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Vehicle Routing Problem: Meta-heuristic Approaches

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Abstract The purpose of this article is to review the literature on the topic of deterministic vehicle routing problem (VRP) and to give a review on the exact and approximate solution techniques. More specifically the approximate (meta-heuristic) solution techniques are classified into: tabu search, simulated annealing, genetic algorithm, evolutionary algorithm, hybrid algorithm, and Ant Colony Optimization. Each of these solution techniques is briefly discussed and a case study from the literature is presented.

Keywords: VRP, Solution Methodologies, Exact Solution Methods, Heuristic Solution Techniques, Meta-heuristic Solution Techniques, Simulation.

1 Introduction

The VRP is a challenging logistics management problem with variations that range from school bus routing to the dispatching of delivery trucks for customer goods. Regardless of the variations, the basic components of the problem are a fleet of vehicles with fixed capacities and a set of demands for transporting passengers or certain objects (customer goods, etc.) between specified depots and delivery points. The problem is complicated because managers must also take into consideration a variety of constraints such as fixed vehicle capacity and the duration of the route. The prospective and prospects on VRP are discussed by Magnanti [1]. The concept of VRP has been addressed within the framework of other management science techniques. For instance, Federgruen [2] discusses a combined knowledge of VRP and inventory problem and Ball discusses planning for truck fleet size in the presence of common-carrier option.

Some of the problems classified under the generic name are the traveling salesman problem (TSP) and its variants Multiple TSP and Time Constrained (MTSPT); Single depot, Multiple Vehicle Node Routing (SMVNR), multiple-depot, multiple Vehicle Node Routing (MMVNR); and single depot, Multiple Vehicle Node routing problem (SMVNR) with stochastic demands. These problems are of discrete type with combinatorial structure and hence these problems are known as “combinatorial Optimization”.

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The TSP, a combinatorial optimization problem with some real life applications is the substructure of all VRP [3] and has been studied extensively in the literature. Dantzig and Ramser [4] described the TSP as follows: "find the shortest route for a salesman, starting from a given city, visiting each of a specified group of cities, and returning to the original point of departure". Mathematically, this problem can be formulated as:

$$Min \quad \sum_{i=1}^{N}\sum_{j=1}^{N} C_{ij}X_{ij} \tag{1}$$

s.t.

$$\sum_{i=1}^{N} X_{ij} = 1 \qquad \text{j} \in S = \{1,...,N\} \tag{2}$$

$$\sum_{j=1}^{N} X_{ij} = 1 \qquad \text{i} \in S \tag{3}$$

$$X_{ij} = \begin{cases} 0 \\ 1 \end{cases} \qquad \text{i.j} \in S \tag{4}$$

$$X_{ij} = \{\text{form a tour}\} \tag{5}$$

where C_{ij} is the cost of traveling from node i to node j, $C_{ij} = \infty$, where i=1,2,…,N. Constraint (5) can thus be written in the form of

$$Z_i - Z_j + NX_{ij} \le N - 1 \qquad 2 \le i \ne j \le N \tag{6}$$

and for some nonnegative real numbers Z_i.

Since 1959 when Dantzig and Ramser [4] first introduced the VRP and proposed a linear programming based heuristic for its solution the heuristic method has been widely researched. Christofieds and Eilon [5, 6] indicated that the largest VRP of any complexity solved to date by exact methods and reported in the open literature contains only 31 demand points. Before considering different approaches for solving the VRP a formulation of the problem as a 0-1 integer program is given. The problem known as the "pure delivery" problem can be formulated as follows [4]:

$$Min \qquad \sum_{i=1}^{N}\sum_{j=1}^{N}\sum_{k=1}^{NV} d_{ij} X_{ijk} \tag{7}$$

s.t.

