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Research Paper

An application of the vehicle routing problem to biomass transportation

Carlos Gracia [a,*], Borja Velázquez-Martí [b], Javier Estornell [c]

[a] Departamento de Organización de Empresas, Universitat Politècnica de València, Camino de Vera s/n, Valencia 46022, Spain
[b] Departamento de Ingeniería Rural, Universitat Politècnica de València, Spain
[c] Departamento de Ingeniería Cartográfica, Geodesia y Fotogrametría, Universitat Politècnica de València, Spain

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Pruning is a cultural operation linked to Mediterranean agricultural management and it offers through its wastes the chance to procure biofuels. Currently, these residues are disposed of by burning or shredding, not being exploited because of several technical difficulties in extraction, handling and transport as well as because of the lack of accurate data on the quantity and suitability of these residues. However, recent work has reported methods of supplying new biomass detection models and concentration locations. These make it possible to tackle reliable collection plans as a part of the decision support system in a biomass supply management information system. This paper addresses the biomass collection problem, as an application of the classical vehicle routing problem, where minimum cost routes have to be calculated for a fleet of several agricultural vehicles (chippers, trucks, tipper trailers and tractors). A hybrid approach based on genetic algorithms and local search methods is presented to solve a real case study. Results show a significant improvement in the operational efficiency obtained by applying such methods that come from the industrial engineering domain.

1. Introduction

Biomass is defined as any organic matter not fossilised and it can have multiple industrial applications in pharmacy, cosmetics, textiles, wood, paper and construction. Biomass can also be a source of energy since it can be converted into biofuels which are end-marketable energy products. Biomass feedstock production can be acquired from numerous sources such as agricultural crops (maize, sorghum, barley, etc), agricultural residues (maize stover, wheat straw, etc), energy crops (switch grass, energy cane, willow, etc), forest residues (logging residues, forest thinning, sawdust, etc) and wastes (manure, food processing waste, etc). Under EU Directive 2009/28/EC on the promotion of renewable energy, the European Union established, in every Member State, the goal of reaching a minimum 10% share of renewable energy in the transport sector by 2020. This directive also intends to ensure the expansion of the use of sustainable biofuels in the EU, in terms that their employment generates a clear and net greenhouse gas (GHG) saving and has no negative impact on biodiversity

* *Corresponding author*. Tel.: +34 645 015700.
E-mail address: cargraca@omp.upv.es (C. Gracia).
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Nomenclature

A	the set of arcs (edges) of the graph G: $A = N^*N$
B	set of biomass collection points
c_{ij}	the cost associated with each arc $(i,j)\in A$ representing the cost of sending a vehicle from i to j
d_{ij}	the distance associated with each arc $(i,j)\in A$
G	the complete graph $G = (N,A)$
N	the set of nodes in the graph
q_i	the non-negative biomass volume associated to each node $i\in N$
V	the set of vehicles, referenced as v, $v\in V$
X_{ij}^{v}	binary variable assigning a vehicle to an arc (i,j)
K	load capacity of each vehicle

Abbreviations

GHG	greenhouse gas
BCP	biomass collection problem
LIDAR	light detection and ranging
VRP	vehicle routing problems
CVRP	capacitated vehicle routing problem
NP-C	non-deterministic polynomial time complete
GA	genetic algorithm
HGA	hybrid genetic algorithm
GIS	geographic information system
BPP	bin packing problem
TSP	travelling salesman problem

and land use. Markevičius, Katinas, Perednis, and Tamašauskienė (2010) recognised up to 35 different criteria to estimate biofuels sustainability. These include, *inter alia*, aspects related to environmental issues such as ecosystems protection, ecosystem connectivity, crop diversity and soil protection.

On the sustainable perspective of ecosystems protection and crop diversity, a large amount of biomass can be obtained from Mediterranean agricultural management, especially from pruning operations, renewal of plantations and crop residues. Up to now, this source of biomass has not been mobilised and used due to several technical difficulties in extraction, handling and transport as well as the lack of enough information on the quantity and suitability of these residues. Currently these wastes are piled up and disposed of by burning or shredding, not getting any direct benefit, but rather a cost and also taking a high risk of fire danger when fields are close to forest areas. In addition to the contribution to sustainable development, using this additional biomass as a source of energy would also provide benefits in relation to maintenance operations and potential extra income for producers, in addition to those obtained from the crop.

Pruning offers the possibility to obtain biofuels, such as chips, pellets or ethanol by means of acid hydrolysis and subsequent fermentation. Fruit tree production in Spain is smallholder-structured, which means that currently the exploitation of such wastes is mostly not viable for an individual small producer to sustain due to high harvesting and transport costs. Nevertheless, it has led to the creation of associated groups (cooperatives, agrarian transformation societies and marketing companies) which link together large areas in order to carry out harvesting operations and selling crops. Consequently, it would be possible for large-scale pruning also to be coordinated by these partnership structures, who could share resources and take advantage of economies of scale, as the equipment needed to accomplish the pruning and removal is expensive. On the other hand, the collection area of a medium-sized cooperative is usually characterised by considerable spatial dispersion as each partner typically has a rather large number of fields in several locations. This type of geographical distribution involves a great organisational effort for technicians responsible for machinery management to make possible cost-efficient pruning and collection operations.

Usually, procedures to plan the working sequences of a cooperative's equipment and vehicles are based on the extensive knowledge of the area, previous experience of past seasons and on negotiations with members. According to the peculiarity of the biomass collection process (small amounts of biomass volume at highly dispersed collection points) this kind of procedure is not good enough to achieve a cost-effective solution to ensure an optimised supply system for long term success of a biomass processing facility. Therefore, beyond the mere association of producers, the execution of biomass collection and transportation operations has to be efficiently planned in order to consider biomass from agricultural pruning as an agroforestry sustainable resource. Consequently, advanced techniques and logistics models need to be developed for determining the optimal collection points, managing the best transportation routes and deciding on the desirable location of the processing industries. Cost-effective planning requires the allocation and dispatch of each vehicle to land parcels, the computation of the in-parcel path for each vehicle, as well as the determination of their appropriates routes. Optimisation criteria taking into account issues such as minimising non-productive time, fuel consumption and distance travelled have to be applied in order to get significant economic and environmental benefits. Hence, it is necessary to describe such operations by mathematical models. Parameters regarding vehicles and machines (travelling speed, capacity, unloading and loading time, operating performance, etc.), parcels (geometry, presence of obstacles, biomass production volumes, etc.), depots (position, capacity, etc.) make such modelling difficult.

