A review of tactical optimization models for integrated production and transport routing planning decisions

Manuel Díaz-Madroñero, David Peidro, Josefa Mula*

Research Centre on Production Management and Engineering (CIGIP)
Universitat Politècnica de València, Spain

Abstract

This paper presents a review of tactical optimization models for integrated production and transport routing planning decisions. The objective of this research is to identify current trends and future research directions in this field, and to propose a classification framework based on the following elements: production, inventory and routing aspects, modelling aspects of the objective function structure and solution approach. All these criteria are expected to be relevant for readers, and will provide researchers and practitioners a starting point for optimization models in the production and routing area at the tactical level.

Keywords: Production; Transportation; Routing; Optimization; Survey.

1 Introduction

Traditionally, production and transportation planning decisions in supply chain environments have been made sequentially and independently. The most habitual procedure was to proceed first with production planning or lot-sizing calculations, used to determine the quantities of each finished good to be produced in a given planning horizon, and to later establish transportation decisions for distributing manufactured products to customers in a separated way. However, in today's globalized supply chains and high competitive markets, firms have to guarantee the efficiency of their resources, increasing customers' service level and reducing lead times and stocks. In this sense, the simultaneous consideration of production and transportation planning activities in an integrated manner may lead to increased efficiency and cost savings as discussed by Chandra & Fisher (1994) and reflected in companies such as IBM (Degbotse et al., 2013) and McKesson (Katircioglu et al., 2014), among others. The literature that addresses models for simultaneous production and transport planning is vast, and several state-of-the-art papers have been published on this topic (Bilgen & Ozkarahan, 2004; Bravo & Vidal, 2013; Erengüç, Simpson, & Vakharia, 1999; Fahimnia, Farahani, Marian, & Luong, 2013; Josefa Mula, Peidro, Díaz-Madroñero, & Vicens, 2010; Vidal & Goetschalckx, 1997). Nevertheless, most of these models oversimplify transportation and only consider direct shipments or full-truck loads as a transport strategy because they disregard merge-in-transit operations (Croxton, Gendron, & Magnanti, 2003) and the less-than-load distribution mode.

In this context, production and transport routing models emerge in order to simultaneously plan production and distribution decisions by considering less-than-load shipments. This kind of integrated production and distribution planning problem is focused on the tactical decision level

*Corresponding author: Josefa Mula, Escuela Politécnica Superior de Alcoy, Plaza Ferrándiz y Carbonell, 2, 03801, Alcoy (Alicante), SPAIN. Tel.: + 34966528423. Fax: + 34966528585. E-mail address: fcodiama@cigip.upv.es, dapeipa@cigip.upv.es, fmula@cigip.upv.es

(Armentano, Shiguemoto, & Løkketangen, 2011) and is called production routing problem by several authors (Adulyasak, Cordeau, & Jans, 2014; Ruokokoski, Solyali, Cordeau, Jans, & Süral, 2010). At this level, and according to Bard and Nananukul (2010) in a production routing problem, four critical decisions have to be made: (1) how many items to manufacture each day; (2) when to visit each customer; (3) how much to deliver to a customer during a visit; and (4) which delivery routes to use. A production routing problem optimizes jointly production, inventory and transport routing planning decisions by integrating a lot-sizing problem to determine production amounts and a vehicle routing problem (VRP) to determine delivery routes. Hence, the production routing problem is a generalization of the production planning problem with direct shipment and of the inventory routing problem (IRP) (Andersson, Hoff, Christiansen, Hasle, & Løkketangen, 2010; Coelho, Cordeau, & Laporte, 2014). In the first problem, products are directly transported from the production factory to the customers minimizing setup, production and direct shipment costs over the considered planning horizon. In the second problem, routing aspects are included but production aspects are disregarded. In this sense, the inventory routing problem consist of a central warehouse from which products are sent to customers by determining the necessary transport routes and the corresponding inventory levels in order to minimize the corresponding total costs. Hence, the production routing problem combines planning decisions considered by production planning problems with direct shipments (production and inventory planning decisions) and by inventory routing problems (vehicle routing and inventory planning decisions).

To the best of our knowledge, despite previous surveys on production and transport planning models, and the increase in the number of published papers in this field in recent years, very few publications focus on reviewing tactical production and routing models. Only Schmid et al. (2013) provide an aggregated overview of basic models for rich routing problems, including production lot-sizing decisions.

In this survey, we briefly describe each paper, but we do not describe or formulate the models considered in detail. We provide the reader with a starting point to investigate the literature on optimization models for production routing problems and their modelling issues. The main contributions of this paper are to: (i) review the literature; (ii) classify the literature based on production, inventory and routing aspects, modelling aspects of the objective function structure and solution approach; and (iii) identify current trends and future research directions.

The remainder of the paper consists of five other sections. The next section introduces the review methodology. Section 3 describes and presents the production routing problem formulation. Section 4 describes the classification criteria of the reviewed papers. Section 5 includes discussion and provides future research lines. Finally, the last section presents some conclusions.

2 References collection methodology

Given the vast amount of published articles on production and transportation planning, the following selection criteria were defined: (1) the production and transport routing planning problem is addressed in an integrated manner; (2) the production and transport routing integrated planning problem is modelled by mathematical programming approaches; (3) the production planning problem is based only on lot-sizing calculations and extensions focused on the tactical decision level; hence the models that focus on production scheduling are not considered; (4) transportation planning issues are based on vehicle routing decisions, and hence direct shipments or full-trucks loads are not considered; (5) the collected references are published only in journals; conference proceedings and doctoral dissertations are not considered since we have assumed their subsequent publication in high-quality research journals.

The search for papers which consider integrated production and transport routing planning decisions was performed using the *Sciverse Scopus* database. The following search criteria were applied to the topic field of this web search engine: *production planning and routing; lot sizing and routing; production planning and VRP; lot sizing and VRP; supply chain planning and routing; supply chain planning and VRP; production and transport planning; production and distribution planning*, and different combinations of them. Furthermore, the bibliographic references of the articles studied have served as a continuous search reference.

After this process, 22 references were selected for reviewing. The reason for this small number of references is that the production and routing planning problem is a recent research area (the first paper in this topic was published in 1994) and it has been mainly developed in recent years. Among the selected papers, a group of six papers was selected from Computers & Operations Research and three came from the European Journal of Operational Research.

3 Production and transport routing model decisions description

In general terms, the production and transport routing problem can be defined in a network $G = (N, A)$, where N represents the set of nodes comprising production plant and customers, and A represents the set of arcs connecting the nodes, where $A = \{(i, j) : i, j \in N, i \neq j\}$. Nodes are indexed by $i \in \{0, \ldots , n\}$, where node 0 corresponds to the production plant which acts as a central depot, while customers are represented by $i \in \{1, \ldots , n\}$ or the set $Nc = N \setminus \{0\}$. In a finite planning horizon, composed of a set of equal planning periods $t = \{1, \ldots , T\}$, the production plant manufactures items, which can be either stored at the manufacturing warehouse or sent to customers, which can also store them at their own warehouses or fulfill their corresponding demands during each period. Transportation of products is done by a set of identical vehicles $k = \{1, \ldots, K\}$over the set of arcs A, which have an associated cost c_{ij} to travel from node i to node j. Hence, the production routing problem combines a lot-sizing problem, on the production side, and a VRP related to the distribution of finished goods to customers, by taking into account the inventories in both the manufacturing plants and customer warehouses.

The integrated production and transport routing problem can be stated as follows:

Given by:

- Production costs such as unitary manufacturing costs and setup costs
- Production capacity at the plant
- Inventory holding costs at the plant and customer warehouses
- Inventory capacity at the plant and customer warehouses
- Initial inventories at each node
- Transport costs such as travel costs between nodes
- Number of available vehicles and their capacity
- Customer demand over the planning horizon

To determine:

- The amount of each product to produce per period
- The inventory levels of each product at each node per period
- Transport routes, number of required vehicles and their occupation

The main goal to meet is:

- Minimization of total costs, including production, inventory and transport costs

Subject to:

- Production capacity constraints
- Inventory capacity constraints
- Typical VRP constraints (Toth & Vigo, 2002)

Moreover, the following assumptions are made:

- Transport routes start and end at the production plant
- Waiting, loading and unloading times are not considered.
- Customer demand must be fulfilled during each period, hence backorders are not allowed.

