower than many TS algorithms. Therefore, it is necessary to speed up the local search in the hybrid GA. In [22], LSVRP is partitioned into two sub problems, the generalized assignment problem and vehicle routing problem intra-region after partitioning. The first problem was solved by an improved location-based heuristics, and the hybrid genetic algorithm was presented for solving the second problem.

(3) Simulated annealing (SA)

Considering their similarities, we classify ITA and VRTR into the category of simulated annealing.

• Improved threshold accepting (ITA). The work of [23] firstly presented the threshold accepting (TA) in 1990. TA is a deterministic variant of simulated annealing in which a threshold value T is specified as the fixed upper bound on the amount of objective function increase allowed, whereas simulated annealing algorithm accepts the state of deterioration of the objective function at a certain probability, which brings the randomness. Tarantilis et al. proposed two kinds of improved TA, backtracking adaptive threshold accepting (BATA) [24] and list-based threshold accepting (LBTA) [25]. In the backtracking algorithm, the threshold value T is allowed to increase during the search. In the list-based algorithm, a list of values for T is used during the search. In 2004, Tarantilis et al. applied it to solve Open Vehicle Routing problem [26].

• Improved version of the record-to-record travel algorithm (VRTR). The work of [27] presented record-to-record travel (RRT) in 1993. RRT and TA resemble in their structures. The differences lie in the initialization of the threshold sequence and the state of the decreasing. RRT set a fixed percentage of a record as a deviation value and establish a rule in advance to stop the search after a solution below the threshold value could not be found. Its initial solution is generated by the Clarke and Wright algorithm. Feasible one-point moves are made using record-to-record travel (uphill moves allowed). Points are exchanged on different routes (two-point exchange) while feasibility is maintained (uphill moves are allowed). Routes are cleaned up (only downhill moves allowed). A local reinitialization allows individual routes to be resequenced and the process of one-point moves, two-point exchanges, and clean-up is repeated. In the end, global reinitialization perturbs the best solution and the process of one-point moves, two-point exchanges, and clean-up is repeated. Li [28] presented VRTR in 2005. The VRTR uses a variable-length neighbor list. The idea is to consider only a fixed number of neighbors for each node when making one-point, two-point, and two-opt moves. There are two key differences between VRTR and RTR. First of all, VRTR considers two-opt moves between and within routes, while RTR considers two-opt moves only within routes. Secondly, VRTR uses a variable-length neighbor list that should help focus the algorithm on promising moves and speed up the search procedure. However, RTR does not use a neighbor list. Then VRTR is used to solve the heterogeneous fleet vehicle routing problem [29].

(4) Local search

Two good heuristics which utilize and improve the strategy of local search have greatly increased the size of the solved instances. The work of [30,31] presents an efficient variable neighborhood search heuristic for the capacitated vehicle routing problem. The variable neighborhood search procedure is used to guide a set of standard improvement heuristics.

In addition, a strategy reminiscent of the guided local search metaheuristic is used to help escape local minima. The developed solution method is specifically aimed at solving very large scale real-life vehicle routing problems. It can find high-quality solutions for experimental instances with up to 20,000 customers within reasonable CPU times. The work of [32] aims to design a set of minimum-cost routes for the multi-depot vehicle routing problem with time windows (m-VRPTW). It presents an m-VRPTW local search improvement algorithm that explores a large neighborhood of the current solution to discover a cheaper set of feasible routes. The neighborhood structure comprises all solutions that can be generated by iteratively performing node exchanges among nearby trips followed by a node reordering on every route. Manageable mixed-integer linear programming (MILP) formulations for both algorithmic steps were developed. A spatial decomposition scheme has also been applied to further reduce the problem size.

