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Research Note

A Solution for Transportation Planning in Supply Chain

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Abstract. *An advanced optimization system for Vehicle Routing and Scheduling Problems (VRSP), which is one of the Supply Chain Planning modules, is introduced. An object oriented system, Computer Aided Routing and Scheduling (CARS) can handle complicated distribution models using advanced heuristic optimization algorithms. To classify various types of routing and scheduling problems in a structured manner, a classification scheme is introduced based on the main objects of VRSP. Also, the modeling and solution approach in the CARS optimization engine has been elaborated. Main static and dynamic objects of the system as well as their relationships and interactions have been explained. The user interface in addition to the planning and operational features of the system is described in detail.*

Keywords: *Vehicle routing; Logistics; Supply chain planning; Advanced optimization system.*

INTRODUCTION

Facing stiff competition and customer pressure for higher service levels, companies are trying to respond by building responsive supply chains and efficient resource utilization. Transportation plays an essential role in the delivery of value in supply chain because value is not realized unless the product gets where it is needed. With the growth of e-commerce and home delivery services, transportation costs have become more important. On the other hand, application of an outsourcing strategy, which has reshaped organizations from centralized manufacturing facilities to geographically dispersed networks of resources, increases the importance of transportation services [1,2].

The most important operational decision related to transportation in supply chain planning is the routing and scheduling of deliveries [1]. The Vehicle Routing and Scheduling Problem (VRSP) is a significant task in both supply chain planning and distribution optimization. A very large body of research and modeling literature has been devoted to address VRSP [3]. But, most of them concentrated on hypothetical or simplified problems and disregarded many practical aspects of such problems. On the other hand, many practical problems have been tackled by different commercial systems for this class of problem, but little has been published about them.

The primary objective of this paper is to introduce a transportation planning system (based on an innovative VRSP classification scheme) in detail. This information is believed to enhance the knowledge of system developers as well as operations managers in developing and evaluating optimization systems for transportation planning and other supply chain areas.

Computer Aided Routing and Scheduling (CARS) is a transportation planning system developed to handle various types of problem arising in practice [4]. In a handful of practice applications to date, CARS has yielded significant improvements over traditional systems or intuitive solutions [5].

Since the system has been developed based on a comprehensive review of various types of practical problems, it is expected to become popular in industries with complicated supply chain requirements. CARS can be efficiently customized to meet a wide range of user needs. Important features of CARS may be stated as follows:

- High flexibility to meet various logistic situations and client needs.
- A powerful optimization algorithm to tackle complex problems effectively.
- An intuitive graphical user interface for effective analysis and improvement of results.

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- Flexibility to integrate the users' know-how with the computational power of advanced optimization algorithms.

The remainder of this paper is organized in the following manner. A classification scheme for VRSP will appear in the next section and the modeling and solution approach for solving real routing problems will be explained later. The optimization algorithms and implementation results will be presented subsequently. Afterwards capabilities and important features of CARS will be discussed. Final remarks and a direction for further research will conclude the paper.

VRSP CLASSIFICATION

A wide variety of variables in VRSP makes the system complex and thus calls for an appropriate classification scheme [6]. Figure 1 illustrates a typical network of production and distribution. The proposed system should handle the whole transportation problem in this network. Such a complex case can be modeled by a proper definition of the attributes of VRSP objects.

VRSP can be simply defined as planning the efficient flow of goods between facilities by a fleet of carriers through the transportation networks. This statement reveals the main components or objects of VRSP problems, namely goods, facilities, carriers and transportation networks. Each object may have its owners who impose their objectives and restrictions to the problem. For example, drivers may be considered as the owners of vehicles who may impose working time or region constraints. The distribution planning model is depicted in Figure 2.