The production routing problems can be defined with the following notation:

Sets of indices

T	Set of time periods $(t=1, \ldots, T)$
N	Set of nodes $(i=0, \ldots, N)$ and $(j=0, \ldots, N)$

Parameters

d_{it}	Demand at node i during period t
I_{i0}	Initial inventory of product p at node i
pc	Unitary manufacturing cost
sc	Setup cost
ic_i	Holding cost at node i
c_{ij}	Travel cost between nodes i and j
$PCap$	Production capacity at the manufacturing plant
$ICap_i$	Inventory capacity at node i
$VCap$	Vehicle capacity

Decision variables:

P_t	Production amount during period t
I_{it}	Inventory level at node i at the end of period t
Q_{it}	Amount delivered to customer i with vehicle k during period t
γ_t	Binary setup variable during period t (γ_t = 1, if a setup is performed during period t, 0 otherwise)

X_{ijt} Binary variable equal to 1 if a vehicle travels from node *i* to node *j* during period *t*, 0 otherwise

W_{it} Load of a vehicle before making a delivery to customer *i* in period *t*

Literature provides different formulations for integrated production and routing planning decisions. Some of them are presented in the following as reference models.The integrated production and transport routing problem is formulated by (Bard & Nananukul, 2009a, 2010) as follows:

$$\textit{(BN): min} \sum_{t\in T}\left(pc\cdot P_t + sc\cdot \gamma_t + \sum_{i\in N} ic_i \cdot I_{it} + \sum_{i\in N}\sum_{j\in N} c_{ij}\cdot X_{ijt}\right) \quad (1)$$

subject to:

$$I_{0t} = I_{0,t-1} + P_t - \sum_{i\in Nc} Q_{it} \qquad \forall t\in T \quad (2)$$

$$I_{it} = I_{i,t-1} + Q_{it} - d_{it} \qquad \forall i\in Nc, \forall t\in T \quad (3)$$

$$\sum_{i\in Nc} Q_{it} \le I_{0,t-1} \qquad \forall t\in T \quad (4)$$

$$P_t \le PCap\cdot\gamma_t \qquad \forall t\in T \quad (5)$$

$$P_0 \ge \sum_{i\in Nc}\left(d_{i1} - I_{i,0}\right) - I_{0,0} \quad (6)$$

$$\sum_{\substack{j\in N\\ j\ne i}} X_{ijt} \le 1 \qquad \forall i\in Nc, \forall t\in T \quad (7)$$

$$\sum_{\substack{j\in N\\ j\ne i}} X_{jit} = \sum_{\substack{j\in N\\ j\ne i}} X_{ijt} \qquad \forall i\in Nc, \forall t\in T \quad (8)$$

$$\sum_{j\in Nc} X_{0jt} \le K \qquad \forall t\in T \quad (9)$$

$$W_{jt} \le W_{it} - Q_{it} + D_t^{\max}\left(1 - X_{ijt}\right) \qquad \forall i\in Nc, \forall j\in N, \forall t\in T \quad (10)$$

$$W_{it} \le D_{it}^{\max}\sum_{j\in N} X_{ijt} \qquad \forall i\in N, \forall t\in T \quad (11)$$

$$I_{it} \le ICap_i \qquad \forall i\in N, \forall t\in T \quad (12)$$

$$W_{it} \le VCap \qquad \forall t\in T \quad (13)$$

$$P_t, I_{it}, Q_{it}, W_{it} \ge 0 \textit{ and integer} \qquad \forall i\in N, \forall t\in T \quad (14)$$

$$\gamma_t, X_{ijt} \in \{0,1\} \qquad \forall i, j\in N, \forall t\in T \quad (15)$$

Where $D_{it}^{\max} = \min\left\{VCap, \sum_{l=t}^{T} d_{il}\right\}$ and $D_t^{\max} = \min\left\{VCap, \sum_{i\in Nc}\sum_{l=t}^{T} d_{il}\right\}$

The objective function (1) corresponds to the minimization of total costs relating to production, setups, inventories at production plant and customers and routing costs over the planning horizon. Constraints (2) and (3) represent the inventory flow balance at the plant and customer warehouses, respectively, in which it is assumed that the initial inventories are given for all customers $i\in Nc$. Constraints (4) limit the amounts for delivery to the avalilable inventory level at the production plant in the previous period. The specific amount delivered to customer I is limited by the parameter $D_{it}^{\max}$ in Constraints (11). Constraints (5) bound production to the capacity of production plant in each period and Constraints (6) ensure that demand on period 1 can be met by allowing production on period 0. Constraints (7) to (12) deal with the VRP. Constraints (7) and (8) ensure that if a customer is serviced on a period, then it must have a successor on its route, which may be the production plant. Moreover, Constraints (8) correspond to vehicle conservation flow; that is, if a vehicle arrives at customer *i* during period *t*, it must leave it during the same period. The number of vehicles that can leave the production plant per period is limited to the number K, as stated by Constraints (9). Constraints (10) are the vehicle loading restrictions and subtour elimination constraints in the form of the Miller-Tucker-Zemlin inequalities (Miller, Tucker, & Zemlin, 1960). Constraints (12) establishe the inventory limits at each node (e.g., plant or customers) while Constraints (13) limit the amounts loaded at each vehicle. Constraint (14) defines the lower bounds and integrality of the production, inventory and shipment amounts, while Constraint (15) defines the binary variables relating to setups, visits to customers and travelled arcs.

Boudia, Louly, & Prins (2007, 2008) propose a vehicle index model considering the additional following decision variables:

Decision variables:

X_{ijkt} Binary variable equal to 1 if vehicle *k* travels from node *i* to node *j* during period *t*, 0 otherwise

Z_{itku} Binary variable equal to 1 if and only if the demand d_{it} for day *t* is brought by vehicle *k* in period $u \le t$, 0 otherwise

The vehicle index formulation by Boudia, Louly, & Prins (2007, 2008) is detailed as follows:

$$(BLP):\ \min \sum_{t\in T}\left(sc\cdot\gamma_t + ic_0\cdot I_{0t} + \sum_{i\in N}\sum_{j\in N}\sum_{k\in K} c_{ij}\cdot X_{ijkt}\right) \quad (16)$$

subject to:

$$\sum_{\substack{j\in N\\ j\neq i}} X_{ijkt} \le 1 \qquad \forall i\in Nc, \forall k\in K, \forall t\in T \quad (17)$$

$$\sum_{\substack{j\in N\\ j\neq i}} X_{jikt} = \sum_{\substack{j\in N\\ j\neq i}} X_{ijkt} \qquad \forall i\in Nc, \forall k\in K, \forall t\in T \quad (18)$$

$$\sum_{\substack{t\in T\\ t\ge u}}\sum_{i\in Nc} Z_{itku}\cdot d_{it} \le VCap \qquad \forall k\in K, \forall u\in T \quad (19)$$

$$\sum_{i\in S}\sum_{j\in S} X_{ijkt} \le |S|-1 \qquad \forall S\subseteq Nc, |S|\ge 2, \forall k\in K, \forall t\in T \quad (20)$$

$$\sum_{\substack{u\in T\\ u\le t}}\sum_{k\in K} Z_{itku} = 1 \qquad \forall i\in Nc, \forall t\in T \quad (21)$$

$$\sum_{j\in N} X_{ijku} \ge Z_{itku} \qquad \forall t\in T, \forall u\in T \text{ with } t\ge u, \forall k\in K, \forall i\in Nc \quad (22)$$

$$I_{it} = I_{i,t-1} + \sum_{k\in K}\sum_{u\ge t} Z_{iuvt}\cdot d_{iu} - d_{it} \qquad \forall i\in Nc, \forall t\in T \quad (23)$$

$$I_{0,t} = I_{0,t-1} + P_t - \sum_{k\in K}\sum_{u\in T}\sum_{i\in Nc} Z_{iuvt}\cdot d_{iu} \qquad \forall t\in T \quad (24)$$

$$\sum_{k\in K}\sum_{u\le t} Z_{itku}\cdot u \le \sum_{k\in K}\sum_{u\le t+1} Z_{i,t+1,ku}\cdot u \qquad \forall i\in Nc, \forall t\in T \quad (25)$$

$$P_t \le PCap\cdot\gamma_t \qquad \forall t\in T \quad (26)$$

$$I_{it} \leq ICap_i \qquad \forall i \in N, \forall t \in T \qquad (27)$$

$$P_t, I_{it} \geq 0 \text{ and integer} \qquad \forall i \in N, \forall t \in T \qquad (28)$$

$$\gamma_t, X_{ijkt}, Z_{itku} \in \{0,1\} \qquad \forall i, j \in N, \forall t, u \in T, \forall k \in K \qquad (29)$$