$$\sum_{i=1}^{N}\sum_{k=1}^{NV} X_{ijk} = 0 \qquad \text{j=2,3,…,N} \tag{8}$$

$$\sum_{i=1}^{N} x_{ipk} \sum_{j=1}^{N} X_{pjk} = 0 \qquad \text{k=1,2,…,NV} \tag{9}$$

$$\text{p=1,2,…,N}$$

$$\sum_{i=1}^{N} d_i (\sum_{j=1}^{N} X_{ijk}) \le Q_k \qquad \text{k=1,2,…,NV} \tag{10}$$

$$\sum_{j=2}^{N} X_{ijk} \le 1 \qquad \text{k=1,2,…,NV} \tag{11}$$

$$Z_i - Z_j + N\sum_{k=1}^{NV} X_{ijk} \le N-1 \qquad i \ne j = 1,2,...,N \tag{12}$$

$$\sum_{i=1}^{N} t_{ijk} \sum_{j=1}^{N} X_{ijk} + \sum_{i=1}^{N}\sum_{j=1}^{N} t_{ijk} X_{ijk} \le T_k \quad \text{k=1,2,…NV} \tag{13}$$

$$X_{ijk} = \begin{cases} 0 \\ 1 \end{cases} \qquad \text{i. j, k and i} \ne j \tag{14}$$

where

N= Number of nodes
M= Number of Vehicles
Q_k =Capacity of truck k
T_k =Maximum time allowed for vehicle k on a route
d_i =Demand at node i (d_1=0)
t_{ik} =Time required for vehicle k to deliver or collect at node $i (t_{1k} = 0)$
t_{ijk} =Travel time for vehicle k from node i to node j ($t_{ijk} = \infty$)
d_{ij} =Distance from node i to j

$$X_{ijk} = \begin{cases} 1 \text{ if arc (i, j) is traversed by vehicle k} \\ 0 \text{ otherwise} \end{cases}$$

Z_i =Arbitrary real numbers, i=1,2,…,N.

The objective function (7) represents minimization of total distance traveled by NV vehicles. Alternatively, costs could be minimized by replacing d_{ij} with C_{ij}, depending on the vehicle type. Equation (8) ensures that each demand node is served by exactly one vehicle; equation (9) ensures that if a vehicle enters a demand node it must exist from that node; equation (10) is the vehicle capacity constraint and (11) guarantees that vehicle availability is not exceeded; equation (12) prohibits sub-tours and finally (13) is the total elapsed route time constraint.

2 Meta-heuristic Techniques and VRP

Meta-heuristics have become prominent approaches in tackling complex and multi-objective problems [7]. Recent examples include a bus driver scheduling problem [8] and a resource-constrained project scheduling problem [9]. What are known as meta-heuristics techniques are tabu search, simulated annealing, genetic algorithm, evolutionary algorithm and Ant Colony Optimization. In the sections that follow each of these techniques are discussed briefly.

2.1 Tabu search

Tabu Search is a direct searching algorithm for optimizing very complicate problems. This method that is based upon the human memory process generates a list of the latest points that are being investigated. The purpose of this list preparation is the prevention of transformation to the points that have been investigated previously. The tabu search implementations of Taillard [10] have obtained the best known results to benchmark VRPs. Similar results were reported by various authors using tabu search [11, 12, 13, 14, 15], or simulated annealing [16]. Taillard et al. [10, 14] recognized possible savings allowing multiple uses of vehicles in VR modeling and scheduling. These researchers applied tabu search in a 3-step procedure to design routes with multiple vehicle uses to minimize the total cost of routes. Golden et al [17] reported on the use of a tabu search based upon the “adaptive memory procedure” for solving a VRP with a min-max objective.

2.2 Simulated Annealing

A methodology known as simulated annealing has its origin in statistical mechanics [16, 18] which draws its concept from the annealing process of solids. The annealing process can be described as heating a solid to high temperature and then cooling that gradually to lower it to crystallize. The process of heating allows the atoms to move randomly. A rapid cooling process gives atoms sufficient time to align itself to reach a minimum energy state known as “equilibrium” or “stability”. As described in [16, 18], this methodology can be used in combinatorial optimizations in which the state of solid corresponds to feasible solution and the energy at each state corresponds to an improvement in the objective function and the minimum energy state will be the optimal solution. Simulated annealing was applied to improve the solution.