Here, based on the main components of VRSP, a classification framework is developed. As Figure 2 shows, objects are related to each other through links. Thus, the system consists of objects with interrelated attributes:

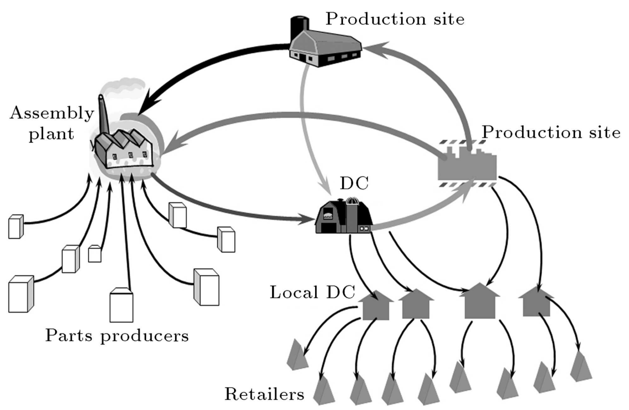

Figure 1. A simplified production and distribution network.

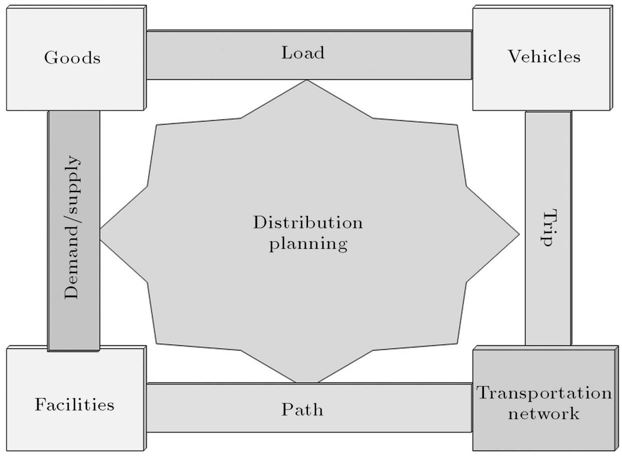

Figure 2. The distribution planning model.

- The link between goods and vehicles is load, which is a set of products or parts which are put on vehicles.
- The link between vehicles and transportation networks is trip, which is a set of paths that a vehicle should traverse.
- The link between transportation networks and facilities is path, which is the set of arcs that connect locations.
- The link between facilities and goods is demand or supply, which is a collection of goods that should be transported between locations.

In this model, the constraints of the problem, which are based on the attributes of objects and links, may be divided into four categories [7]:

1. Constraints based on the attributes of objects, like the capacity limit of vehicles.
2. Constraints based on the attributes of links, like the consistency between types of goods and vehicles.
3. Constraints based on the consistency of elements of an object, like the constraint on a mixture of two types of goods in transportation.
4. Constraints imposed to the system by the owner of objects, like the limitation on working hours of drivers.

The objective function of the problem may be defined based on a function of any attribute of the problem solution. The objective function might be maximization like maximizing capacity utilization; minimization like minimizing travel time; mini-maxing like the balance of loads between trucks, or any combination of the above.

CARS MODELING AND SOLUTION APPROACH

The most critical point in developing an optimization system for real problems is considering the complexity and broad range of requirements of clients in the design stage. Developing system architecture without taking a particular function into account would either hinder application of the system or deteriorate its efficiency. The architecture of CARS is developed based on the distribution object models, considering most of the variations found in practice.

The dynamic environment of business requires flexible systems. A powerful optimization algorithm without the ability to handle specific user needs is completely ineffective. In real cases, numerous circumstances arise based on a specific situation in one or some objects. For example, if the user wants to avoid assignment of a specific driver to a store, the system should efficiently support it. On one hand, the development of a system architecture to handle the detailed requirements of users results in the high complexity of the system. On the other hand, from a practical point of view, the complexity of the system is regarded as a disadvantage. The most appropriate solution is to build enough flexibility into the system to meet any user requirements. For example, providing a utility to assist users in deciding some parts of the solution enables the system to cope with most dynamic business requirements.

The data structure is the foundation of an optimization system. The flexibility of the system and the configuration of objects to represent the real world problem are based on the data structure. Also, development of a data structure, according to the logic of the algorithm, greatly enhances the efficiency of the system in solving the problem.