Previous work has already been reported by the authors supplying biomass detection models, harvesting techniques analysis and biomass concentration locations. This paper addresses the biomass harvesting and collection problem (BCP) within the context of a sustainable biomass supply chain management. The solution of BCP obtains optimised minimum cost routes for a fleet of agricultural vehicles (chippers, trucks, tipper trailers and tractors) describing the sequence in which biomass has to be harvested and collected from different production locations (orchards) and transported to a common storage location (biomass concentration node) for further distribution to a conversion facility. The biomass concentration node needs to have been determined in a previous planning step. Models already developed by the authors (Velázquez-Martí & Annevelink, 2009) integrate diverse sources as official cartographic and/or spatial bases with images of satellite in raster format or clouds of points from airborne light detection and ranging (LIDAR) to determine the location of the biomass concentration nodes.

The BCP belongs to a class of Operations Research problems known as vehicle routing problems (VRP). The VRP has been extensively discussed and has, for over fifty years, provided optimal solutions to fleet planning in many real applications involving planning of vehicle fleets. However, despite the fact that field tasks involve the collaborative use of vehicles, only recently have these concepts been transferred to the agricultural environment (Bochtis & Sørensen, 2009, 2010; Bochtis et al., 2013).

The VRP was first introduced by Dantzig, Fulkerson, and Johnson (1954) and it has been widely studied since. It is a complex combinatorial optimisation problem to define the efficient use of a fleet of vehicles that must make a number of stops to pick up and/or deliver products (Fisher, 1995). Each stop corresponds to a certain customer and has to be assigned to exactly one vehicle in a specific order.

According to the theory of computational complexity, most of these problems are non-deterministic polynomial time complete (NP-C) (Garey & Johnson, 1979). Therefore, procedures proposed usually focus on the use of algorithmic methods based on the application of meta-heuristics. These techniques have become recognised as one of the best approaches to solve many real complex combinatorial problems. During the last decade, nature-inspired intelligence has become popular through the development and use of intelligent paradigms in advanced information systems design. The use of meta-heuristics methods representing successful animal team behaviour has been extended, i.e., particle swarm optimisation inspired by flocks of birds or schools of fish (Kennedy, Kennedy, Eberhart, & Shi, 2001), artificial immune systems (Dasgupta, 1998; De Castro & Timmis, 2002), optimised performance of bees (Baykasoglu, Ozbakor, & Tapkan, 2007), or ant colony optimisation (Dorigo & Stützel, 2004). However, the most popular of these are genetic algorithms (GAs). Since their introduction in 1975 by Holland, a very large number of applications have been developed in the context of GAs and more generally in evolutionary computation (Goldberg & Chie, 1987).

A simple hybrid approach based on genetic algorithms (HGA) and local search methods is presented to solve a real case study. The paper is organised as follows. First, the problem of harvesting and collecting residual agricultural biomass is described and modelled in Section 2. Next, the proposed HGA approach to solve the problem is developed in Section 3 and an experimental study is carried out in Section 4.

2. Problem description and mathematical formulation

Pruning fruit trees is usually performed annually. It is usual to distinguish between traditional and hedge pruning techniques. Hedge pruning is performed by disk machines and consists of flat indiscriminate cuts in the row of fruit-trees. On the other hand, traditional pruning is done with hand tools and it discriminates the parts to cut from thick branches to small sideshoots. Today either technique can be found or the concurrence of both as they can complement each other. In the case of hedge pruning, work rates are much higher (about 100 trees person^{-1} h^{-1}) than in the manual pruning (2 trees person^{-1} h^{-1}) due to the use of high-clipper machine performance. However, the use of hedge pruning machines obviously requires having either large plantations or concurrence of multiple farms. Once the pruning operations are done, debris on the soil is windrowed to be harvested.

Most of the operational issues with biomass harvesting are very similar to other agricultural operations. However some key points are worth emphasising:

- Use of low impact logging techniques to protect soil from rutting and compaction from harvest machines
- Use of appropriate equipment matched to site and operations
- Integration of biomass harvesting with other agricultural operations such as pruning to reduce site impacts such as soil compaction which may harm post-harvest regeneration.

Under these guidelines, transportable chippers are appropriate machines to employ when harvesting biomass from fruit trees such as citrus. These chippers are generally pulled by tractors or directly mounted on a truck. They work in the road next to the field because they cannot be driven into the orchard or forest plot. Therefore they require a previous collection of materials to carry out the chipping in a fixed position. This previous collection can be carried out manually or by means of a tractor with a rake. If a tractor with a rake is used, it will create piles separated by a variable distance of around 60–80 m, which means that the chipper will be forced to move short distances during its working time. The chipper places the materials in the feed platform by means of a crane. After the grinding, these machines have a continuous system of discharge. Chips are thrown directly into a container by pneumatic impulsion for further transportation to the biomass concentration location. Tipper trailers or trucks are the standard, widely available equipment used for a wide range of loads. They are appropriate for wood chips, pellets, some industrial, agricultural or forestry residues, etc. With suitable design of biomass storage, delivery can be as simple as tipping the load into the store, thus removing the requirement for any additional handling or equipment. As the tractor stacks piles of residual biomass, the rest of the machines that make up the collection and harvesting equipment can tour the perimeter of the orchard to deal with each of the piles. The number of piles on the plot depends on its size but at least there will be one at each corner.

Therefore harvesting operations involve several collaborative machines: a chipper and its propelled machine (either a tractor or a truck), another tractor with a rake and a tipper trailer to transport biomass. These machines work together and therefore need to be coordinated, requiring accurate planning of their routes and sequences in order to complete their tasks efficiently.

When developing a logistics model to achieve minimum delivery costs and a sustainable biomass supply chain, input data must at least contain information regarding biomass quantification, harvesting techniques and the location of biomass concentration points.

Table 1 – Biomass obtained from fruit trees pruning.

	Dry biomass (kg tree^{-1})		Dry biomass (t ha^{-1})	
	Average	Standard deviation	Average	Standard deviation
Oranges	8.52	3.36	4.68	1.75
Mandarins	6.50	4.40	4.34	2.72
Olive trees	22.13	7.61	4.41	3.32
Vineyards (wine) in vase shape	1.25	0.31	2.03	0.50
Vineyards (wine) in trellis	1.29	0.46	2.74	1.07
Vineyards (fresh fruit) in trellis	1.40	0.25	3.18	0.58
Vineyards (fresh fruit) in Y-trellis	3.27	0.45	5.46	0.76
Vineyards (fresh fruit) in horizontal trellis	7.04	0.97	7.82	1.08
Almond	8.42	4.85	1.05	0.60
Peach	7.92	3.81	3.73	1.65

Previous work by the authors has reported quantification of residual biomass production from pruning operations. Depending on the agronomic characteristics of the different plantations (species in cultivation, tree size, age, plantation width, fruit production, rain fed or irrigated), prediction equations can be implemented to determine the spatial distribution of potential biomass obtainable in a particular area (Callejón-Ferre, Velázquez-Martí, López-Martínez, & Manzano-Agugliaro, 2011; Velázquez-Martí, Fernández-González, López-Cortes, & Salazar-Hernández, 2011).