(5) Cluster first-route second

An effective way to deal with LSVRP by decreasing the problem's state space largely is the method of cluster first-route second. Different features are utilized to cluster the customers, e.g., road information, customer information, vehicle information, and depot location. Besides simple sweep technology [18], there are several new customer clustering methods. In [2], the customers were firstly segregated into districts according to the main road grid system. Then the customer districts were assigned to vehicles using the vehicle flow formulation model and the combined saving and 3-option algorithm. Finally, the vehicle routes were determined as a traveling salesman problem. Yu and Liu [33] designed an architecture of a spatial decision support system (SDSS) which is composed of three stages, merging the large numbers of customers according to their space attributes, assigning the merged customers to vehicles using a sweep algorithm, and determining each vehicle route order as a Traveling Salesman Problem. Ouyang [34] proposed algorithms to automatically discretize vehicle routing zones from continuum approximation guidelines by utilizing a combination of spatial partitioning techniques to systematically obtain optimum zone designs.

The idea of introducing qualitative process into solving LSVRP, especially in the stage of customer clustering, has appeared in a few results. For example, the work of [35] tackles the more realistic tactical or operational case (a French manufacturer of furniture with 775 destination stores), with a fixed number of vehicles of each type, and the optional possibility for each vehicle to perform several trips. The author presents two human experiences could be utilized to decrease the solution space of the problems. First of all, professional dispatchers assign a 'full load' by hand to a truck going directly to the client. It is assumed that such manual assignments are already removed from input data. Secondly, a good priority rule is then to use the largest trucks first. And in the work of [36], the concept generalized workload is introduced to balance the different routes, which comprehensively considers route distance, the number of customers and the quantity of the delivery goods in one route. The above ideas taking advantage of qualitative factors are beneficial to quickening satisfied schemes acquisition and improving the practicability of the solution method.

For the results in the categories (1) $\sim$ (4), by adding adaptive techniques to deal with LSVRP, they improve the traditional heuristic algorithms and increase their efficiencies to some extent. They encourage the practical applications of theoretical results of LSVRP. However, the solution efficiency is contradiction to the quality of the solution, which has not been solved very well, especially for LSVRP. There is a way to mitigate the contradiction from two aspects. One is to decrease the problem's state space through incorporating human's heuristic knowledge. The other is to bring the computer's powerful computing ability into play. That is, the problem maybe solved better under condition of the combination of human's intelligence and computer's efficiency and the integration of qualitative reasoning and quantitative computing.

For the category of (5), the two stages clustering and routing are entirely independent, which causes the common weakness of local optimization. [18] considered the comprehensive optimization of adjacent areas. It improves the global search ability of the algorithm. [34] proposed a method to divide the area from the perspective of mathematical computation, however, it lacks the consideration of qualitative factors involved in the solution process, which results in worse practicality. There are still some other remarkable general limitations of approaches. For example, most of them can not deal with the parameters' dynamic changes. And for the practitioner, the most relevant issue is that metaheuristics are not guaranteed to find the optimum or even a satisfactory near-optimal solution. All metaheuristics will eventually encounter problems on which they perform poorly. The practitioner must gain experience in which optimizers work well on different classes of problems.

Therefore, a general solution procedure that can find optimal routing schemes in real time, and meanwhile, can accommodate real world instances' dynamic changes is in great need. The objective of this paper is to present an intelligent procedure for synthesizing qualitative and quantitative processes for solving LSVRP. Comparing with the above results, there are two most important features of our solution procedure. (1) The number of feasible travel schemes is no longer determined by the number of customers (the scale of the problem), but by the number of the customer clusters. And the computation time stays almost unchanged as the number of customers grows. This significantly increases the utilization of the solution procedure for LSVRP. (2) The procedure aims to identify the feasible routing schemes by considering several adjacent clusters and then using OR programming model to find the final solution. It overcomes the weakness of local optimization caused by entirely independent of the clustering and routing to some extent.

3. **A Framework of the New Generalized Procedure to Solve LSVRP.** The difficulty for solving LSVRP is due to the problem's solution space increases exponentially with the increase of the size of the problem. And the key point is to significantly reduce the problem's solution space. Therefore, focusing on the reduction of the state space of feasible vehicle routes, combining the techniques of qualitative reasoning and quantitative computing, a framework of the procedure synthesizing qualitative and quantitative processes for solving LSVRP is presented, which is shown in Figure 1.