2.3 Genetic Algorithms (GA)

Genetic Algorithm is a new optimization technique used mostly for solving nonlinear and very complicate programming problems. This method is based upon the evolution process which has an evolutionary path as a biological path would own. In a simple term, this method by generating various generations (solution sets) of feasible solutions try to move toward the optimal solution point of the problem. Among the modern meta-heuristics, GA is used widely with several applications reported in the area of VRP [19, 20, 21, 22]. GA is used for solving the VRP with backhauls, multi-depot routing problem [23], and school bus driving [24, 25]. Baker and Ayechew [26] put forward a conceptually straightforward genetic algorithm for the basic VRP, which is competitive with other modern heuristics in terms of computing time and solution quality.

2.4 Evolutionary Algorithms

Under the most frequent classification, Evolutionary Algorithms, together with Fuzzy Logic and Neural Networks, is part of so-called Soft Computing. Evolutionary Algorithms is comprised of Genetic Algorithms, Evolutionary Programming, Evolutionary Strategies and Genetic Programming and some similar techniques. Evolutionary Algorithm may have following structure [27, 28, 29, 30, 31]:

- Search space – space of all possible solutions.
- Population – set of actual candidates for solution; elements of population are called individuals or items, or search nodes, or points in search space.
- String space – space that contains string representations of individuals in population.
- Functions for conversion between points in search space and points in string space (coding and decoding).
- Set of genetic operators for generating new strings (and new individuals).
- Fitness function – it evaluates fitness (degree of adaptation) for each individual in population.
- Stochastic control of genetic operators.

Basic steps in Evolutionary Algorithms are:

1. Initialization (using random sampling to generate initial population).
2. Evaluation (to calculate fitness for all individuals in population).
3. Selection (to choose surviving individuals in population in accordance with the values of fitness function).
4. Recombination (includes crossover and mutation) – to change individual's representation.
5. Repeating steps 1 to 4 until fulfilling finishing criteria.

In multi objective vehicle routing problems, the Pareto concept is frequently used within an evolutionary framework. Many authors [3, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45] have used evolutionary algorithms methods to solve multi-objective routing problems. Some have used evolutionary algorithms with Pareto methods [46] to solve the MOVRP as well. Others have employed hybrids based on evolutionary algorithms and local searches, heuristics, and/or exact methods for the considered problem [30, 35, 47, 48, 49, 50, 51]. Pareto dominance has also been used by El-Sherbeny [52] in a simulated annealing technique called Multi-Objective Simulated Annealing (MOSA) while Paquete et al. [38, 53] have called upon Pareto Local Search techniques. These techniques are based on the principle that the next current solution is chosen from the non-dominated solutions of the neighborhood.

2.5 Ant Colony Optimization

There are some researches that report the application of Ant Colony (AC) in the combinatorial optimization [54, 55, 56, 57, 58, 59]. These published works have reported successful applications. Baker and Ayechew [26] pointed that with a 2-opt heuristic applied to improve individual routes produced by artificial ants this approach provided results which are only slightly inferior to those from tabu search. Baràn and Schaerer [55] do not use a standard multi-objective approach for solving multi objective VRP. They had considered the reality of dealing with the problem of multiple objective nature using appropriate mechanisms in the ant colony system being proposed. Chitty and Hernandez [56] reported an ant colony system adapting bi-objective situation considering total mean transit time and the variance in the transit time. Pareto Ant Colony Optimization (PACO) is a multi objective meta-heuristic approach used by Doerner et al [48] for solving the location-routing problem with several objective functions.