Dry biomass quantification for fruit trees in pruning operations can be achieved by different techniques such as regression models, LIDAR or multispectral images. Table 1 shows the mean residual biomass obtained from pruning in the most important fruit trees in the Mediterranean area; it shows a large standard deviation.

Technical, economic and energy analysis of biomass harvesting systems and their costs has been studied by Velázquez-Martí and Fernández-González (2009, 2010a), and models based on algorithmic approaches to obtain biomass concentration locations in a region have been reported by Velázquez-Martí and Fernández-González (2010b). Biomass is further distributed from these concentration points to biomass conversion facilities. These locations cover a wide area of biomass production and are considered as source nodes for conversion facilities (power plants) in the biomass supply chain. The criteria followed in these models for the selection of such source areas are: firstly, a minimum

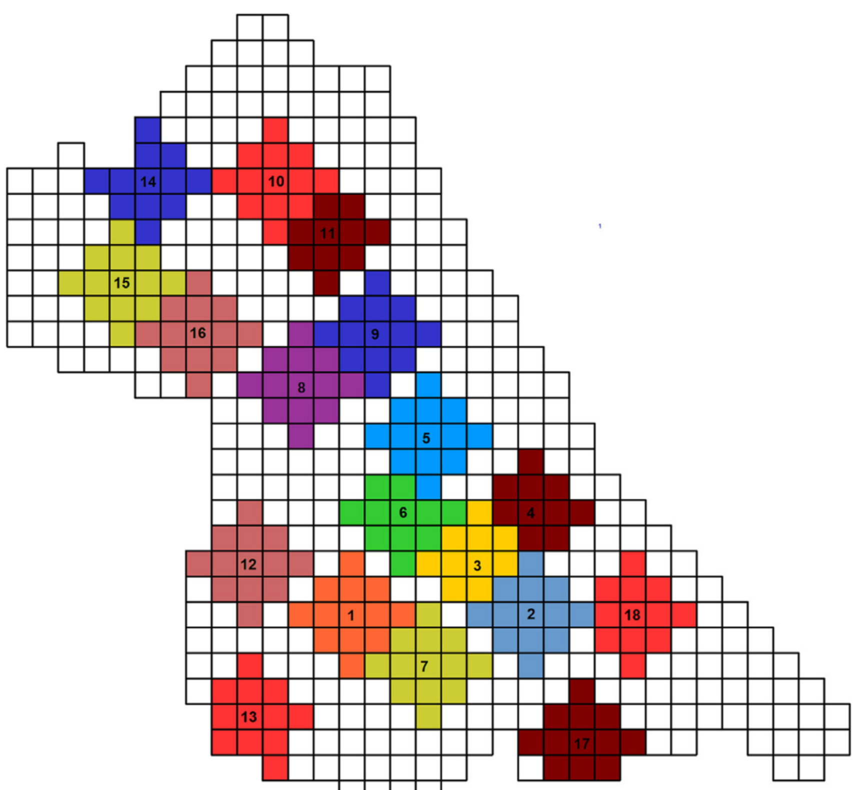

Fig. 1 – Biomass concentration points and associated sub-areas in La Safor County (Valencia, Spain) after applying the *Borvemar* model (parameters: Q = 60 t year^{-1}; R = 2 km; 18 iterations).

production of available biomass type; and secondly, minimum harvesting and collection costs. The database for these models is composed of spatial surveys of forest and agricultural biomass in geographic information system (GIS) maps (shape files). The area associated with each concentration point is divided into 1 km^2 subareas so that land use and diversity are ensured sufficiently over the territory. A BCP has to be solved independently for every 1 km by 1 km grid square. Figure 1 shows an example for La Safor County in the Valencian Community (Spain). In this Figure, 18 biomass concentration points and their areas/subareas are depicted in different colours (in the web version). These were obtained after applying the *Borvemar* model developed by Velázquez-Martí and Annevelink (2009).

The BCP, as well as the VRP, can be considered as a combination of two optimisation problems: the bin packing problem (BPP) and the travelling salesman problem (TSP). The BPP can be described as follows: given a finite set of objects of different volumes, they must be packed into a finite number of bins of a certain capacity so that the number of bins used is minimised. The TSP is about a travelling salesman who has to visit a certain number of towns exactly once and has to start and end at his home town. The problem is to find the shortest tour connecting all towns. As an example of TSP, Fig. 2 shows a graph with eight numbered vertices (nodes) in which edges are showing all possible paths as well as distances (costs) to travel to go from one vertex to another. A possible solution to the problem (tour) is marked with a thicker line. Relating this to the BCP, biomass collection points can be assigned to vehicles by solving BPP and the order in which they are visited can be found by solving TSP. Notice that TSP is also a special case of VRP when there is only one vehicle with an unlimited capacity.

The following assumptions are considered when modelling the BCP mathematically:

- The collaborative team of vehicles involved in harvesting and collection operations (chipper, truck, tractor, …) is considered as a single vehicle with a loading capacity constrained to the transportation vehicle characteristics (truck or tipper trailer). This approach is appropriate so long as they all execute their tasks together and at the same time.
- Since all vehicles mostly travel around the perimeter of the plot, the centroids of the parcels are used to determining the distance matrix between plots.
- The distance between plots is determined as the Euclidean distance by a coefficient of curvature of the path that can vary between 1.1 and 1.8 as explained by Perpiñá et al. (2009).

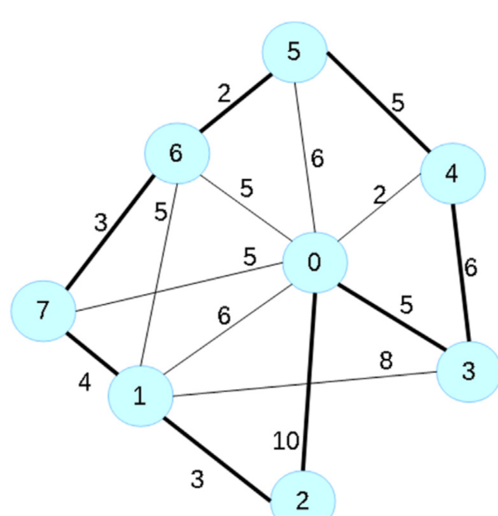

Fig. 2 – Example of tour in an eight vertex graph.

As in the VRP, the BCP can be represented as a graph theoretic problem. Let $G = (N,A)$ be an undirected graph. The node set N corresponds to location of the biomass collection points from 1 to n in addition to the biomass concentration point (depot) numbered as 0 ($N = \{0,1, \ldots,n\}$) which has been determined in a previous planning step. A quantity $q_i > 0$ of biomass volume has been assigned to each position node i ($1 \le i \le n$) according to a previous quantification operation. Moreover, $A = \{(i,j)/i,j \in N;\ i < j\}$ represents the set of the $n(n+1)/2$ existing edges connecting the $n+1$ nodes. Each of these edges has an associated aprioristic cost, $c_{ij} > 0$, which represents the cost of sending a vehicle from node i to node j. These c_{ij} are assumed to be symmetric ($c_{ij} = c_{ji}$, $0 \le i,j \le n$), they are expressed in terms of distance, d_{ij}. The collection process is to be carried out by a fleet of V vehicles ($V \ge 1$) with equal capacity, $K \ge \max\{q_i/1 \le i \le n\}$. Some additional constraints associated with the problem are the following:

- Each biomass node is supplied by a single vehicle, and exactly once
- All vehicles begin and end their routes at the biomass concentration location (node 0),
- No vehicle can be loaded exceeding its maximum capacity.