In Figure 1, we divide all the functions of the solution process into qualitative reasoning and quantitative computing, which are enumerated in the left and right column respectively. These functions are interrelated consecutively finishing the solution process. The qualitative process includes the following 5 parts.

In Part 1, the qualitative factors are selected from the influence factors on customer clustering and then represented by knowledge. The qualitative factors include experts' distribution experience, drivers' preferences, customer features, traffic information, and city's geographical features. The features of customers could be customer's importance level, the level of customer's demand amount, etc., City's geographical features concern the characteristics of city layout. In China, there are four typical city structures, axis-oriented structure, multi-block oriented structure, block-oriented structure, and blocks and loops mixed structure. Such factors are difficult to be utilized and incorporated to the computing process. To take advantage of them to decrease the solution space, the information structure of qualitative factors should be firstly built up, based on which they could be represented by knowledge. Comparing with the traditional knowledge representation schemes [37] (e.g., Logic, Production Rules, Semantic Nets and Frames),

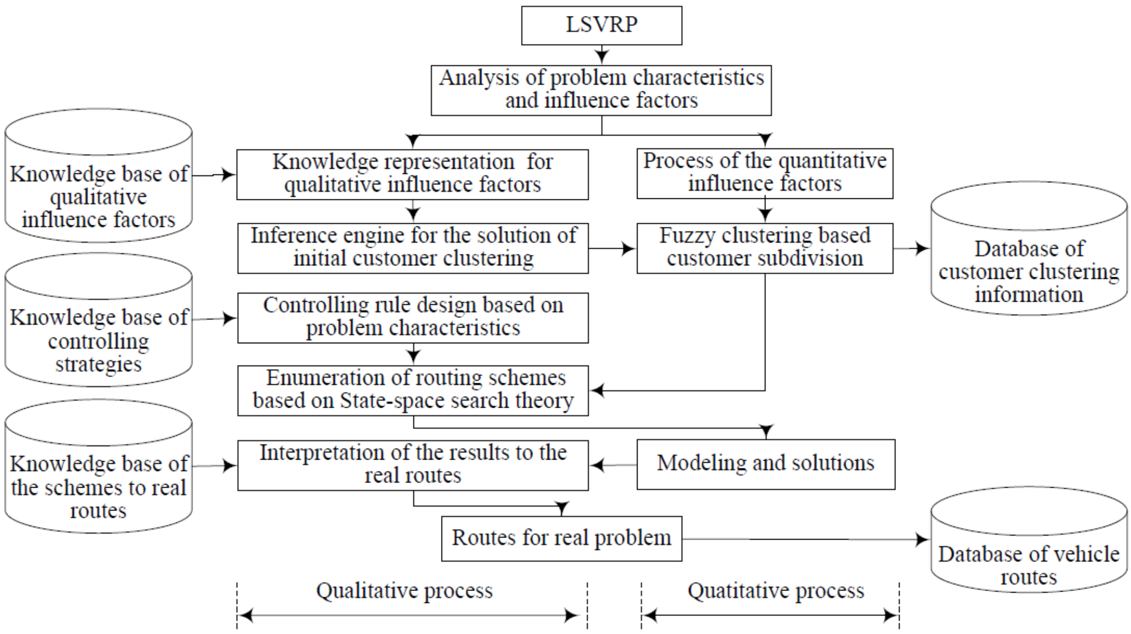

FIGURE 1. The framework of the procedure synthesizing qualitative and quantitative processes for LSVRP