The objective function (16) represents the total cost to be minimized, taking into account setup costs, transportation costs and inventory holding costs in production plant. Constraints (17) to (20) come from VRP. Constraints (17) and (18) are equivalent to Constraints (7) and (8) respectively. Constraints (19) forbid exceeding vehicle capacity *VCap*. Subtours defined over the set *Nc* are prevented by the exponential number of Constraints (20). In Constraints (21), the demand of each customer in each period must be delivered by only one vehicle in one day $u \leq t$. Constraints (22) determine that if vehicle k does not visit customer *i* on day *u*, it cannot bring this customer a demand for this period *u* or beyond. Constraints (23) and (24) correspond to inventory balance equations related to customers and production plant, respectively. Constraints (25) enforce a FIFO rule, that is, for each customer *i*, the demand on period *t+1* cannot be delivered before the demand of period *t*.Constraints (26) and (27) correspond to setup, production capacities and inventory limits, respectively. Constraints (28) determine the non-negativity and integrality of decision variables related to production and inventories while Cosntraints (29) are related to the binary conditions of setups and routing decision variables.

Previous formulations deal with the production of one single item. Based on Fumero & Vercellis (1999), a multiproduct and index vehicle formulation is proposed by Armentano, Shiguemoto, & Løkketangen (2011) as follows, by adding to the previous notations the following parameters and decision variables:

Parameters:

d_{pit}	Demand of product *p* at node *i* during period *t*
b_p	Time required to produce one unit of item *p*
pc_p	Unitary manufacturing cost of product *p*
sc_p	Setup cost of product *p*
ic_{pi}	Holding cost of product *p* at node *i*
f	Fixed cost per used vehicle
$PCap$	Production capacity at the manufacturing plant (in time units)
$ICap_{pi}$	Inventory capacity for product *p* at node *i*
$IMin_{pi}$	Minimun inventory level for product *p* at node *i*
L	Maximun length of each route
M	Large number, as for example $\sum_{p \in P} \sum_{i \in N} \sum_{t \in T} d_{pit}$

Decision variables:

P_{pt}	Production amount of product *p* during period *t*
I_{pit}	Inventory level of product *p* at node *i* at the end of period *t*
Q_{pikt}	Amount of product *p* delivered to customer *i* with vehicle *k* during period *t*
V_{pijkt}	Amount of product *p* transported from customer *i* to customer *j* with vehicle *k* during period *t*
γ_{pt}	Binary setup variable for product *p* during period *t* (γ_{pt} = 1, if a setup is performed for product *p* during period *t*, 0 otherwise)

X_{ijkt} Binary variable equal to 1 if vehicle *k* travels from node *i* to node *j* during period *t*, 0 otherwise

The multiproduct model by Armentano, Shiguemoto, & Løkketangen (2011) is detailed as follows:

(FV-ASL):

$$min \sum_{t\in T}\left(\sum_{p\in P}\left(pc_p \cdot P_{pt} + sc_p \cdot \gamma_{pt} + \sum_{i\in N} ic_{pi} \cdot I_{pit}\right) + \sum_{i\in N}\sum_{j\in N}\sum_{k\in K} c_{ij} \cdot X_{ijkt} + \sum_{k\in K}\sum_{j\in N} f \cdot X_{0jkt}\right) \quad (30)$$

subject to:

$$I_{p0t} = I_{p0,t-1} + P_{pt} - \sum_{i\in Nc}\sum_{k\in K} Q_{pikt} \qquad \forall p\in P, \forall t\in T \quad (31)$$

$$I_{pit} = I_{pi,t-1} + \sum_{k\in K} Q_{pikt} - d_{pit} \qquad \forall p\in P, \forall i\in Nc, \forall t\in T \quad (32)$$

$$\sum_{p\in P} b_p \cdot P_{pt} \le PCap \qquad \forall t\in T \quad (33)$$

$$P_{pt} \le M \cdot \gamma_{pt} \qquad \forall p\in P, \forall t\in T \quad (34)$$

$$\sum_{\substack{i\in N\\ i\neq k}} V_{pijkt} - \sum_{\substack{m\in N\\ m\neq k}} V_{pjmkt} = Q_{pikt} \qquad \forall p\in P, \forall j\in N, \forall k\in K, \forall t\in T \quad (35)$$

$$\sum_{i\in N}\sum_{k\in K} V_{pi0kt} - \sum_{m\in N}\sum_{k\in K} V_{p0mkt} = -\sum_{i\in N}\sum_{k\in K} Q_{pikt} \qquad \forall p\in P, \forall t\in T \quad (36)$$

$$\sum_{p\in P} V_{pijkt} \le VCap \cdot X_{ijkt} \qquad \forall i, j\in N, \forall k\in K, \forall t\in T \quad (37)$$

$$\sum_{i\in N}\sum_{j\in J} c_{ij} \cdot X_{ijkt} \le L \qquad \forall k\in K, \forall t\in T \quad (38)$$

$$\sum_{i\in N} X_{0jkt} \le 1 \qquad \forall k\in K, \forall t\in T \quad (39)$$

$$\sum_{\substack{i\in N\\ i\neq k}} X_{ijkt} - \sum_{\substack{m\in N\\ m\neq k}} X_{jmkt} = 0 \qquad \forall j\in N, \forall k\in K, \forall t\in T \quad (40)$$

$$\sum_{i\in N}\sum_{k\in K} X_{ijkt} \le 1 \qquad \forall j\in N, \forall t\in T \quad (41)$$

$$IMin_{pi} \le I_{pit} \le ICap_{pi} \qquad \forall p\in P, \forall i\in N, \forall t\in T \quad (42)$$

$$P_{pt}, I_{pit}, Q_{pikt}, V_{pijkt} \ge 0 \text{ and integer} \qquad \forall p\in P, \forall i, j\in N, \forall k\in K, \forall t\in T \quad (43)$$

$$\gamma_{pt}, X_{ijkt} \in \{0,1\} \qquad \forall p\in P, \forall i, j\in N, \forall k\in K, \forall t\in T \quad (44)$$

The objective function (30) determines the minimization of production costs, setups cost, inventory cost at production plant and at customers, and transportation costs, considering fixed per vehicle and variable distance-dependent costs. Constraints (31) and (32) represent the inventory balance at production plant, and customers, respectively. Constraints (33) establish the limits according to production capacity while Constraints (34) ensures that a setup cost is incurred in period *t* only if there is production in this period. Constraints (35) and (36) express the product conservation flow at the customers and at the production plant. According to Fumero & Vercellis (1999) the demand fullfillment in these constraints preclude the existence of subtours. On the other hand, Constraints (37) and (38) determine limits on vehicle capacity and route length, respectively. Constraints (39) ensure that each vehicle is assigned to at most one route, in each period. Moreover, each vehicle has to return to the production plant at the end of the route, as stated by Constraints (40), and no more than one vehicle can visit a customer in every period, as determined by Constraints (41). Inventory lower and upper bounds are indicated in Constraints (42). Constraints (43) define the lower bounds and integrality of the production, inventory and shipment amounts, while Constraints (44) defines the binary variables relating to setups, visits to customers and travelled arcs.

Other alternative formulations have been reviewed and classified in the next section.