Three types of data are considered in the mathematical model: those which have to do with the vehicles, loading capacity; those which have to do with the biomass concentration area, storage node location; those which have to do with the harvesting and collection subarea, plot dimensions, centroid coordinates, estimated residual biomass productions, coefficient of curvature.

Biomass production volume for each plot is obtained by the detection techniques described above. Biomass concentration areas and subareas are defined in a previous planning step.

The decision variable is defined as X_{ij}^{v}, where:

$$X_{ij}^{v} = \begin{cases} 1 \text{ if vehicle } v \text{ drives from node } i \text{ to node } j \\ 0 \text{ otherwise} \end{cases} \quad (1)$$

The objective function of the mathematical model is:

$$\min \sum_{v \in V} \sum_{(i,j) \in A} c_{ij} X_{ij}^{v} \quad (2)$$

subject to

$$\sum_{v \in V} \sum_{j \in N} X_{ij}^{v} = 1 \quad \forall i \in B \quad (3)$$

$$\sum_{i \in B} q_i \sum_{j \in N} X_{ij}^{v} \le K \quad \forall v \in V \quad (4)$$

$$\sum_{j \in N} X_{0j}^{v} = 1 \quad \forall v \in V \tag{5}$$

$$\sum_{i \in N} X_{ik}^{v} - \sum_{j \in N} X_{jk}^{v} = 0 \quad \forall k \in B \text{ and } \forall v \in V \tag{6}$$

$$X_{ik}^{v} \in \{0,1\}, \ \forall (i,j) \in A \text{ and } \forall v \in V \tag{7}$$

Equation (3) ensures that each collection point is assigned exactly to one vehicle. One arc from position i is chosen, whether or not the arc goes to another collection point position or to the biomass concentration point. Equation (4) states capacity constraints, so that the whole amount of biomass collected by a vehicle has to be less than or equal to the loading capacity of the vehicle (transporting wagon). Finally flow constraints, shown in Equations (5) and (6), guarantee that each vehicle will leave the depot node once and that the number of vehicles entering every collection point k and the depot are equal to the number of vehicles leaving. There will be a lower bound on the number of vehicles necessary to collect all biomass in the working area,

$$V_{\min} = \left\lceil \frac{\sum_{i \in B} q_i}{K} \right\rceil \tag{8}$$

3. Hybrid solution approach based on GAs

The VRP is NP-hard, and so is BCP, since the TSP is a special case of VRP. In practice, the VRP is significantly more difficult to solve than a TSP of the same size. The literature is rather extensive and research approaches extend from the use of pure optimisation methods for small size problems, to heuristics and meta-heuristics for medium and large-size problems with complex constraints (Cordeau, Gendreau, Laporte, Potvin, & Semet, 2002; Toth & Vigo, 2002).

3.1. *Solution approach description*

In most meta-heuristics, each stage (iteration) of the search algorithm starts with a solution (or set of solutions). In the next stage a new candidate (or set of candidates) is evaluated within the local space of the previous solution. The evaluation will estimate the performance of the new candidate and compare with the performance reached in the previous stages. Based on this evaluation, the candidate or candidates can be accepted, becoming part of the solution for that stage, or rejected, in which case the solution is maintained. The process is repeated until certain stopping criteria are met.

In a GA, a population of chromosomes encoding candidate solutions (individuals) of the problem evolves toward better candidates. A GA is notable for a number of discrete phases, i.e. the initialisation of a population, the selection of the parents, the crossover operator, the mutation operator and the replacement of each generation. A number of parent solutions are selected at each iteration, and genetic operators (mutation and crossover) are applied producing new descendants. The new population is selected from both old and new individuals. Solutions are ranked according to a fitness function so that the worst ones are usually rejected and the best ones take part in the next iteration population (elitism). Goldberg (1989) summarises the following attributes of GAs:

- work with an encoding of the parameter set, not the parameters themselves.
- search from a population of points, not a single point.
- use payoff (objective function) information, not derivatives or other auxiliary knowledge.
- use probabilistic transition rules, not deterministic rules.

However, due to constraints in the problem, it is very difficult for a pure GA to effectively explore the solution space. Therefore, it is advisable to combine it with some sort of heuristic in order to guide the local search optimisation, so that they complement each other. Numerous practices based on hybrid approaches have produced more successful results than either of their pure methods applied separately (Chen, Pan, & Lin, 2008), always relying on the synergy of both methods to provide search guidance while balancing solution exploration and exploitation. Previous hybrid approaches applied successfully to solve routing problems include Berger and Barkaoui (2003), Alba and Dorronsoro (2008) and Wang and Lu (2010).

Our approach consists of a GA which includes another GA together with local search methods in its mutation procedure. It evolves a diverse initial population of solutions obtained from several random and constructive (nearest neighbour and nearest addition method in the sweep algorithm) methods. The recombination procedure is performed by the linear order crossover operator. The mutation procedure gives the hybrid nature to the approach. Mutation is fulfilled first by the utilisation of another nested GA that solves the TSP for some of routes of the chosen individual and then by applying local search methods (swap procedure, sliding procedure and 2-Opt movement procedure). The idea behind this mutation procedure is similar to that attributed to Gillett and Miller (1974). They proposed a two-phase method for routing problems: in the first phase feasible routes (not exceeding loading capacity) are constructed, in the second phase the shortest path is solved for each route.

One feasible solution for the BCP will have all the nodes to visit clustered in different routes, none of them exceeding the vehicle's capacity constraint. As said before, getting the shortest path for one of the routes in the solution is equivalent to solving one TSP. That is what the TSP_GA will do for some of the routes of the chosen solution using the mutation procedure. On the other hand, the average quantity of biomass collected from pruning together with the usual capacity of transporting wagons turn the TSPs contained in the BCP into small/medium size problems. Johnson and McGeoch (1997) conclude that in the case of a medium size TSP, GAs provide good solutions. The main features of the approach are summarised in the following subsections.