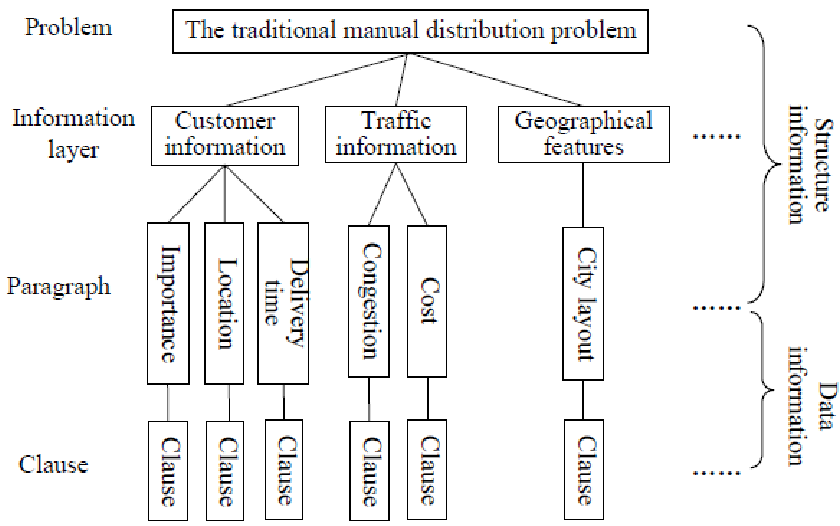

FIGURE 2. Tree-like knowledge representation of qualitative factors in the distribution

a new one named Tree-like knowledge representation [38] is more appropriate for the representation of qualitative factors in the distribution industry. A representation example is given in Figure 2. Then a dynamic knowledge base should be built for storing the knowledge of qualitative influence factors.

In Part 2, an inference engine is designed for the solution of initial customer clustering. This is a rough and initial classification based on qualitative factors. The inference engine, that is, an 'interpreter' for the knowledge base, enables the knowledge to solve the actual problems. Here the reasoning strategy of forward chaining is applied. Forward chaining starts with the knowledge of available qualitative factors and uses inference rules to match the actual until a satisfied clustering result is achieved.

In Part 3, according to the characteristics of the problem, controlling rules can be designed to decrease the number of feasible routes while they are enumerated. So the total searching time is reduced and the searching process is simplified. For example, for open vehicle routing problems, where vehicles are not required to return to the depot, a vehicle will require less travel time if it finishes tasks in the nearer clusters before the further ones to the depot. Furthermore, if adding a delivery task inside the area in which the customer being served is located violates the travel time or the load capacity constraint, then there is no need to consider customers outside this area. In [39], two search rules have been designed for a real distribution problem in cities with a circular transportation infrastructure.

In Part 4, after achieving the customer clustering results, vehicle routing schemes are enumerated among all the clusters. The corresponding relationship between the set of routing schemes and a state-space is built, in which a customer is a search node. A routing scheme is a path spanning through the state-space from an initial state to a goal state. In this case, the central depot is a search node corresponding to the initial state, and the last customer which a vehicle will serve within the constraints is the goal state. Therefore, the generation of vehicle routing schemes is turned into the path searching through the state-space. Considering the characteristics of search strategies and the problems, we adopt the depth-first search strategy to enumerate the schemes.

Finally, in Part 5, the results should be interpreted to real routes. The solutions indicate only the service sequences in customer clusters, and do not specify which specific customers are served. To address this, solution policy to determine the specific customers should be developed. Nearest neighbor principle is appropriate to determine the specific customers.

In the quantitative process, quantitative influence factors are firstly analyzed and then customers are subdivided by clustering tools (e.g., fuzzy clustering) after they are initially classified in the qualitative process. A mathematical model is developed to select the satisfied routing schemes from the set of feasible routing schemes achieved by enumeration work. Here, the traditional programming theories (e.g., linear programming, integer programming) can be used for modeling and solving.

We have studied VRP in [39,40], which concern several parts in the framework shown in Figure 1. The result in [39] solves a food wholesalers' distribution decision, and [40] presents a relatively general approach to a specific kind of VRP. Both of them study the problems from the perspectives of qualitative processing (enumeration of routing schemes based on State-space search theory) and quantitative processing (modeling and solution). They verify the feasibility of the framework in Figure 1 in solving small and medium sized problems. Owning to the number of feasible vehicle routes is no longer determined by the scale of the problem (the number of customers), but by the number of the customer clusters in the new procedure, it can be concluded that the new procedure will be effective for LSVRP.