4 Classification criteria

The production and transport routing problem has been tackled mainly in recent years (more than 80% of reviewed papers have been published in the last 10 years). For this reason, we propose a classification scheme based on five groups of aspects relating to modelling and solving the production routing problem: production, inventory, routing, the model of objective function and solution approach. The classification criteria corresponding to all these categories are described as follows:

1. Production aspects:
   a. Number of products: it refers to the number of manufactured products considered in each model
   b. Number of production plants: if there is/are only one single production plant or several manufacturing facilities
   c. Production capacity: it refers to the capacities of the resources available in the production system
   d. Setups characteristics: consideration of setups by including the corresponding setup costs and/or setups times, and any other characteristics relating to complex setup structures, such as sequence-dependent setups and setup carry-overs, are identified.
2. Inventory aspects:
   a. Inventory modelling: it refers to the modelling of a production plant and customer warehouses in which products can be stored
   b. Inventory capacity: the limitation of the amounts of product at the plant and/or customer warehouses imposed by inventory capacities is identified
   c. Inventory policies: it details whether the vendor-managed inventory policies for the replenishment of customers, such as, order-up-to level, maximum level, fill-fill-dump, have been considered. The existence of safety stocks levels is also described.
3. Routing aspects:
   a. Fleet of vehicles: characteristics of the available vehicles in relation to their number (single or multiple, and limited or unlimited) and capacity (if vehicles are capacitated and if capacity is equal in all the vehicles or differs)
   b. Number of trips and visits per vehicle: it refers to the numbers of trips each vehicle can do during one period by starting and finishing at the central depot
   c. Transport data: they detail the consideration of different transport parameters, such as transport time between a pair of nodes; transport distance between a pair of nodes; service, unloading or loading times; waiting times; time windows; and available operations time to complete a route
4. Modelling aspects of the objective function structure: it identifies the composition of the objective functions and enumerates their members

5. Solution approaches: these are mathematical methods and solution algorithms that have been developed to solve the proposed production and routing models, such as mathematical programming-based approaches, Lagrangian heuristics, decomposition heuristics, metaheuristics and other heuristics

4.1 *Production aspects*

According to Pochet and Wolsey (2006), production planning can be defined as planning the manufacturing activities required to transform raw materials into finished products by meeting customer demand in the most efficient or economical way possible. In this sense, production planning decisions are related to the determination of the size of the production lots for the different manufactured products, the time at which these lots have to be produced, and sometimes sequencing the production lots. The complexity of not only the production planning problem, but also its modelling and resolution, may be influenced by the number of items manufactured in the production system, the number of production facilities, and the restrictions imposed by the available productive resources. However, the consideration of production facilities manufacturing multiple products with capacity constraints enables more realistic models. Additionally, setup issues are often included in production models by considering setup costs to be a penalty in the objective function, and the setup times that can model the production changeovers between several products and the decreasing production available time capacity. In this sense, additional more complex setup types can also be considered, such as setup carry-overs and sequence-dependent setups (Karimi, Fatemi Ghomi, & Wilson, 2003), which also increase the complexity of the models because they are usually modelled by introducing zero-one variables.

Table 1 shows the above-described production aspects for each reviewed article. Among the analyzed papers, it is highlighted that the majority include models with a single production plant. Only Lei et al. (2006) and Calvete et al. (2011) propose production and routing models with production systems composed of several manufacturing plants. However, in relation to the number of products whose production planning is addressed, the difference is not as clear as in the previous case. The number of papers that propose single product models is slightly higher than the number of papers that consider manufacturing multiple products, with a difference of only four.

The capacity constraints related to available productive resources also prominate in the reviewed papers. In this sense, the authors opt for different ways to formulate production bounds, such as the maximum number of units to produce during a period, the maximum available production time, or a combination of both these options. Among them, the consideration of the maximum number of units to produce is the commonest, while the maximum available production time is addressed only in Chandra and Fisher (1994), Fumero and Vercellis (1999), Kuhn and Liske (2011) and Amorim et al. (2013). Moreover, Çetinkaya et al. (2009) include two kinds of production capacity constraints, the first corresponding to an aggregated production capacity expressed in time units, and the second is related to product-based capacity constraints, expressed in production units. A group of five references (Archetti, Bertazzi, Paletta, & Speranza, 2011; Bertazzi, Paletta, & Speranza, 2005; Chen, Hsueh, & Chang, 2009; Shiguemoto & Armentano, 2010; Van Buer, Woodruff, & Olson, 1999) assumes unlimited production capacity or productive resources with excess of production capacity without constraining the amount to manufacture during each period.

Of all the reviewed works, the vast majority deal with setups and include an associated penalty cost in the objective function. Among them, only Kuhn and Liske (2011) and Amorim et al. (2013) consider setup costs and setup times simultaneously. Moreover, Amorim et al. (2013) include sequence-dependent setup times and setup costs in their model because they address a production lot-sizing and scheduling problem which focuses on the short term. Van Buer et al. (1999) consider only sequence-dependent setup times. Despite setup carry-overs being a typical lot-sizing extension and the possibility of carrying over a setup between periods being a common practice in many industries, none of the reviewed papers includes this additional class of setup issue.

4.2 *Inventory aspects*

Since production routing problems are simultaneously composed of a production lot-sizing problem and an inventory routing problem, the corresponding mathematical programming models can present inventory balance equations that model the amounts of products stored at production plants and customer warehouses (e.g., Constraints (2) and (3)). Generally, the storage space for parts, raw materials and finished products is limited, hence upper limits for inventory can be set to model this limitation. These upper bounds for storage capacities can also determine several inventory replenishment policies on the customers side. In this sense, by assuming that there is a single decision maker responsible for providing finished products to the customer warehouses from production plants, one can distinguish models with different policies, such as a maximum level (the level of inventory on the customer side after delivery and consumption is not higher than its maximum level or upper limit), the order-up-to level (the quantity shipped to customers is such that the inventory level in the customer warehouse reaches exactly the maximum level at the end of the delivery time instant after delivery and consumption) and fill-fill-dump (the order-up-to level quantity is shipped to all but the last retailer on each delivery route, while the minimum between the order-up-to level quantity and the residual transportation capacity is shipped to the last retailer). Readers are referred to Bertazzi et al. (2005) and to Archetti et al. (2011) for a description and analysis of these policies. Moreover, the lower limits for inventories can also be taken into account in order to protect against uncertainty or due to technical restrictions, among others.

Table 2 summarizes the works reviewed in terms of modelling inventory amounts at production plants and customer warehouses, inventory capacity constraints and inventory policies. Sixteen of the analyzed papers model inventories at both the production plants and customer warehouses by setting proper inventory balance equations to the corresponding production and routing models. Two references (Kuhn & Liske, 2011; Metters, 1996) consider only inventories at the production plant because they address a different problem in which transport routes are related to inbound logistics, hence customers are not contemplated. Conversely, four references do not consider inventories at any node because they present allocation and aggregated models (Calvete et al., 2011) or short-term planning models with scheduling operations for perishable products which cannot be stored (Amorim et al., 2013; Chen et al., 2009; Van Buer et al., 1999).

Most of the reviewed papers taken into account maximum level inventories in order to reproduce realistic conditions relating to industrial environments with warehouses that have limited storage space. They all include upper levels of inventories at production plants and at customer warehouses, except Archetti et al. (2011), which consider only limitations at the customer warehouses. Order-up-to level and fill-fill-dump policies always address customers' inventories levels in the reviewed papers (Adulyasak, Cordeau, & Jans, 2013; Archetti et al., 2011; Bertazzi et al., 2005). Minimum inventory levels or safety stocks simultaneuosly at the plants and customer warehouses are mentioned only in Lei et al. (2006) and in Armentano et al. (2011).

4.3 *Routing aspects*

Transportation planning in production routing problems is based on capacitated vehicle routing problems (CVRP) principles. According to Toth and Vigo (2002), the basic version of CVRP assumes that there is a set of identical and sufficient vehicles, each with capacity *C*, available at the central depot, to serve all the customers' demand. Each vehicle may cover one route at the most and each customer can be visited only once per period at the most; that is, each customer demand cannot be split into several vehicles. Moreover, each customer demand is known deterministically. However, in order to capture more realistic constraints relating to routing aspects and available transport resources, some papers neither consider nor modify these assumptions, but may add other data parameters which address additional contraints for transportation and routing activities.