The VRSP objects and their rough relationships are shown in Figure 3. This object map is developed by using the VRSP basic model presented in previous sections, and is a foundation for CARS development. These objects are divided into two categories: static and dynamic. Static objects results from the problem data, while dynamic objects are created by the system during the construction of a solution to the problem. Static data are related to locations, goods, orders, the transportation network and vehicles. Dynamic objects are mainly the components of the problem results. Each object has individual attributes and some relational attributes, which maintain its relation with other objects. The constraints of the problem are formed by using the individual or relational attributes of objects.

The cost function is the weighted sum of several attributes of the solution. The user can set the components of the solution as well as their weights. Several predefined cost components are available, and the user can select them from a list and set their weights to construct the cost function. In real cases, it is preferred to allow the system to handle soft constraints. In some cases such as a time window constraint company policies tolerate some deviation from the target values. The weighted sum of soft constraints is also included in the cost function. An overview of the optimization algorithm will be described in the next section.

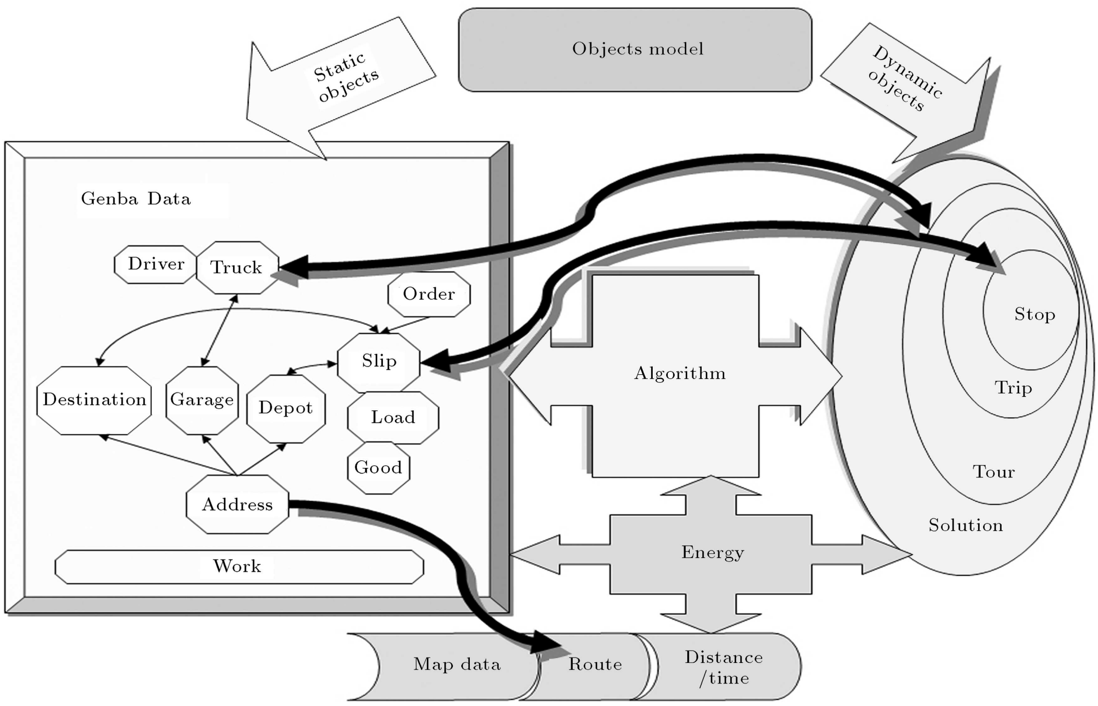

Figure 3. The VRSP objects map.

CARS OPTIMIZATION ENGINE

VRSP are known to be NP-hard and, therefore, efficient heuristic algorithms should be exploited to tackle this class of problems. Several families of heuristics have been developed for VRSP. Heuristic approaches for solving VRSP can be broadly classified into four categories, namely construction, improvement, evolutionary and learning approaches [8]. A smart combination of the routines from two or more approaches may also provide promising hybrid algorithms [9,10]. In this part, first the framework of these approaches will be reviewed.