3.1.1. *Parameter settings*

To run the GA the following input parameters need to be determined: population size (*Pop*); maximum number of iterations (*iter*) and stopping criteria; size of cloning proportion (*Elite*) maintained through iterations; and proportion of individuals generated by mutation (*Mut*) and crossover (*Xover*) according to the following expression:

$$1 = Elite + Mut + Xover \quad (9)$$

3.1.2. *Genetic encoding*

The main snag when developing a GA lies in an effective encoding so that genetic operators can be applied whilst ensuring that the obtained solutions are feasible. A solution for BCP will consist of a number of V ordered sequences (one for each route to plan) each of which containing some different nodes from set N. A good representation of BCP solution must identify the number of vehicles, the biomass collection nodes that are assigned to each vehicle and in which order they are to be visited. Several encodings have been used for VRP in the literature. Sometimes solutions are represented as binary strings, but that kind of representation does not suit BCP well.

It is not difficult to specify the number of vehicles and which nodes are visited by each, but it becomes too intricate when the order of the nodes needs to be given. If the order of collection nodes is used instead that problem is cleared up. Then, an efficient encoding to represent the solutions, which is easily applicable to the BCP, is to define a solution as a pair of vectors. The first vector (sequence vector) contains a permutation of n elements that represents the ordered sequence that will reflect all different biomass collection points (B) from which biomass needs to be collected. The second vector (breakpoints vector) contains the position of $V-1$ elements from the above sequence vector delimiting the different routes.

As an example, to illustrate the genetic encoding, suppose a BCP in which the routes begin and end at a depot location identified as node 0, biomass has to be collected from nine different locations ($n = 9$) which are identified by different integer numbers (1 through 9) and the nodes contain the following volumes of biomass (1, 2, 3, 2, 3, 4, 1, 1, 2). Suppose the maximum load capacity of each transporting wagon is $K = 5$, which means that the minimum number of trips to do is four ($V_{min} = 4$). One arbitrary solution will be identified by the following sequence (S) and breakpoints (R): S = [4 6 5 9 2 3 7 8 1], R = [1 2 4 6 9], this will lead to the following routes: route1 = [0 4 0]; route2 = [0 6 0]; route3 = [0 5 9 0]; route4 = [0 2 3 0]; route5 = [0 7 8 1 0]. Notice that the capacity constraint is never violated.

3.1.3. *Initial population generation method*

The way individuals belonging to the initial population are constructed is of great importance to the performance of the algorithm, since it contains most of the elements of which the final best solution is made. Sometimes individuals are randomly generated, but the initial population may also be obtained from other constructive methods. Seeding is when solutions from other algorithmic techniques join the randomly chosen solutions in the population. A requirement for the good performance of the proposed approach is the generation of a wide variety of initial solutions. Similar to the approach proposed for VRP by Wang and Lu (2010), our approach to the production of initial individuals seeks to create a well-structured and diverse initial population to solve the BCP, and utilises a random creation method in combination with the nearest neighbour constructive heuristic (Jünger, Reinelt, & Rinaldi, 1995) and the incorporation of the nearest addition method into the sweep algorithm from Gillett and Miller (1974). Therefore the initial population is expected to explore the space of solutions globally so that capability of the GA is improved.

The random generation of solutions consists of random permutation sequence of n nodes (all except the depot node). Further breakpoint vectors are obtained by partitioning chromosomes into segments within the vehicle's capacity constraint.

The nearest neighbour constructive heuristic was first used to determine a solution to the TSP. The sequence solution is constructed by adding the nearest node from current position of the vehicle. This algorithm suits quite well the common assignment rule followed by an experienced operator when collecting the biomass from different locations in an area. The solution obtained by this heuristic will be used further as a lower bound to estimate the efficiency of the HGA approach. The steps of the algorithm can be summarised as follows:

Step 1. Set count = 0
Step 2. Stand on the depot vertex as current vertex. Set available capacity $c = K$ (maximum capacity of the vehicle)
Step 3. Find out the shortest edge connecting current vertex and an unvisited node i.
Step 4. Set current vertex to i. Mark i as visited. Set $c = c - q_i$ and count = count + 1.
Step 5. If all the vertices in domain are visited, then terminate.
Step 6. If $c = 0$ then set breakpoint = count and go to step 2. If $c > 0$ go to step 2.

The ordered sequence of the nodes (excluding the depot node) together with the sequence of breakpoints are the two output vectors encoding solution provided by the algorithm.

The sweep method, or Gillett and Miller (1974) algorithm, belongs to a class of heuristic algorithms called "cluster first, route second". In this type of algorithm, nodes are grouped in clusters. Later the way nodes belonging to each cluster are sequenced is optimised. The algorithm starts from the polar coordinates (r_i, θ_i) of all nodes relative to the depot node which is adopted as the origin ($r_i = 0$). The construction of one route begins with the union of the origin node to an arbitrary node and the remaining nodes of the chromosome are determined in terms of angle increases of sweep. The route covers as many points as the vehicle's capacity constraint allows. The process is completed when all the points of the system have been swept. Each group of nodes forming a whole route will later use another algorithm to generate the sequence that the vehicle has to follow. As described by Wang and Lu (2010), the following steps depict the nearest addition method into the sweep algorithm.

Step 1. Calculate the coordinates of all nodes relative to the depot (X,Y)

$$\begin{cases} X_i = x_i - x_0 \\ Y_i = y_i - y_0 \end{cases} \quad (10)$$

where (X_i, Y_i) are the coordinates of the ith node relative to the depot node (x_0, y_0), and (x_i, y_i) are original coordinates of the ith node.

Step 2. Calculate polar coordinates (r_i,θ_i) of nodes from relative coordinates obtained in step 1
Step 3. Sort the nodes in ascending order of their polar angles
Step 4. Generate the structured population

The nodes permutations are determined on the sorted θ_i. Given n nodes, a total of n individuals, each starting at a different node, are generated. Every of the n sequences are partitioned into different segments according to vehicle's capacity constraint.

Step 5. Strengthen the chromosome structures

The routes are improved using the nearest addition method described by Bentley (1992). Within each route, the sequence of nodes is constructed by the nearest neighbour heuristic starting at the depot node.

3.1.4. *Fitness value*

In order to perform a natural selection, each individual is evaluated in terms of its fitness value which is obtained by a fitness function. The fitness value weighs the quality of a solution and enables it to be compared to others. The total distance travelled will be the fitness value used. The shorter the distance, the more efficient is the solution.

3.1.5. *Crossover procedure*

A common recombination operator is the Simple Crossover which chooses a random cut to divide each parent into two strings. Children are generated by exchanging parents' strings. However, in BCP the only difference between an individual and another is the order in which the elements of the chromosome are permuted, and in most cases it makes no sense to talk of pure recombination (Djerid & Portmann, 2000), since the association of different parents would generate infeasible solutions (doubling some positions and excluding others). Therefore BCP is better suited by an operator such as the linear order crossover operator (Davis, 1985, pp. 136–140). In linear order crossover, two break points are selected randomly, the elements between these points are copied to the same positions of the offspring. The copied elements are deleted from the other parent, and the remaining symbols are inherited, beginning with the first position following the second crossover point.