Table 3 classifies the references reviewed according to the nature of the vehicle fleet, the number of trips and visits to customers, and additional transport data. The assumption of having a homogeneous fleet of vehicles with an identical capacity available at the central depot is made in all of the reviewed papers, except Metters (1996), Lei et al. (2006) and Çetinkaya et al. (2009), which address problems closer to real-world production and routing environments. Hence they reflect the existence of several kinds of vehicles with different capacities. Moreover, this assumption implies that the fleet is composed of a set of multiple vehicles. Only Archetti et al. (2011) present different models that consider the existence of only one single vehicle available at the depot, as well as multiple vehicles. The dimension of this fleet of vehicles is mostly modelled as a limited set, although some references consider that there are no fleet size constraints (Amorim et al., 2013; Çetinkaya et al., 2009; Pankaj Chandra & Fisher, 1994; Kuhn & Liske, 2011; Metters, 1996). According to Amorim et al. (2013), this assumption is realistic since reference contracts with logistics suppliers are usually established to ensure that a fleet of sufficient size is always available.

According to the CVRP assumptions, the number of trips per vehicle during each period is limited to only one. This condition is explicitily considered in most of the papers under study because it is more appropriate because completing several routes is difficult if the considered time periods are short (e.g., days). Nevertheless, the possibility of reutilizing vehicles which have returned to the central depot after visiting all their corresponding nodes can be considered a way of making transport cost savings. In this sense, four papers allow multiple trips per period per vehicle (Adulyasak et al., 2013; Çetinkaya et al., 2009; Chandra and Fisher, 1994; Van Buer et al., 1999). Yet when customer demands exceed vehicle capacity, assuming only one visit per customer means that the routing problem becomes unfeasible. In this case, it is necessary to allow visits of multiple vehicles to each customer. This relaxation of the original CVRP conditions is known as splitting demand or SVRP (a split vehicle routing problem) and has been proposed in the following reviewed papers: Chandra and Fisher (1994), Fumero and Vercellis (1999), Lei et al. (2006), Çetinkaya et al. (2009) and Shiguemoto and Armentano (2010). Routing costs reductions can be obtained when split deliveries are allowed given the possibility of reducing the number of delivery routes. Readers are referred to Archetti et al. (2008) and to

Archetti and Speranza (2012) for a detailed study of possible savings and a survey on SVRP, respectively.

From the review process, it can be concluded that additional data parameters are linked to the time contraints to complete the corresponding routes in production routing problems. Along these lines, the papers proposed by Van Buer et al. (1999), Lei et al. (2006), Chen et al. (2009) and Amorim et al. (2013) include the travelling times between each pair of nodes and the service times related to the loading and unloading of goods. These service times are also considered explicitly as an independent parameter in Lei et al. (2006), Chen et al. (2009) and Amorim et al. (2013), while they are considered to be included in the travelling time in Van Buer et al. (1999) and Lei et al. (2006). The time spent on transport and the loading and unloading activities is limited by using two kinds of constraints: by defining a maximum available time to complete routes, or by setting time windows in each customer. In line with this, Lei et al. (2006) establish a maximum duration time for each transport route, while Van Buer et al. (1999) consider an available maximum operation time during which production and transport activities must be completed. Amorim et al. (2013) perform a set of strict time windows during which customers must be served. On the contrary, Chen et al. (2009) define soft time windows, which imply that if any vehicle arrives late at a node, it will incur a penalty, while if any vehicle arrives early, it will have to wait until the beginning of the time window.

Table 1. Production aspects of the reviewed papers

	Production aspects								
	Plants		*Product*		*Production capacity*	*Setups*			
	Single	Multiple	Single	Multiple		Setup cost	Setup time	Sequence-dependent	Setup carry-over
Chandra and Fisher (1994)	●			●	●	●			
Metters (1996)	●		●		●				
Fumero and Vercellis (1999)	●			●	●	●			
Van Buer et al. (1999)	●			●				●	
Bertazzi et al. (2005)	●		●			●			
Lei et al. (2006)		●	●		●				
Boudia et al. (2007)	●		●		●	●			
Boudia et al. (2008)	●		●		●	●			
Bard and Nananukul (2009a)	●		●		●	●			
Bard and Nananukul (2009b)	●		●		●	●			
Boudia and Prins (2009)	●		●		●	●			
Chen et al. (2009)	●			●					
Çetinkaya et al. (2009)	●			●	●				
Bard and Nananukul (2010)	●		●		●	●			
Shiguemoto and Armentano (2010)	●			●		●			
Calvete et al. (2011)		●	●		●				
Archetti et al. (2011)	●		●			●			
Armentano et al. (2011)	●			●	●	●			
Kuhn and Liske (2011)	●			●	●	●	●		
Adulyasak et al. (2012)	●		●		●	●			
Adulyasak et al. (2013)	●		●		●	●			
Amorim et al. (2013)	●			●	●	●	●	●	

Table 2. Inventory aspects of the reviewed papers

	Inventory aspects							
	Inventory modelling		*Inventory Capacity*		*Inventory policies*			
	Plant(s)	Customer(s)	Plant(s)	Customer(s)	Safety stock	Maximum level	Order-up-to level	Fill-fill-dump
Chandra and Fisher (1994)	●	●						
Metters (1996)	●							
Fumero and Vercellis (1999)	●	●						
Van Buer et al. (1999)								
Bertazzi et al. (2005)	●	●		●			●	●
Lei et al. (2006)	●	●	●	●	●	●		
Boudia et al. (2007)	●	●	●	●		●		
Boudia et al. (2008)	●	●	●	●		●		
Bard and Nananukul (2009a)	●	●	●	●		●		
Bard and Nananukul (2009b)	●	●	●	●		●		
Boudia and Prins (2009)	●	●	●	●		●		
Chen et al. (2009)								
Çetinkaya et al. (2009)	●	●	●	●		●		
Bard and Nananukul (2010)	●	●	●	●		●		
Shiguemoto and Armentano (2010)	●	●	●	●		●		
Calvete et al. (2011)								
Archetti et al. (2011)	●	●		●		●	●	
Armentano et al. (2011)	●	●	●	●	●	●		
Kuhn and Liske (2011)	●							
Adulyasak et al. (2012)	●	●	●	●		●		
Adulyasak et al. (2013)	●	●	●	●		●	●	
Amorim et al. (2013)								

Table 3. Routing aspects of the reviewed papers

	Routing aspects														
	Fleet and number of vehicles							*Number of trips and visits*			*Transport data*				
	Homegenous	Heterogeneous	Single	Multiple	Unlimited	Limited	Capacitated vehicles	Single	Multiple	Split deliveries	Travel times	Travel distances	Loading or unloading time	Time windows	Available operations time
Chandra and Fisher (1994)	●			●	●		●		●	●					
Metters (1996)		●		●	●		●	●							
Fumero and Vercellis (1999)	●			●		●	●	●		●					
Van Buer et al. (1999)	●			●		●	●		●		●		●		●
Bertazzi et al. (2005)	●			●		●	●	●							
Lei et al. (2006)		●		●		●	●	●		●	●		●		●
Boudia et al. (2007)	●			●		●	●	●							
Boudia et al. (2008)	●			●		●	●	●							
Bard and Nananukul (2009a)	●			●		●	●	●							
Bard and Nananukul (2009b)	●			●		●	●	●							
Boudia and Prins (2009)	●			●		●	●	●							
Chen et al. (2009)	●			●		●	●	●			●		●	●	
Çetinkaya et al. (2009)		●		●	●		●		●	●					
Bard and Nananukul (2010)	●			●		●	●	●							
Shiguemoto and Armentano (2010)	●			●		●	●	●		●					
Calvete et al. (2011)	●			●		●	●	●							●
Archetti et al. (2011)	●		●	●		●	●	●							
Armentano et al. (2011)	●			●		●	●	●							
Kuhn and Liske (2011)	●			●	●		●	●							
Adulyasak et al. (2012)	●			●		●	●	●							
Adulyasak et al. (2013)	●			●		●	●		●						
Amorim et al. (2013)	●			●	●		●	●			●		●	●	

4.4 Modelling aspects of the objective function structure

In the last few decades, mathematical programming formulations have been proposed for a wide range of production and transport planning problems. These formulations are optimization methods based on operations research, which determine the best possible production and/or transport plans by generally minimizing total costs, maximizing total profit, or considering other objective functions. Of the different mathematical programming techniques, most reviewed papers opt for integer linear programming or mixed integer linear programming approaches with total costs minimization objective functions, except Van Buer et al. (1999), Bertazzi et al. (2005) and Archetti et al. (2011), who propose non-linear programming models, and Chen et al. (2009), who present a non-linear programming model with a maximization profit function. Absence of transportation-related objectives, such as travel distance minimization, minimization of delays, etc., is emphasized. Indeed only Van Buer et al. (1999) address a production routing problem with a model that contains an objective function which minimizes the total travel time.