Construction Algorithms

In construction heuristics, nodes are selected successively until a final solution has been built. Saving [11] and Sweep [12] are the most popular algorithms in this class. In sequential implementation, one route is constructed in each iteration, while in a parallel version several routes are simultaneously built [13]. Other well-known construction algorithms are "cluster first then route" [14] and "route first then cluster" [15]. In applied algorithms, this type of routine is widely used to construct the initial solution.

Improvement Algorithms

In this type of algorithm, the initial solution is iteratively improved by exploring the solution space. Local search algorithms are the most widely used classical improvement algorithms. The structure of local search algorithms can be divided into three components [16]. The first component is routine for constructing the initial solution. The algorithm may start with a solution constructed randomly or utilize a construction algorithm to obtain a good starting point. A neighborhood structure is another component which heavily influences the behavior of the algorithm. It can be defined by choosing the type of move and the length of string for the move [13].

Evaluation rules are other component of local search algorithms. Two extreme strategies are accept-first and accept-best [17]. In the accept-first strategy, the first neighbor to improve the current solution will be accepted, while in the accept-best strategy the best possible neighbor will be accepted.

In advanced improvement algorithms, which are known as metaheuristics, a sophisticated search routine is exploited to escape the local optima trap and obtain high quality results. Simulated Annealing (SA) [16] and TS [18-20] are the most well-known algorithms in this category. The high flexibility and performance of these algorithms make them the most promising candidates for the optimization engine in advanced optimization systems. In our experience, SA algorithms need more parameter adjustment and provide lower robustness compared to those of TS.

Evolutionary Algorithms

The basic mechanism in the evolutionary approach is combining selected members in a set of generated solutions. Genetic Algorithms (GA) [21,22] and Memetic Algorithms [23] are the most applied heuristics in this class. The foundation of GA is the survival of fitness principle, which maintains a high probability of generating the highest level compatible with the environment. Solutions interact, mix together and produce new offspring that, hopefully, retain the good characteristics of their parents. Selection, recombination and mutation are basic operators of GA that conduct the evolution process toward higher quality solutions. The most important issue in the application of GA to a specific problem is the representation phase, in which features of the problem are encoded as a chromosome to define a member of the solution population. This condition hinders the application of GA to environments in which the specification of the problem continually changes according to new situations in business.

Learning Algorithms

The Neural Network (NN) and Ant Algorithms [24] are the most prominent approaches in this category. We have developed several NN algorithms for Traveling Salesman and Vehicle Routing Problems [25-28]. In these algorithms, specifications of the optimization problem should be embedded into the configuration of the network and learning process. Therefore, the algorithm is highly problem specific. Despite their promising results, these algorithms need more enhancements to be incorporated into commercial optimization systems.

CARS Optimization Algorithm

As indicated by Cordeau et al. [8], "Algorithms are highly accurate and some are also quite fast. What is now needed is greater stress on simplicity and flexibility." Our experiences confirm the above statement. In developing the CARS algorithm, the most important criteria have been flexibility and speed. Most of new routines developed by researchers are problem specific. They might improve the quality of results at the expense of reducing the flexibility of the algorithm in handling new constraints or by increasing its computation time.

Among various families of heuristics for optimization problems, TS, GA and SA have shown a promising performance in solving various combinatorial problems. TS has several features which make it a suitable candidate for real life complex cases. Robustness, simplicity and flexibility are the most important features of TS. In our experience, the flexibility of GA is questionable and SA needs complicated parameter adjustments to gain high quality results. Therefore, we selected TS as the framework for developing a specific optimization algorithm for CARS.

In the TS algorithm, during the search process, the current solution may deteriorate from one iteration to the next. To avoid cycling, recently explored solutions are temporarily declared forbidden by putting their selected attributes in the tabu list. The TS algorithm has been evolved over time and several innovative features are included in this algorithm by researchers to enhance its performance [17]. An enhanced neighborhood generation mechanism, using various diversification and intensification strategies to guide the search, post optimization, combination with other algorithms and parallel implementation, are various strategies that have been considered by researchers. The granular tabu search algorithm of Toth and Vigo [29], the unified tabu search algorithm of Cordeau et al. [30,31] and the Taillard et al. algorithm [32] are recent algorithms that have shown promising results.