Selection of individuals for crossover is made through the classic Roulette Wheel method, in which each individual is assigned an occurrence probability proportional to its fitness value. If considering a pin at the top of the wheel, when spinning the wheel it would most frequently point at individual with the highest fitness value.

3.1.6. *Cloning and mutation procedures*

Mutation is applied to a single solution with a certain probability. The philosophy is based on making small random changes in the solution adding some new characteristics gradually.

The mutation procedure is accomplished through two steps: in the first step a GA is applied to solve the TSP (TSP_GA) for a maximum of five randomly chosen routes in the individual; in the second step, three different classical mutation operations are employed (also used in the TSP_GA), swap procedure, sliding procedure and 2-Opt movement procedure. Such mutation procedures have been widely applied when solving the TSP (Brady, 1985; Martin, Otto, & Felten, 1991). To apply all three mutation operations, two random positions from the sequence vector of the individual will first have to be selected. The swap procedure consists of exchanging the elements at those two positions. The sliding procedure glides all elements contained between selected positions one position to the left. The 2-Opt movement belongs to local search algorithms. A 2-Opt movement deletes two edges of the tour and reconnects the vertices thus obtaining new ways. This procedure is based on the observation that if a cycle crosses over itself, it can be shortened by replacing only the edges that cross so that the final cycle is shorter than the original. Figure 3 illustrates the movement in which the edges (i, d) and (c, h) are replaced by (c, d) and (i, h). In this procedure there is only one way to reconnect the two paths.

According to Gendrau, Laporte, and Potvin (1999), combining local search algorithms with GA is necessary to solve VRP efficiently. Most local search heuristics can be described by Lin's λ-Opt algorithm (Laporte, Gendrau, & Potvin, 2000). The algorithm removes λ edges from the tour and the remaining segments are connected in every other possible way. The 2-Opt algorithm removes two edges from a tour and reconnects the resulting sub-tours in the other possible way as shown in Fig. 3 Elitism maintains certain individuals from one generation to the next one by cloning them.

Cloning and mutation processes are made through the following steps:

Step 1. Random positions are assigned to all initial elements of the population.
Step 2. All individuals in population are grouped in equal sets.
Step 3. In each set the individual with the highest fitness value is chosen.
Step 4. TSP_GA is applied to a maximum of five routes to the chosen individual.
Step 5. The resulting mutated individual is cloned to take part in the next generation population (elitism).
Step 6. Two random positions are selected from its sequence vector

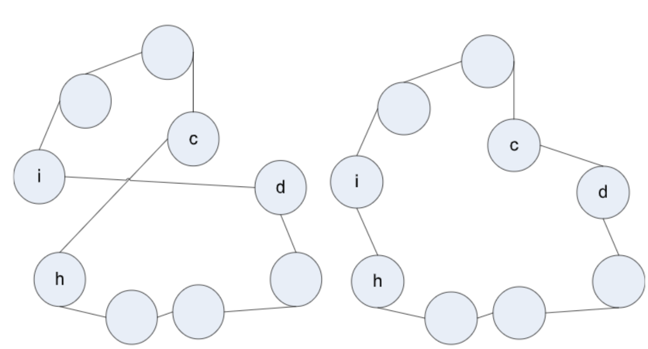

Fig. 3 – Improved solution from a 2-Opt movement.

Step 7. The three mutation procedures are applied at those positions.
Step 8. Three new individuals take part in the next iteration population.

Note that according to this procedure, the mutation rate (Mut) will be three times the elite rate (Elite) so for the HGA proposed here Equation (9) can be rewritten as:

$$1 = 4*\text{Elite} + \text{Xover} \quad (11)$$

Figure 4 shows an example of how mutation procedures are applied to a sequence [1 2 3 4 5 6 7], at positions {2} and {6}.

The TSP_GA used in the mutation procedure will have the same parameter settings as the GA described above but the crossover rate is set equal to 0 (there is no recombination procedure). Its main characteristics are:

Genetic encoding. One solution consists of an ordered sequence of nodes to travel. Therefore, any permutation of the biomass collection points of the route is a feasible solution. The encoding will be defined by the ordered sequence of previous numbered collection points.

Initial population generation method. The production of initial individuals proposed is accomplished randomly.

Fitness Value. As for the whole BCP solutions, the total distance travelled will be the fitness value used to evaluate routes within the TSP.

Cloning and mutation procedures. As in the GA above, the same three different classical mutation operations are also employed: swap procedure, sliding procedure and 2-Opt movement procedure. All three mutation operations are applied at two randomly selected positions.

Cloning and mutation processes for the TSP_GA are made through the following steps:

Step 1. Random positions are assigned to all initial elements of the population.

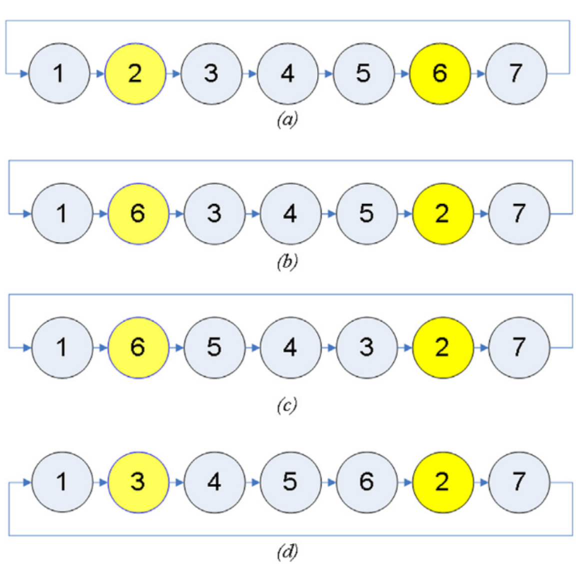

Fig. 4 – Mutation operations applied to an original sequence (a): swap procedure (b); 2-Opt movement (c); and sliding procedure (d).

Table 2 – Crop areas (net areas) percentages in Eastern Spain provinces.	
Crop	Percentage
Citrus	2–10%
Olive	1–8%
Vineyards	0.2–6%
Fruit trees (other than citrus)	2–10%
Vegetables	0.1–1.3%
Fallow	1–5%

Step 2. All individuals in population are grouped in equal sets.
Step 3. The individual in each set with the highest fitness value is chosen. It is cloned to take part in the next generation population (elitism).
Step 4. Two random positions are selected from its sequence vector
Step 5. The three mutation procedures are applied at those positions.
Step 6. Three new individuals take part in the next iteration population.

Now Equation (9) can be rewritten as:

$$1 = 4*\text{Elite} \quad (12)$$

4. Experimental study

The proposed algorithm has been implemented in the commercial software MATLAB® release R2007b. The set of input parameters for the HGA were {Pop = 80, Iter = 6000, Elite = 0.125, Xover = 0.375, Mut = 0.5}. These settings are similar to those determined by Wang and Lu (2010), where the response surface methodology is employed to conduct systematic experiments with various crossover and mutation probabilities in order to determine the optimal combination of these parameters when solving the capacitated vehicle routing problem (CVRP). The set of input parameters for the TSP_GA were {Pop = 30, Iter = 300, Elite = 0.25, Xover = 0, Mut = 0.75}.