Table 4 presents the different costs included in the objective functions of the reviewed papers. Production costs, setup costs, inventory costs, and transport costs associated with travelling between a pair of nodes are the commonest costs included in the production and routing mathematical programming models. Regarding manufacturing costs, only seven references (Adulyasak et al., 2013, 2014; Amorim et al., 2013; Archetti et al., 2011; Armentano et al., 2011; Bertazzi et al., 2005; Shiguemoto & Armentano, 2010), mainly published in recent years, contemplate jointly production and setup costs. On the contrary, it is reported that the consideration of only setup costs was more usual in those papers published until 2011 (Bard & Nananukul, 2009a, 2009b, 2010; Boudia et al., 2007, 2008; Boudia & Prins, 2009; Pankaj Chandra & Fisher, 1994; Fumero & Vercellis, 1999; Kuhn & Liske, 2011). Inventory costs are included in all the reviewed models, except in those inventories where they are not allowed because of their short-term or operational orientation (Amorim et al., 2013; Chen et al., 2009; Van Buer et al., 1999) or in those where they are not modelled due to the model’s level of aggregation (Calvete et al., 2011). Despite Metters (1996) explicitly considering the decision variables representing inventory levels, their corresponding warehousing costs were not included in the objective function. Generally, these decision variables represent inventory levels at the end of each planning period, hence total inventory costs in the objective functions represent the total ending inventory costs. However, Lei et al. (2006) propose an objective function with ending inventory levels and total costs for customers and an average level of inventory costs for plants.

Transportation costs can be considered differently. The most habitual way is to include transportation costs between nodes, which are generally proportional to the distances between them. However, Metters (1996), Fumero and Vercellis (1999), Van Buer et al. (1999) and Chen et al. (2009) neglect such transport costs in order to include others. For example, Metters (1996) includes fixed costs per vehicle used in each route, as do Fumero and Vercellis (1999), who also consider fixed costs per empty vehicles returning to the production plant and variable shipping costs per unit transported between nodes. Although they can be similar to the transport costs between nodes, some authors prefer considering the transport costs between location according to the time required to complete a journey (Chen et al., 2009; Lei et al., 2006; Van Buer et al., 1999). Additionally, other costs, such as the fixed costs per delivery made to a customer, and the costs of acquiring and unloading purchased items at customer warehouses, are considered in Bard and Nananukul (2009a) and in Calvete et al. (2011), respectively.

The progressive consideration of unitary production costs in objective functions over the years is highlighted. While setup, inventory holding and transportation costs were considered jointly in first published references, except Metters (1996), Van Buer et al. (1999) and Lei et al. (2006), the production unitary costs appear for the first time in the objective function proposed by Bertazzi et al. (2005). In recent years, production costs in addition to setup, inventory and transportation costs can be considered a common pattern in the objective function models for production routing problems. However, the consideration of fixed costs per vehicle is more prevalent in those papers published until 2005. The reviewed papers do not mention whether the vehicle fleet is owned by the manufacturing company or if it is outsourced to logistics suppliers. In this context, fixed costs are associated with the vehicles owned by companies and can relate to the acquiring, maintenance or depreciation costs, while outsourced transport corresponds proportionally to distance costs, which are more frequent in those articles dealing with production routing problems which were published after 2005.

4.5 *Solution approach*

In this work, we have taken into account the classification for production planning models proposed by Buschkühl et al. (2010), who differentiate among several solution approaches types, such as mathematical programming-based approaches, Lagrangian heuristics, decomposition heuristics and metaheuristics, etc.

Among the mathematical programming-based approaches relating to the reviewed papers, it is possible to distinguish among exact methods (EX), branch and price (B&P) approaches, branch and cut (B&C) approaches and mathematical programming-based heuristics. This work considers EX as those embedded in default solvers, such as the typical branch and bound algorithm for solving mixed-integer programs, and which stop after an optimal solution has been found, regardless of any efforts made in terms of the required computation time and memory. Based on the idea that most variables are non-basic and assume a value of zero in the optimal solution, in theory, it is necessary to consider only one subset of variables when solving the production routing problem. Hence the column generation method takes into account only those variables that have the potential to improve the objective function. Column generation can be hybridized with the branch-and-bound algorithm to generate a solution method called branch-and-price (B&P). Another possibility to cut the size of the solution space is to generate valid inequalities in order to cut off irrelevant parts. If valid inequalities are introduced into the course of a branch-and-bound algorithm, the solution approach is called branch-and-cut (B&C). The hybridization of mixed-integer mathematical programming solution procedures with heuristics (MP-H) can help find high quality solutions in a reasonable computational time by profoundly exploring the promising parts of the solution space (Archetti et al., 2011).

Other solution approaches to solve a difficult optimization problem by approaching it with a simpler one are Lagrangian heuristics and decomposition heuristics. Lagrangian heuristics includes iterative solution approaches based on Lagrangian relaxation (LR). This method incurs an additional cost for violating relaxed inequality constraints by using Lagrangian multipliers. The solution to the relaxed problem comes very close to the optimal solution of the original problem. Decomposition heuristics divides the original problem into subproblems (generally production subproblems and routing subproblems), and then coordinates the solutions obtained by applying improvement heuristics.

According to Verdegay et al. (2008), the impossibility of discovering exact solutions corresponding to optimization problems, and the need to respond to the practical situations considered in many real-world cases, have led to an increased use of heuristic-type algorithms, which have proven valuable tools to provide solutions where exact algorithms do not. Metaheuristics has emerged as a result of the extensive application of these heuristic-type algorithms to many optimization problems. A metaheuristics can be defined as an iterative master process that guides and modifies subordinate heuristics operations to efficiently produce high quality solutions (Voss, Osman, & Roucairol, 1999). Metaheuristic procedures start from an initially provided solution. By exploring the search space and by exploiting accumulated search experience, they are able to obtain non-optimal solutions, which can largely satisfy the decision maker. Examples of metaheuristics algorithms include genetic algorithms (Holland, 1975), tabu searches (TS) (Glover & McMillan, 1986; Glover, 1989, 1990), simulated annealing (SA) (Černý, 1985; Kirkpatrick, Gelatt, & Vecchi, 1983), the greedy randomized adaptive search procedure (GRASP) (Feo & Resende, 1989), memetic algorithms (MA) (Moscato, 1989), ant colony optimization (ACO) (Dorigo, Maniezzo, & Colorni, 1996), the ant colony system (ACS) (Dorigo & Gambardella, 1997a, 1997b), adaptive large neighbourhood search (ALNS) (Ropke & Pisinger, 2006), scatter searches and path relinking (Glover, Laguna, & Martí, 2000; Glover, 1998), etc.