While we have considered the innovative features of the proposed algorithm by researchers, the CARS TS algorithm has unique features. The details of the CARS TS algorithm are described as follows. First, the initial solution and neighborhood generation, which are two pillars of improvement heuristics, will be described and then the algorithm will be outlined.

Initial Solution

The TS algorithms start with an initial solution that can be developed by a simple construction algorithm. In selecting the construction algorithm, there is a tradeoff between the quality of the initial solutions and the computation time. Since CARS has been developed to handle various types of VRP, using a complex algorithm to build high quality initial solutions will increase computational time without meaningful impact on the final results.

Solomon [33] proposed several heuristics for the VRP that are suitable candidates for building the initial solution of TS algorithms. Among them, the I1 algorithm, which is the cheapest insertion routine, has been used by several researchers for building initial solutions. We have implemented a modified version of Solomon's I1 algorithm for general VRP.

The algorithm starts with initializing a route with a seed customer. The remaining unassigned customers are sequentially inserted into this route as far as the capacity restriction of the truck or other hard constraints permit. For inserting a customer in a route, the total cost of insertion will be evaluated. The seed customer is the customer with the lowest cost when assigned. The initialization and insertion procedure continue until all customers are serviced.

Generating the Neighborhood

The most popular neighbor structures are Relocate, Exchange, 2-opt* and CROSS [17]. The Relocate operator moves one visit from its position into a new position, while the Exchange operator swaps two visits. The basic idea of 2-opt* is to combine 2 routes, so that the last customer of a given route is introduced after the first customer of another route. The 2-opt* operator is illustrated in Figure 4, where edges $(i, i+1)$ and $(j, j+1)$ are replaced by $(i, j+1)$ and $(j, i+1)$. By this exchange, the end portions of two routes are exchanged. As illustrated in Figure 4, in CROSS, the first two edges, $(i-1, i)$ and $(k, k+1)$, are removed from a first route, while two edges, $(j-1, j)$ and $(l, l+1)$, are removed from a second route. Then, $(j-1, i)$ and $(k, l+1)$ are introduced. In this way, several numbers of customers are swapped between routes.

In order to improve the quality of the solution or speed up the algorithm, numerous enhanced routines have been proposed by researchers [13,17]. λ-interchange [5], GENI-Exchange [34], eject chain [35] and cyclic transfer [36] are other successful routines.

Relocation, Exchange and 2-opt* are implemented in CARS. By using Relocate and Exchange operations, we have four types of movement:

- Relocation of a visit inside its route,
- Relocation of a visit into another route,
- Exchange of two visits in a route,
- Exchange of two visits from two different routes.

Practical experiments show that a combination of relocation, exchange and 2-opt* can provide high

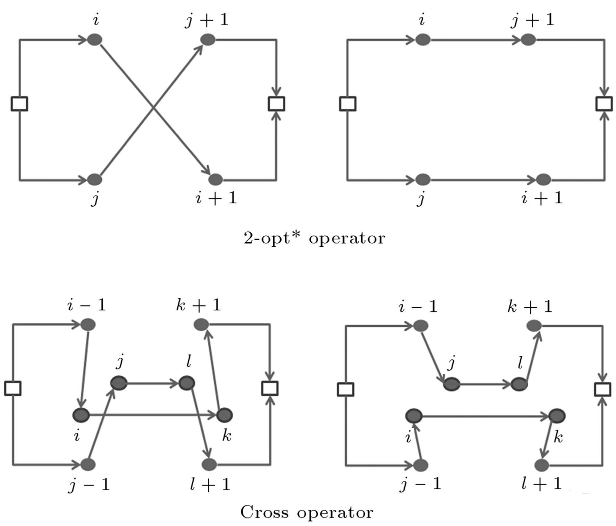

Figure 4. The 2-opt* and cross operators.

quality results within low computational time. We have examined more complex routines, like CROSS and 3-opt, which resulted in no meaningful value and higher computation time. Since the problem contains contradicting objectives, using specific strategies [37,38] to artificially help the algorithm find better solutions is harmful and reduces the effectiveness of the algorithm.