2.6 Hybrid Algorithm

A technique that is known as hybrid algorithm combines one or more of meta-heuristics techniques along with an optimization or heuristic technique that can solve the problem accurate, fast and easy. A two-stage hybrid algorithm for pickup and delivery vehicle routing problems with time windows and multiple vehicles is studies by Bent et al [60]. In the first stage, a simple simulated annealing algorithm is used for decreasing the number of routes while the second stage uses large neighborhood search for decreasing total travel cost. Studies on VRP and LRP [61] suggest that building hybrid meta-heuristics, like tabu search and simulated annealing, helps to combine their best features to gain best possible results. A hybrid approach to vehicle routing using neural networks and GA has also been reported [20]. A hybrid heuristic which incorporates neighborhood search into GA is also considered.

3 Case Studies

Gebresenbet and Ljungberg [62] conducted a research on the goods that flow to, from, and within the agricultural sector in Uppsala region in Sweden. A large increase in the transportation of agricultural and related goods in the sector and the empty haulage that is up to 45% caused environmental degradation by contributing to air pollution, global warming, ozone depletion, resource reduction, and congestion and traffic accidents. The key objectives of this problem are identified as:

1. Map out goods from, to and between farms

2. Investigate possibilities of loading different goods on the same truck during the same trip, and also integration of goods collection and distribution and thus co-ordinate transports in the region as a whole
3. Identify constraints that may limit the possibilities of coordination, and
4. Study the effect of route and distribution optimization and its environmental benefits.

Farms in Sweden are categorized as: (1) farms with crop production; (2) animal husbandry; and (3) integrated production (mix production). By the use of a global positioning system (GPS), all data necessary for daily distribution and collection, including geographical location of collection/distribution points and routes, were collected. Software LogiX [DPS, 1996] was used for optimization of distribution/collection and route optimization. Air emissions were calculated using the model proposed by Gebresenbet and Oostra 1997 [63]. The parameters used during this study are: vehicle type, goods type, loading time, unloading time, idling time, load capacity utilization level, transportation distance, speed of vehicle, location of depot and delivery points, and routes and air emissions from vehicles.

In the region that this study was conducted the crop production farm is of the dominating type (about 35%). Data regarding working hours, agricultural production in the region and the studied companies in the region are shown with sufficient details in the article [62]. The main flows of material in the Uppsala region are shown in Figure 2. Farms are classified as crop production, two classes of animal production and farms with integrated production. The latter have material flows similar to the complete subsystem of farms as shown in Figure 3, only with smaller quantities since most of the crop production is internally used on the farms as fodder.

The crop farms sell grain to farmers, private grain trade companies, mills or fodder factories or to other farmers to be used as seed or fodder [62]. The means of production, such as fertilizer, chemicals for plants protection, machines and parts, etc. are distributed to the farms by the farmers' cooperative or by private grain trade companies, as indicated in Fig 1. Commercial fertilizer is produced mainly at two factories in Sweden.

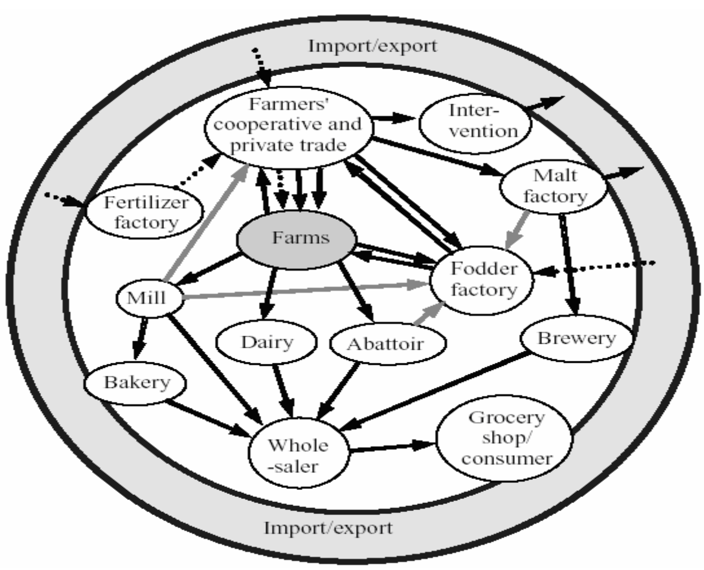

Fig. 1 Material flows from and to farms and others [62]