4.1. *Test problem generator*

In order to validate the proposed approach, a computational experiment has been conducted. For testing the approach under different crop situations, a problem generator able to generate problem instances from a certain set of parameters is required. As described in Section 2, a problem will be defined by the capacity constraint of the vehicles (K) and by the $n + 1$ exact locations in an area: n corresponding to the collecting points, and one corresponding to the starting/ending point of the route: biomass concentration point.

So as to best suit the reality of different crops and especially in citrus, which is the dominant crop in Eastern Spain, test problems are generated taking into account the following considerations:

Table 3 – Results obtained for 80 problem runs.

Number of runs	Capacity constraint (t)	Crop	HGA performance
			Savings respect to NNH (%)
10	9.5	Almond	17.45
10	9.5	Vineyards	15.24
10	9.5	Peach	15.76
10	9.5	Oranges	11.51
10	24	Almond	14.52
10	24	Vineyards	17.11
10	24	Peach	20.93
10	24	Oranges	15.46

- The area percentage in Eastern Spain provinces (Valencia, Castellón and Alicante) dedicated to each crop compared to total geographical area is shown in Table 2 (reported by Spanish Ministry of Agriculture).
- Two different transport trailer loading capacities will be considered. The first is set to 36 t and a volume capacity equal to 48.1 m^3; the second is set to 14.5 t and a volume capacity equal to 19 m^3. These data correspond to two commercial models from a local manufacturer. The density of residual agricultural pruning is 1 t m^{-3}, the bulk density of the chipped pruning residual biomass is 0.5 t m^{-3}. That means that the first vehicle has a residual biomass loading capacity due to its volume constraints of 24 t. In like manner, the second vehicle would have a loading capacity of 9.5 t.
- The biomass concentration node covers an area consisting of several sub-production areas of dimensions 1 km by 1 km.
- The biomass concentration node (storage location) in most cases is located outside the subarea of production over which the problem is solved. It can be regarded without loss of generality on the experimental results as if the storage location is set at the perimeter of the subarea.

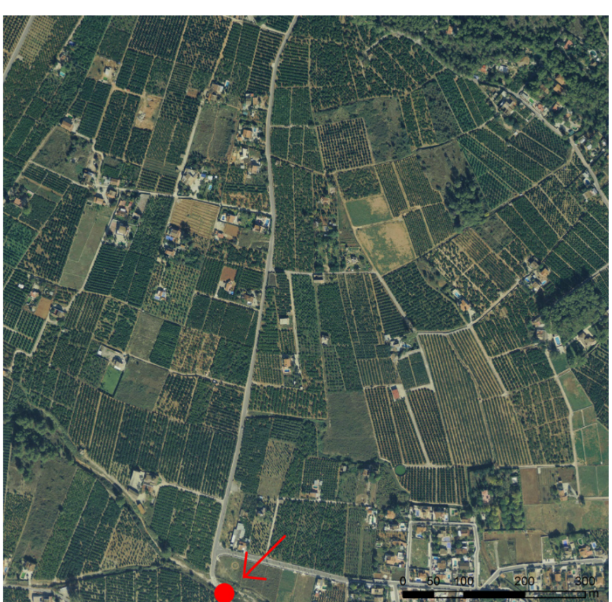

Fig. 5 – Area of study's Orthophoto. The arrow and the circle indicate the entrance location to the plots in the grid.

- Biomass production for each crop follows a normal distribution according to data shown in Table 1.
- The area of the plots is assumed to follow a normal distribution of mean 0.44 ha and standard deviation of 0.46. The proportion of land for agricultural use ranges from 40% to 60%. These data has been obtained from the Land Registry for different Eastern Spain districts.
- Road curvature values are high because they are mainly secondary and rural roads

Each test problem will be generated in the following way:

- Plot dimensions (length and width) and their residual biomass production are randomly generated following the distributions mentioned above.

(a)

(b)

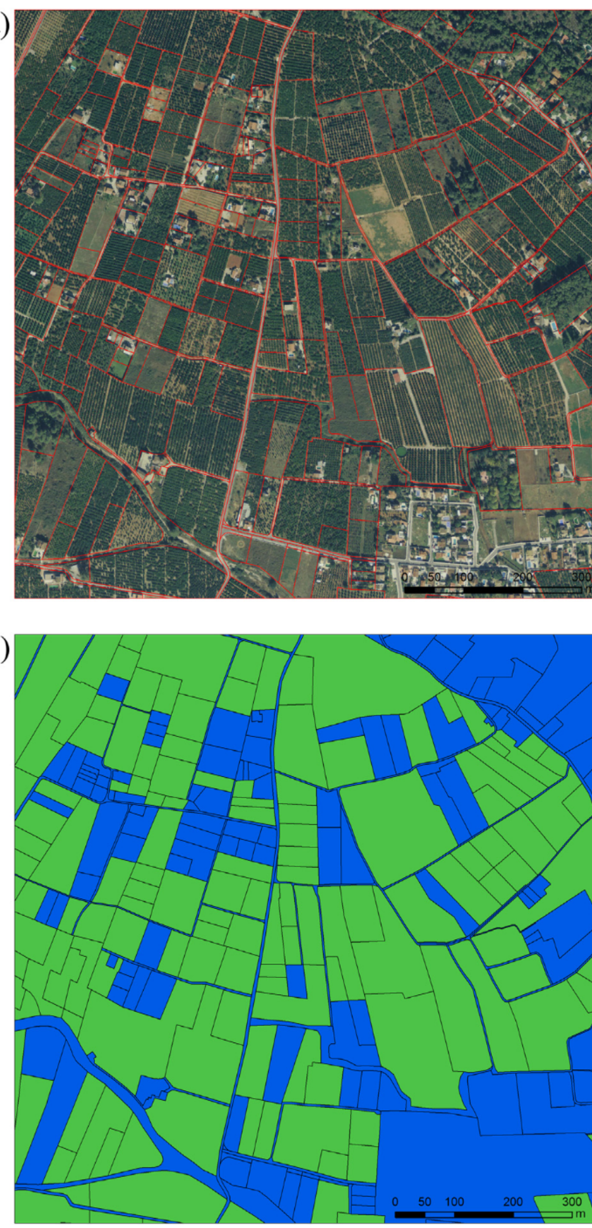

Fig. 6 – (a) Plot configuration; (b) Land Uses: agricultural plots (green); and non agriculture plots (blue).