CARS TS Algorithm

To handle the real problem by TS, restrictions should be considered as soft constraints. For each soft constraint, a penalty term will appear in the objective function. In CARS, only basic constraints, like capacity restriction or route length limit, are considered a hard constraint. By increasing the weight of the penalty term for a given soft constraint in the objective function, the possibility of satisfying this constraint will increase.

The algorithms starts by generating an initial solution based on the procedure explained earlier. The neighborhood generating mechanisms, namely Relocate, Exchange and 2-opt* are selected randomly. The chance of selecting the 2-opt* operator is set to be five times less than Relocate and Exchange. Since the associated cost of each stop, trip and tour is maintained separately, the search procedure is guided by considering attractive moves. This is a specific implementation and an extended application of the candidate-list strategy [11], which has been applied in several other algorithms [29,39]. This innovative strategy considerably speeds up the search process and leads to high quality results.

When customer i in route k is moved, its reinsertion is forbidden for the next θ iteration by keeping $(i.k)$ attributes in the tabu list. Through an aspiration criterion, neighbor solutions with a lower cost than the best found solution are permitted to be accepted, even if their attributes are in the tabu list. In generating a neighbor solution, hard constraints are also controlled. It has been shown by researchers [32] that a dynamic tabu list size tends to give better results than a fixed one. The parameter θ, which indicates the size of the tabu list, is a randomly generated number between $\theta_{\max}$ and $\theta_{\min}$. We set $\theta_{\max}$ to 10 and $\theta_{\min}$ to 5, similar to other researchers [29,34]. The algorithms stop after reaching either the time set by the user or the maximum allowed iterations.

IMPLEMENTATION RESULTS

In order to evaluate the performance of the CARS optimization engine, a comprehensive experiment is conducted on a set of standard problems available in the literature. In this experiment, we have used the Christofides, Mingozzi and Toth (CMT) 14 standard VRP benchmark instances [40]. These problems contain 50 to 199 cities, in addition to the depot. Problems marked as C type have a capacity restriction and type D problems have a route length constraint. Our intention was to demonstrate the capability of the CARS optimization engine on the classical VRP for which enormous amounts of research and experiments has been undertaken. The performance of CARS is compared with several best known advanced heuristic algorithms, namely Taburoute [41], Taillard TS [42], Berger and Barkaoui algorithm [43], Granular TS [29] and Unified TS [30].

Table 1 demonstrates the results of CARS in comparison with the selected algorithms. The reported results for CARS are the best found solutions over 5 runs. As this table shows, the average deviation of CARS results from the best known solutions is 0.55 percent. In three instances, CARS provides the best known solutions. This experiment shows that CARS can provide comparable results with sophisticated TS algorithms for classical VRP. Since CARS is designed for real complex problems, we believe that it can easily attain higher quality solutions than algorithms which are designed and tested for standard problems. Most available algorithms are quite specific and need special modification for more complex cases.

The computation time of algorithms cannot be compared directly, since they have been run on different machines. CARS average run time for a CMT set is 0.5 minutes, which is also an outstanding performance. This experiment shows that CARS can provide high quality results compared to the leading edge heuristic algorithms. Another important feature of CARS is simplicity. Although most algorithms have specific parameters to be adjusted by users, CARS has no optimization parameter.

In order to demonstrate the performance of CARS in solving real problems (from recent practical applications) some actual results are also provided here. Therefore, the performance is compared to systems which can handle comparable practical problems. Table 2 illustrates the results of improvements achieved by CARS for two companies in the food industry. The number of trucks for each company is around 150 and 250. To demonstrate the effectiveness of the system, a sample of ten consecutive days planning data is obtained from the two companies who are willing to utilize CARS as their new logistics planning system. The results attained by CARS are compared with those of their current system.