There are two categories of animal transports that are named as transport of slaughter animals to the abattoirs and transport of small pigs and calves between farms. In Sweden, only one dairy company operates mainly in one region of the country. The dairy in Uppsala is Arla which is the biggest of the 16 in the whole country. Of the yearly milk delivery to dairies for processing, almost 58% is delivered to Arla and the rest to other three companies at the levels of 13%, 7% and 6%. Natural fertilizer is sold from animal husbandry farms to crop production farms. These transporters involve short distances and are performed by tractor. More details on such numbers can be found in the article [62].

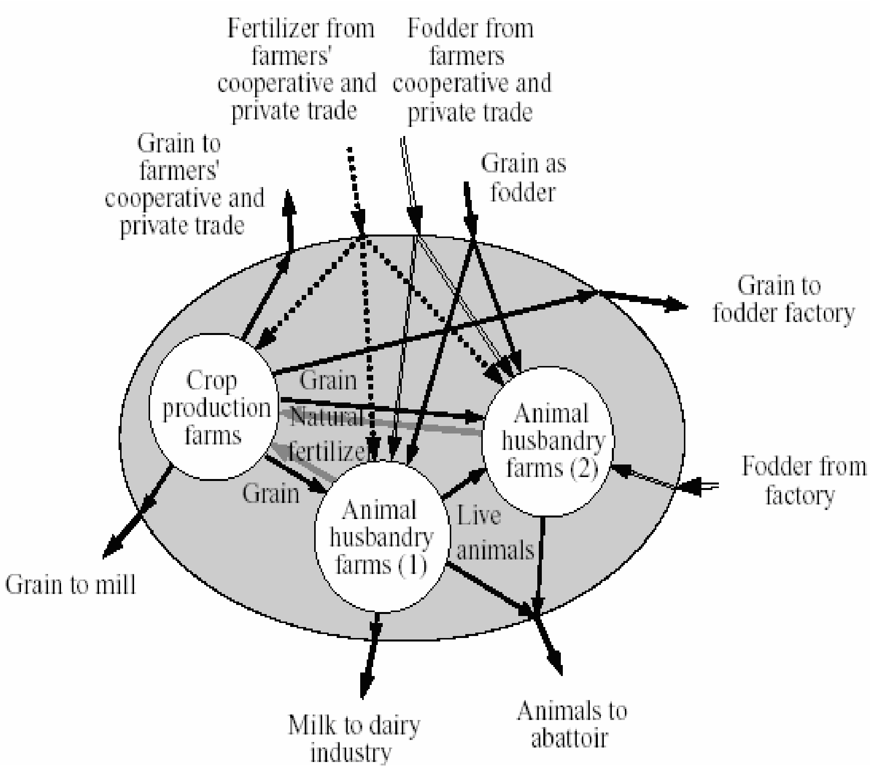

Fig. 2 Material flows from and to farms and others [62]

4 Optimization of routes and goods distributions/collections

During the field test, a total of 196 vehicle routes are measured: 76 for transport of grain-and grain-related commodities, 15 for slaughter animals, 17 for meat distribution, 60 for milk collection, and 28 routes during distribution of dairy products. Data were collected on the choice of routes but also on the type of goods, quantities, motor idling and time used at each stop. The measured routes are optimized with the software Route LogiX and compared to the actual routes. Software package LogiX is a road database containing information on distance, speed limits and constraints related to the heavy vehicle traffic. The program algorithm calculates shortest/quickest path, optimal call sequence and vehicle scheduling [62]. For grain and grain-related goods such as fertilizer, fodder and seed, route measurements were made on 16 routes in the Norrkoping region, and 60 routes in Uppsala region. Due to insufficient data quality [62], as authors indicated, not all routes have been optimized. As a result of route optimization, total distance and time were reduced by 17 and 29%, respectively.