Table 5 provides the solution approaches proposed in the reviewed papers. Metaheuristics and decomposition heuristics emerge as the commonest solution methods to tackle complex production routing problems. Eight reviewed papers propose different metaheuristic algorithms, while decomposition heuristics are proposed in six of the analyzed works. Mathematical programming-based approaches are proposed only by seven references. Finally, Lagrangian relaxation and ε-exact solution methods are presented only in Fumero and Vercellis (1999) and in Kuhn and Liske (2011), respectively. The progressive utilization of mathematical programming-based approaches is highlighted, especially B&P, B&C and MP-H to the detriment of decomposition heuristics, which has been proposed until 2009. Metaheuristics has been considered to be solution methods throughout the time frame corresponding to this survey. Among them, TS is the most frequent given its simplicity and the good results obtained, especially when combined with complementary improvement methods, such as path relinking. The rest of the metaheuristics are found only in one reference each, and they progressively appear in the corresponding references in performance and sophistication order.

Next, details of each solution approach adopted by the different reviewed works are provided.

4.5.1 Mathematical programming-based approaches

Metters (1996) focuses on a practical application of a combined production routing problem about postal service division. The proposed model is solved near optimality after eliminating infeasible routes to hence reduce the possible number of routes and integer variables, and by using a mixed integer linear programming solver based on EX, such as a Simplex algorithm. Moreover, Amorim et al. (2013) quantify the impact of considering lot sizing versus batching in the production and distribution planning of perishable goods by solving the corresponding models with EX embedded in commercial solvers for small randomly generated instances.

In Bard and Nananukul (2009b) and Bard and Nananukul (2010), the original production routing problem is decomposed into a restricted master problem (relating to production problem) and several subproblems (corresponding to distribution and routing decisions) as they apply a column generation procedure. Bard and Nananukul (2009b) propose a two-step solution approach, which improves the initial B&P algorithm proposed by these authors to solve the corresponding subproblems based on firstly determining delivery quantities and then finding delivery routes by applying a VRP tabu search code (Carlton & Barnes, 1996) within the B&P framework. The computational results obtained by this solution approach improve the results obtained by the CPLEX solver within 1 hour of the CPU time by an average 12.2% for instances with up to 8 time periods and 50 customers. This improvement of solution approach performance in relation to the CPLEX solver is confirmed by the B&P algorithm used by Bard and Nananukul (2010), which adds a new branching strategy to deal with master problem degeneracy, to reduce the effects of symmetry, and to combine rounding heuristics and a tabu search with the original branch-and-price method.

Adulyasak et al. (2013) present B&C approaches for both vehicle and non-vehicle index formulations. The vehicle index uses the minimum *s-t* cut algorithm of the Concorde callable library (Applegate, Bixby, Chvátal, & Cook, 2001). Moreover, subtour elimination inequalities are added to improve the proposed algorithm's performance. For the non-vehicle index formulation, three different separation algorithms are employed to address the three different subtour eliminations constraints. Since it is very time-consuming to solve all the separation problems at each node of the branch-and-bound tree, an improvement cut generation strategy is adopted. Moreover, a heuristics to compute the upper bounds used in branch-and-cut algorithms is proposed. This heuristics is based on the adaptive large neighbourhood search (ALNS) framework proposed by Ropke and Pisinger (2006) for the VRP. Maximum level (ML) and order-up-to level (OU) inventory replenishment policies are made in the proposed index and non-index vehicle formulations. The results reveal that the vehicle index formulations are much better at finding optimal solutions. Problem instances with up 35 customers, 3 periods and 3 vehicles are solved to optimality for the ML policy within 2 hours, as are problem instances with up 25 customers for the OU policy. Moreover, problem instances with up to 50 customers, 3 time periods and 3 vehicles for the ML policy, and 35 customers, 6 time periods and 3 vehicles, can also be solved with a multi-core CPU with 8 processors in an average computing time of 2.1 hours and 0.8 hours, respectively.

Archetti et al. (2011) present two production and routing mathematical programming models. The first, which corresponds to a problem in which only one vehicle can be used in each delivery time instant, is solved by using a B&C algorithm in which the subtour elimination constraints by Gendreau et al. (1998) are introduced by using the separation algorithm of Padberg and Rinaldi (1991), and other valid inequalities (Archetti, Bertazzi, Hertz, & Speranza, 2012) are added at the beginning of the optimization process. A set of generated instances is used to evaluate the proposed B&C algorithm's performance, which obtains optimal results for instances with up 15 nodes in few seconds of computational time. Moreover, a model that considers an homogeneous fleet of vehicles with limited capacity is also presented. A three-step hybrid heuristic algorithm is proposed to solve the multivehicle problem by decomposing the problem into two subproblems, one on production and the other dealing with distribution, which are solved sequentially. Firstly, the distribution problem is solved by assuming infinite production capacity at the plant. The distribution subproblem is solved by applying a heuristics in which one retailer is inserted into the solution in each iteration. For each retailer, a mixed integer linear programming model, referred to as the single retailer problem, is solved by applying an exact algorithm based on the properties of the optimal solution, and also on the feasibility and dominance relations among the partial solutions. The production subproblem is optimally solved because it's a Wagner and Whitin (1958) class problem. Finally, the obtained solution is improved iteratively by removing and reinserting two retailers at a time, provided the solution is improved. The performance of this solution method is evaluated with the same data sets as in the B&C algorithm, and results that come close to optimality can also be obtained in short CPU times.

4.5.2 Lagrangian heuristics

Fumero and Vercellis (1999) consider a Lagrangian relaxation solution method based on relaxing balance inventory and vehicle capacity constraints, and by applying Lagrange multipliers to transform the original production routing problem into a dual model composed of four subproblems: (1) production; (2) inventory; (3) distribution; and (4) routing. These subproblems are solved by applying a simple procedure based on all-or-nothing criteria for the production subproblem; by a simple greedy procedure for the inventory subproblem; by using a linear programming solver with a distribution subproblem; and by transforming the routing subproblem into a minimum cost flow formulation. Moreover, a primal feasible solution and upper bounds are obtained heuristically to evaluate the effectiveness of the proposed solution method, which obtains an average gap of 5.5% if compared to this upper bound for instances with up to 12 customers, 10 finished goods and 8 time periods.

4.5.3 Decomposition heuristics

Chandra and Fisher (1994) decouple the original production routing problem to solve production and distribution subproblems separately and sequentially. Production scheduling is solved to optimality by adding valid inequalities and by using exact algorithms from the literature (Barany, Roy, & Wolsey, 1984; Leung, Magnanti, & Vachani, 1989). The distribution scheduling problem is then solved by taking into account the available inventories and production amounts obtained in the first step, and by also applying different heuristics, such as sweep (Gillett & Miller, 1974), neighbour rule (Rosenkrantz, Stearns, & Lewis, 1974) and 3-opt interchange (S. Lin & Kernighan, 1973), for each route created. Moreover, a coordinated production and distribution approach is proposed by using a local improvement heuristics to search for cost-reducing changes in the decoupled approach through the consolidation of deliveries and production schedules changes. Computational experiments run with three datasets demonstrate the value of coordinating production and routing with savings ranging between 3% to 20%, if compared to the decoupled approach, of 6% on average.

Two hierarchical algorithms are proposed by Bertazzi et al. (2005) to solve a production routing problem after its decomposition. The first, referred to as VMI-PDP, is similar to that proposed by Chandra and Fisher (1994). In the VMI-PDP, the production subproblem is firstly solved by assuming that all the retailers are served daily. Then given the production quantities, the distribution subproblem is solved. Given the quantity to ship to each retailer in each time instant, the production subproblem is solved again. The second algorithm, referred to as heuristic VMI-DP, is based on firstly solving the distribution subproblem, fixing the quantity that suffices to serve retailers as the initial production quantity, and then solving the production subproblem. The production problem is solved to optimality by building an acyclic network reformulation and by also determining the shortest path, as described in Lee and Nahmias (1993). The distribution and routing problem is solved by an iterative heuristic algorithm which inserts a retailer in each iteration. The solution obtained by hierarchically solving the subproblems can be improved by applying the iteratively improvement and coordination procedures between the production and distribution problems. In each iteration in the former, two retailers are temporarily removed from the current solution. Then retailers are inserted into the current solution and the production subproblem is solved in order to determine the optimal quantity to produce in each time instant. If this reduces the total cost, then the solution is modified accordingly. This iteration is repeated as long as the total cost is improved. The proposed algorithms are compared for the OU and fill-fill-dump inventory policies in relation to a traditional retailer managed inventory (RMI) policy based on randomly generated instances with 50 customers and 30 periods. The results illustrate the quality of the solutions obtained by using VMI-DP, which outperforms the RMI policy for all the considered instances, despite the required computational time being an average of 4 minutes.