4. **A Comparative Study.**

The comparison work was carried out with eight large-scale OVRPs reported in the research of Li et al. [41]. These problems have 200 to 480 customers but do not have route durations. Moreover, only one vehicle type and two demands, 10 and 30 are considered in these problems. In order to apply our solution procedure, we use 20 as the average demand. Considering the feature of customer layout in these 8 problems, we divide the customers in each instance into three equal circular areas by three parallel loops dispersing from the depot. After enumerating the routing schemes by the depth-first search strategy, an integer programming model has been built to calculate the final solution. In Table 1, we present the results (the minimum number of vehicles ($K_{\min}$), the solution distance, computation times, and percent of improvement) obtained from the ORTR by Li et al. and from the procedure presented in this paper.

Table 1. Comparison on eight large-scale OVRPs from Li et al.'s ORTR and the procedure presented in this paper

Prob.(n, C)	ORTR by Li et al.			Our Procedure			Percent of Improvement (%)		
	$K_{\min}$	Solution Distance	Time (min)	$K_{\min}$	Solution Distance	Time (min)	Vehicles	Solution Distance	Time
O1(200, 900)	5	6018.52	6.09	**4**	7658.86	**0.25**	**20.00**	–27.25	**95.89**
O2(240, 550)	9	4584.55	7.33	**5**	4823.26	**0.30**	**44.44**	–5.21	**95.91**
O3(280, 900)	7	7732.85	8.21	**6**	9937.26	**0.30**	**14.29**	–28.51	**96.35**
O4(320, 700)	10	7291.89	9.56	**7**	8223.72	**0.31**	**30.00**	–12.78	**96.76**
O5(360, 900)	8	9197.61	12.78	8	11590.32	**0.35**	0.00	–26.01	**97.26**
O6(400, 900)	9	9803.80	16.29	**8**	11823.11	**0.35**	**11.11**	–20.60	**97.85**
O7(440, 900)	10	10374.97	15.59	**9**	12442.10	**0.35**	**10.00**	–19.92	**97.75**
O8(480, 1000)	10	12429.56	18.78	10	16472.64	**0.36**	0.00	–32.53	**98.08**

Note:

- n = The number of customers
- C = Vehicle capacity
- $K_{\min}$ = The minimum number of vehicles
- Percent of improvement = 100* (ORTR Solution – Our Procedure)/ORTR Solution
- Bold fonts indicate the values better than the results obtained from ORTR

It is shown from Table 1 that, each solution in terms of distance indicated by the procedure presented in this paper is longer than that from ORTR. However, the computation times of our procedure are much shorter than those of ORTR, and increase negligibly as the number of retailers grows. For example, for O2, compared with the 5.21% increase of the travel distance, the number of vehicles needed in our procedure reduces that needed in ORTR by almost half (44.44%). These results indicate that the solution procedure proposed in the paper is superior in terms of computation time. In addition, the ability to deal with multiple types of vehicles and its independence of the problem size also make our procedure competitive to some extent.

5. Concluding Remarks.

In this paper, we first review the results of LSVRP, and then we present a new solution procedure for LSVRP from the perspective of simultaneously utilizing qualitative and quantitative factors. The new idea of incorporating the qualitative reasoning into quantitative approaches can strengthen the procedure's capability of dealing with empirical information. It is beneficial to greatly decreases the number of possible routing schemes to be considered for final selection, and meanwhile, improve the practicability of the procedure. It also provides a reference for solving other complex decision-making problems, for example, disruption management problem in distribution, and emergency management problems in electric power system.

It is necessary to point out that the classification of customers may lead to a loss of better solutions or even the best solutions. With the increase in the number of customer clusters, the efficiency of the solution process in terms of computation time decreases. In order to improve the accuracy, we still need to improve the solution procedure by applying more appropriate methods for customer clustering and by taking more complicated travel times into considerations.

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