The first company was using an advanced planning and scheduling system. The second company was using an uncomplicated planning system with an optimization engine, which can interact with planners and let them improve the results based on their knowledge.

To evaluate the system performance, three mea-

Table 1. Comparison of CARS results for the selected algorithms on CMT benchmark instances.

No.	Size	Type	Taburoute[1]		Taillard[2]	Berger & Barkaoui[3]		Granular TS[4]		Unified TS[5]		CARS		Best Known
			Value	Minutes[6]	Value	Value	Minutes[7]	Value	Minutes[8]	Value	Minutes[9]	Value	Minutes[10]	Solution
1	50	C	524.61	6.00	524.61	524.61	2.00	524.61	0.81	524.61	4.57	524.61	0.11	524.61
2	75	C	835.77	53.80	835.26	835.26	14.33	838.6	2.21	835.45	7.27	839.61	0.31	835.26
3	100	C	829.45	18.40	826.14	827.39	27.90	828.56	2.39	829.44	11.23	829.18	0.22	826.14
4	150	C	1036.16	58.80	1028.42	1036.16	48.98	1033.21	4.51	1038.44	18.72	1033.21	0.45	1028.42
5	199	C	1322.65	90.90	1298.79	1324.06	55.41	1318.25	7.50	1305.87	28.10	1298.79	0.70	1291.45
6	50	C,D	555.43	13.50	555.43	555.43	2.33	555.43	0.86	555.43	4.61	555.43	0.20	555.43
7	75	C,D	913.23	54.60	909.68	909.68	10.50	920.72	2.75	909.68	7.55	913.33	0.53	909.68
8	100	C,D	865.94	25.60	865.94	868.32	5.05	869.48	2.90	866.38	11.17	869.48	0.30	865.94
9	150	C,D	1177.76	71.00	1162.55	1169.15	17.88	1173.12	5.67	1171.81	19.17	1176.50	0.83	1162.55
10	199	C,D	1418.51	99.80	1397.94	1418.79	43.86	1435.74	9.11	1415.4	29.74	1397.94	0.90	1395.85
11	120	C	1073.47	22.20	1042.11	1043.11	22.43	1042.87	3.18	1074.13	14.15	1074.13	0.63	1042.11
12	100	C	819.56	16.00	819.56	819.56	7.21	819.56	1.10	819.56	10.99	819.56	0.57	819.56
13	120	C,D	1573.81	59.20	1541.14	1553.12	34.91	1545.51	9.34	1568.91	14.53	1545.98	0.77	1541.14
14	100	C,D	866.37	65.70	866.37	866.37	4.73	866.37	1.41	866.53	10.65	868.50	0.53	866.37
Percent deviation from the best known			0.86%		0.06%	0.48%		0.69%		0.69%		0.55%		

[1] Gendreau et al [41]
[2] Taillard [42]
[3] Berger & Barkaoui [43]
[4] Toth and Vigo [29]
[5] Cordea et al. [30]
[6] Silicon Graphics workstation 5.7 MHz, (36 Mflops).
[7] Pentium 400 MHz PC
[8] Pentium 200 MHz PC
[9] Sun Ultrasparc 10 (440 MHz).
[10] Pentium 2 GHz PC

Table 2. Percent of improvement in performance using CARS in sample companies.

	Company A			Company B		
No	Distance	Cost	Customer Service	Distance	Cost	Customer Service
1	4.3	6.4	12.6	8.2	12.2	2.3
2	5.1	8.4	14.8	9.0	10.9	2.0
3	8.4	9.2	15.5	13.8	16.3	0.5
4	7.5	10.1	9.8	18.4	22.3	-2.0
5	2.9	3.2	11.6	14.0	17.2	0.1
6	6.1	7.0	10.1	12.7	14.1	2.0
7	5.0	11.8	14.0	9.3	11.0	4.5
8	7.9	8.5	8.3	7.1	10.7	5.4
9	4.7	9.7	10.6	10.4	16.5	1.9
10	5.4	6.3	19	11.9	15.2	1.3

surement indices are considered. Distance, which is a traditional index in the evaluation of VRSP, is the primary index. The most important index, in practice, is the distribution cost. This cost is comprised of the transportation mileage cost, the fixed cost of utilized trucks and the overtime cost. The customer service is another important index, in practice. This index is calculated by multiplying time window satisfaction and customer priority.