There exist 444 farmers who deliver milk to Arla with total production of 101000 tones. To reduce transport work, a tank trailer is placed in a central and convenient place (see figure 3). The tank driver collect milk up to their full capacity and then pump to the tank trailer, and repeat this twice and then deliver the remaining to Kallhall dairy in Stockholm, the nearest dairy to the Uppsala province. Route measurement was made using GPS during 2 weeks to cover all 444 farms. A total of 60 routes were measured. The transport distance and time were 6357 Km and 185 h, respectively. Then optimization was made and notice that time and distance were reduced by 5% and 32%, respectively.

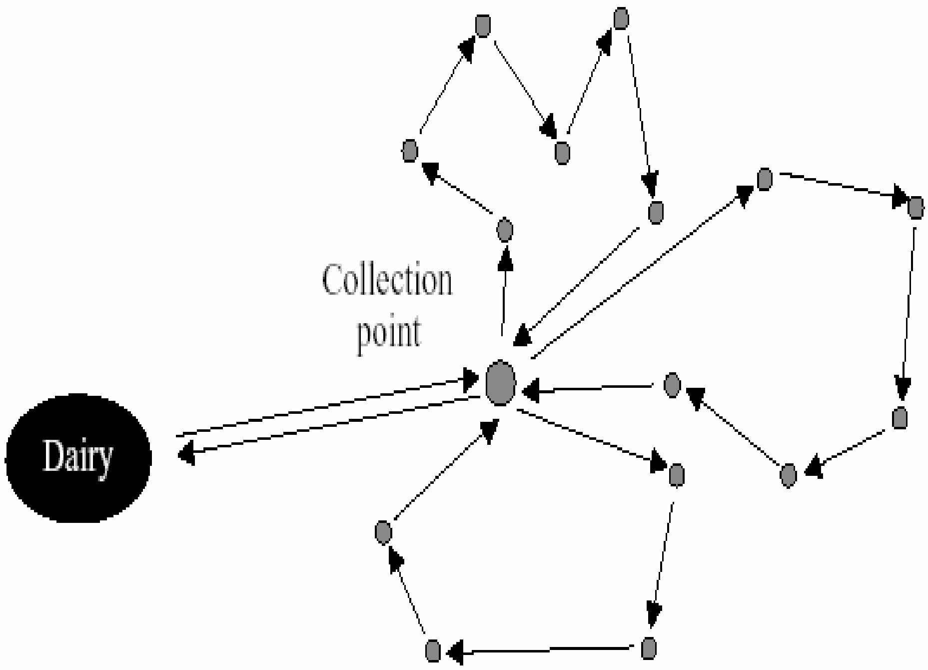

Fig 3. Schematic presentation of milk and delivery to the dairy industry, in Kallhall branch [62]

For meat distribution, eight vehicles are involved and 17 routes were measured. After optimization, the number of vehicles reduced from eight to seven, and the total distance reduced from 3168 to 2629 km. For one single route, distance and time saving of up to 23 and 26% respectively, were obtained.

5 Coordination of milk and meat distribution

There is a great potential to coordinate milk and meat distribution in Uppsala region.

1. The dairy terminal and the Swedish meats abattoir are located very near to each other
2. Both meat and milk require the same level of temperature (4 degrees Fahrenheit) during transport
3. Most of the customers and delivery points are common for both components, and distribution routes are the same or similar.

By combining those routes, the distance and time of distribution reduces by 44 and 36%, respectively. Fig 4 shows an example of a route with a combined loading and return loading. Goods from several suppliers are collected at a central terminal, for common distribution with a truck to farms. The route ends with return loading of grain.