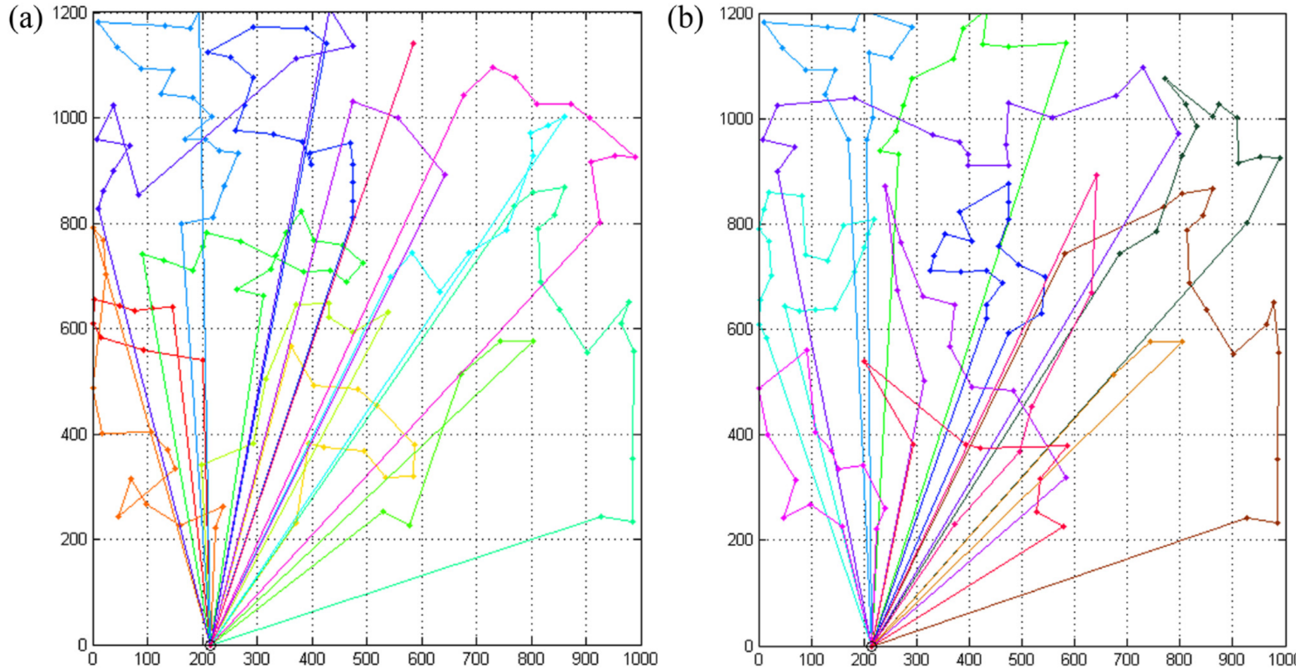

Fig. 7 – (a) Nearest Neighbour heuristic performance. Total distance travelled = 32.7 km; (b) HGA performance. Total distance travelled = 27.7 km.

- The centroid coordinates are set randomly over the total subarea of 1 km^2
- Storage nodes are set randomly at the perimeter of the subarea
- Road curvatures between nodes are randomly set between 1.6 and 1.8

4.2. *Benchmark results*

The HGA was run 80 times for different test instances corresponding to four different crops: almond, peach, oranges and vineyards and two different capacity constraints: 24 and 9.5 t, (ten runs for each crop-capacity). In order to validate the effectiveness of the approach, the results obtained by the HGA are compared to those obtained by the nearest neighbour heuristic (NNH), the corresponding percentages of savings are calculated and are shown in Table 3. As seen, savings varies between 19% and 13% depending on the capacity of the vehicle and on the crop. This raises awareness of the appropriateness of implementing this algorithmic approach.

4.3. *A case of study*

The proposed HGA enables one further step in facilitating a global perspective in sustainability of the biomass supply chain management. In order to serve as an illustration and also give an overview of how the algorithm presented here complements the earlier work by the authors, the proposed HGA has been applied to a real 1.2 km by1 km area of land located in the province of Valencia (Spain). In a previous step, the *Borvemar* model developed by Velázquez-Martí and Annevelink (2009) was applied to *La Safor County*, Valencia, and 18 biomass concentration points were obtained. Each concentration point comprises several 1 km by 1 km grids. One of these grids has been chosen here as a case study. Figure 5 shows the 1.2 km by 1 km grid case study. Note that the entrance location to the grid has been highlighted in a red circle, so that all vehicles must go through that point in order to arrive to the storage location.

The division in plots is available from the Agricultural Plots Geographic Information System (SIGPAC) from Spanish Ministry of Agriculture. Figure 6(a) shows the superposition of such a division (lined in red) and its orthophoto. The Land Registry supplies specific information regarding each plot: area, slope of land, irrigation and pasture coefficients and use. Not all plots in this area are dedicated to agricultural uses. Figure 6(b) differentiates the intended use of each plot according to the Land Registry. Agricultural use (citrus) plots are coloured in blue and plots for other uses (roads, forest, etc) are coloured in green.

From all this information, we are able to obtain data needed to define the problem and apply the HGA. That is: road curvature among plots, residual biomass production estimated and its centroid for each plot. Specifically 146 agricultural plots are contained in this 1 km by 1 km surface. Their average area is 0.438 ha ranging from 400 m^2 to 2.5 ha.

Figure 7(a) illustrates the solution obtained for this problem with the nearest neighbour heuristic. Each point represents the centroid of each agricultural plot. Each route is identified by a different colour; note that all routes have their starting and ending point at the same location identified above in Fig. 5. The solution obtained by the approach is shown in Fig. 7(b). Note how the HGA performance improves the solution obtained by the NNH by 15.4%.

Recently Abbas et al. (2013) presented a cost analysis of forest biomass supply chain logistics and concluded that "of the total supply and delivery cost, transportation averaged 28.5%". Transportation costs therefore form a significant part of overall supply chain costs, and a 20% reduction in distance travelled might have a significant impact on total cost.

5. Conclusions

An algorithmic approach based on genetic algorithms and local search heuristics to generate the collecting sequences of residual biomass has been developed. The resulting sequences are optimal in the sense that they minimise the total travelled distance in the field. The BCP was formulated and modelled in terms of mathematical programming.

The proposed translation of vehicle routing applications to the agricultural engineering domain enables a global perspective on sustainability of the biomass supply chain management by developing effectiveness logistics models within its major elements (feedstock production and logistics). Experimental results showed that by using solutions generated by the HGA instead of other common assignment rules, the total distance can be reduced significantly. These reductions depend basically on the loading capacity constraint and on the type of crop to which the approach is applied but can be as high as 20%. These savings have been obtained by comparison with an approach with assignment patterns (nearest neighbour heuristic) that are far from real situations. Real savings will be even more significant since sub-optimal patterns may need further corrections which would increase the total distance travelled.

Programmable navigation-aided systems and auto-steering systems, which are already a reality in agricultural machines, can make the appliance of such route planning optimisation techniques possible within an everyday context.

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