Table 2 shows the percentage of improvement in the results of distribution, compared to previous systems, in two sample companies over ten days. The results indicate that CARS can substantially improve the effectiveness of distribution planning in both cases.

Although it is not a solid statistical proof, it provides an initial indication of the value of our system, in practice.

The system in Company A, compared with Company B, can provide better results regarding distance and cost minimization at the expense of lower service levels. Since, in Company B, the results are refined by experts, they can easily improve the customer service level. However, this increases distance and cost. Overall, it seems that the optimization engine of CARS provides a much better compromise between different objectives and a higher solution quality.

CARS FEATURES

The complexity of VRSP requires a sophisticated planning and evaluation system. It is very difficult for a dispatcher to evaluate and possibly modify the results provided by the system just by examining the sequence of events. The system should help him/her to consider the results from several dimensions. To meet this requirement, several viewing tool are embedded in CARS. Users can browse the final results in tabular, Gantt chart, tree and map formats.

Since several aspects of an actual problem are not quantifiable, the user may need to override the solution provided by the system in some cases. CARS provides the possibility to utilize the power of the algorithm, considering the modification procedure. For example, if the user wants to remove a stop from its position, the system immediately guides him to the best position where it might be inserted. The system can search for the best position in the solution in a trip or in a route. In the same way, the whole load of a truck can be transferred to the best available positions to take the truck out of service. Users can also develop a plan from a clean slate.

The Geographic Information System (GIS) is an essential part of the system, since the transportation network data is the basis for schedule and cost calculations. It also facilitates accurate address registration by marking the location of sites on the map. CARS calculates the distance or travel data between locations in offline mode and saves it for future use. This data can be improved by using daily driver reports or using GPS to track vehicles and record actual travel time. This feature enables the system to improve the accuracy of the plan by lowering the discrepancy between the planned and actual data.

CARS also supports dynamic vehicle routing and scheduling, which is highly demanded by the recent development of e-Commerce [3]. By using a Global Positioning System (GPS), it is possible to track vehicles from a remote location and trace the actual implementation of the constructed plan. CARS browses the real time status of the plan in all of its views. According to actual data, the system will recommend necessary changes in the plan. It may also send necessary messages to influenced parties. In the same way, it can receive new orders or change the status of existing orders and then rebuild the plan. The new plan should be constructed considering cost and service level to minimize the operations' costs and changes in the services promised to customers.

It is worthy to note that CARS has the potential to be used for Strategic Distribution Planning issues such as territory planning and location analysis. Similarly, the configuration of a supply chain may be analyzed by virtual generation of the candidate site and based on actual data or assessment of transportation and site costs.

CONCLUSION

This paper described the modeling and design approach as well as the main features of an advanced optimization system for various types of VRSP. CARS system can be used within an integrated supply chain planning system to optimize inbound and outbound logistic operations in the entire supply chain. It can handle various logistic configurations and may be applied to any industry with minor customization. The main contribution of CARS is using advanced heuristics to tackle such a complex problem and practically improve the efficiency of logistic systems. The optimization algorithm, based on advanced heuristics, is being improved continuously by new ideas from researchers and internal developers.

The system is uniquely developed to handle a large variety of objects and configurations in transportation planning problems. It is a specialized optimization system whose underlying structure is based on the proposed classification. CARS is a flexible system able to solve VRSP with complex constraints by its powerful optimization algorithms. It provides the user with advanced functionalities for analyzing the results, modifying problem instances and evaluating alternative solutions.

Research in progress shows that CARS is able to incorporate real time traffic data into the planning process. This feature would enable the system to match the precise requirements of e-Commerce fulfillment and home delivery problems.

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