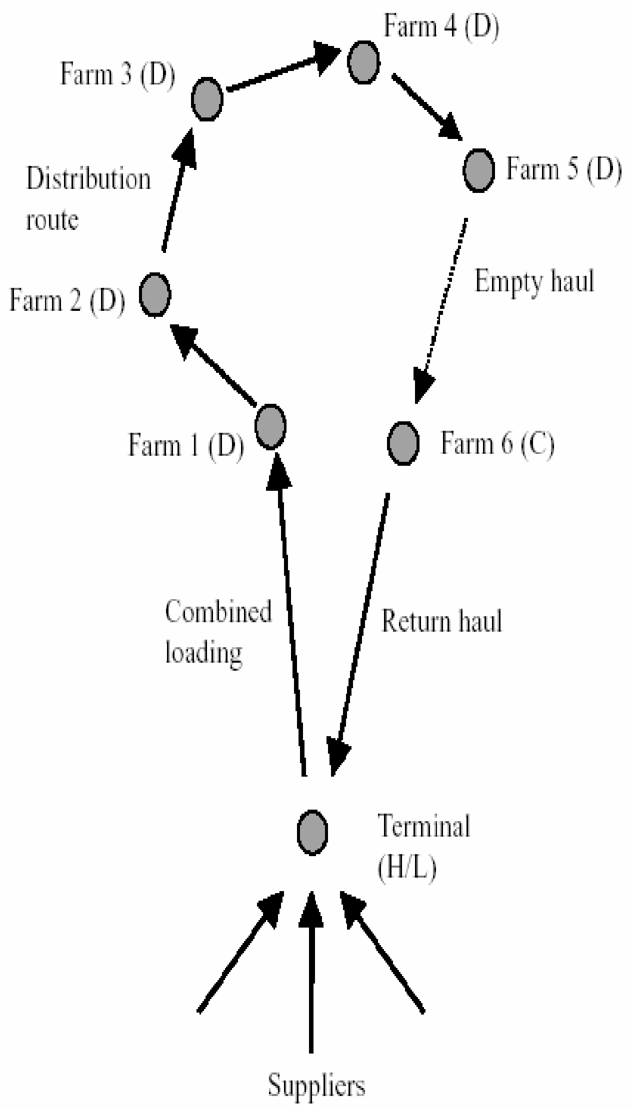

Fig. 4 Route with transport coordination through combined loading and return loading [62]

This study had shown that there are several possibilities for improving coordination and transport planning of agricultural goods transports in general. Routes can be combined to deliver goods at the same paste and reduce cost and environmental impacts. Route optimization can reduce transport distance and time by up to 29% particularly when routes are dealing with many delivery points. Using sophisticated operations research tools and meta-heuristic techniques, one can solve very large VRP problems in a short time period to make on time sophisticated decisions.

6 Summary

This article has presented a literature review of the VRP, multiple-depot VRP, and SVRP. As indicated, the single-depot, multiple vehicle, node routing problem has attracted the attention of most researchers whereas little research has been conducted on the SVRP and multi-depot, multiple-vehicle, node routing problem.

As previously discussed, solution techniques for the VRP are divided into two main categories: those which solve the problem optimally and those which solve the problem heuristically. Optimal seeking procedures are only practical for solving small-sized problem while heuristic techniques are the most promising tools for solving large scale problems. For this reason, a great deal of attention has been given to the Clarke and Wright [64, 65] heuristic approach and its modifications as to the Gillett and Miller [66] approach.

In this summary, the heuristic methods were categorized into four groups: tour building heuristics, tour improvement methods, two-phase methods and Lagrangian relaxation heuristic approaches. It should be noted that there are relatively few interactive approaches that solve the VRP and only two procedures that are capable of handling the VRP in a multiple objective environment. Moreover, each of the procedure described, with the exception of has a single objective cost, time or distance minimization.

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