Lei et al. (2006) propose a two-step solution approach to solve a production routing problem. In the first step, the model is solved as a mixed integer linear programming problem that is subject to all the constraints in the original model, except the vehicle routings are restricted to direct shipments. This phase determines production quantities, the inventory levels in the plants and distribution centres, and the number of shippings and trips per vehicle, during each time period. Then a heuristic algorithm to consolidate less than load shipments to the distribution centres is proposed to avoid direct shipments proving inefficient in the first phase by determining the routes per vehicle at each plant during each period by dropping the respective indices. When compared to the CPLEX solver, the proposed two-step approach provides the same, or a better, solution in most of the numerical instances generated with a single plant and up to 12 distribution centres, 2 vehicles and 4 time periods. Moreover, the proposed solution method is validated in a real-life supply network relating to a chemical company.

In Boudia et al. (2008), two heuristics are proposed to solve the production routing problem. The first corresponds to an uncoupled approach in which the production plan is firstly calculated to optimality with a Wagner and Whitin (1958) method and after determining the distribution plan without modifying production decisions. Firstly, the set of deliveries to customers is calculated, then the routing problem is solved by applying Clarke and Wright (1964) heuristics for VRP. Finally, a local search improvement based on 2-opt and customer exchanges with two different strategies is performed. Two coupled heuristics are also proposed, which differ only as far as the local search procedure applied at the end is concerned. The first algorithm uses the same local search improvement as the decoupled approach. The second solution method considers a local search improvement procedure which can modify the quantity delivered to each customer in 1 day, the production day, the delivery date, the delivery trip and the position in this trip. These heuristics are composed of three phases prior to the local search improvement procedure: (1) determination of the quantities to deliver each day; (2) trip construction; and (3) determination of the definitive production dates. The first phase returns a provisional amount to produce and to deliver to each customer. The second phase also applies Clarke and Wright (1964) heuristics for VRP. The third phase determines the definitive production plan based on the Wagner and Whitin (1958) algorithm. Computational tests are performed with benchmark instances, as presented in Boudia et al. (2005), which contain datasets with 50, 100 and 200 customers, 20 time periods and only one single product. The best results are obtained for the instances with 200 nodes by reducing total costs by an average of 13.40% for the first coupled version algorithm and by 15.22% for the second coupled approach if compared to the decoupled solution method. Moreover, the corresponding average running times are 3.42 seconds and 10.43 seconds, respectively.

An integer non-linear mathematical programming model for production and vehicle routing planning with time windows (VRPTW) and perishable products is proposed by Chen et al. (2009). The original model is converted into a non-linear programming model with non-negative constraints and a VRPTW in the objective function. Hence two subproblems are obtained: production scheduling and VRPTW. The production scheduling problem is solved by using a direct search algorithm, called the Nelder-Mead method, which considers boundary constraints. The routing problem is solved by applying a heuristic insertion algorithm by considering production quantities and the time start production obtained in the production phase. Then customers are inserted with a minimum cost criteria or new routes are created. Finally, routes are improved by inserting or removing nodes. For the purpose of evaluating the proposed solution method, a group of instances has been generated and is based on the benchmark instances by Solomon (1987), with 3 products and a number of customers ranging from 5 to 100. The results illustrate that the proposed algorithm can solve the considered problem for instances with up to 75 retailers within 10 minutes. Small sized instances with 5 and 6 retailers are generated to compare the performance of the proposed solution method in relation to the LINGO solver. The solutions of the proposed algorithm are better than the local optimal solutions found by LINGO with CPU times under 1s in most cases, while LINGO takes hours to find a local optimal solution.

In Çetinkaya et al. (2009), the original problem is decomposed into inventory and routing subproblems, which are solved iteratively until a cost-based improvement for the overall solution cannot be found or the limit of the maximum number of iterations is reached. The inventory subproblem seeks to determine the weekly replenishment and shipment quantities at the distribution centres, bins, and direct delivery (DD) customers, and also considers requirements at other plants. Given the weekly replenishment and shipment quantities, the routing subproblem specifies the truck routes and minimizes the actual loading and routing costs. The algorithm starts with an initial solution in which the shipment quantities for each potential DD customer is set, based on that customer's corresponding demand, to satisfy the demand constraints. The replenishment quantities from the factory warehouse to the distribution centres, bins, and other plants are set, based on the remaining overall requirements of the corresponding locations, using inventory balance constraints. The load balance constraints and demand constraints are also taken into account to determine the remaining overall requirements by the shipment quantities of the other customers. After obtaining an initial solution, the routing subproblem is solved to determine the route-based setup costs and routes by applying pre-processing to check the possible full-truck-load shipments and to then determine less-than-truck-load routes. The routing subproblem is solved for each period separately by using the Clarke and Wright (1964) algorithm with an additional improvement phase. Finally, the production subproblem is solved optimally by using the CPLEX solver. The proposed model is validated by the real data from Frito-Lay North America and is compared with benchmark instances in relation to the policies used in the considered firm. The obtained results are up to

11% better than current policies on total costs and are calculated within approximately 10 minutes.

4.5.4 Metaheuristics

Van Buer et al. (1999) solve a production routing problem based on the newspaper industry by using two local search algorithms and by also considering the option of recycling empty trucks at the end of routes to obtain cost savings. Starting with an initial solution obtained by a heuristic sort, a neighbourhood search relating to full insertion moves, lot and trucks insertion, and whole trucks insertions are included in the TS and SA heuristics. By means of computational experiments with real data from a newspaper producer, the authors conclude that the use or non-use of recycling is much more important than the choice between the better performing search algorithms. Furthermore, based on other nature behaviours, Calvete et al. (2011) present a bi-level ACS algorithm to solve the production-distribution-routing problem with multiple depots. In order to obtain an initial feasible solution, a nearest neighbour heuristics is applied. That is to say, while it is possible to add another retailer to the route, the nearest retailer to the incumbent retailer is selected to be visited from the set of accessible retailers that have not yet been visited. Then the lower level problem is solved to optimality. Next the algorithm parameters are initialized. In each iteration, a prescribed number of M feasible solutions for the bi-level problem is computed. The ant-based procedure starts with an ant that constructs a feasible multi-depot VRP solution. For this purpose, the ant, which represents a vehicle, starts at the super-depot (which is connected to the rest of depots with a null cost) and selects the depot to visit first. Afterwards, it successively selects the following retailer from the set of accessible retailers still to be visited. Whenever the selection of a retailer leads to an unfeasible solution due to the bounds imposed by vehicle capacity or because the driver's working time is exceeded, the ant returns to the super-depot via the depot visited and starts again until all the retailers have been visited. After crossing an arc, the local pheromone trail is updated. At the end of this iteration phase, the ant provides a set of routes that start and end at any depot. Then the lower level production problem is solved to optimally consider the information provided by the previous phase. Once the M feasible solutions of the bi-level problem have been obtained, the global pheromone trail is updated to reflect the quality of the solutions found. This process is iteratively run until a stop condition is reached. A set of small-sized generated instances and a group of benchmark problems ranging from 48 to 288 retailers and 4 or 6 depots and plants have been used to perform computational experiments, and have shown efficiency in terms of the CPU time consumed.

Boudia et al. (2007) propose a GRASP and two improved versions using either a reactive mechanism or a path-relinking process. The basic GRASP algorithm is based on a construction phase and a local search phase. The first phase determines the subset of customers to be visited, the amount to be delivered to each one (this amount may cover several consumption days), and the associated trips. First of all, the goal is to fulfil all the unmet demand for period t. A second step attempts to meet some of the demand during period t for future periods. In a third step, the Clarke and Wright (1964) savings heuristics is applied to improve the routing plan of vehicles. The production plan is also modified in a second phase by shifting some production days to achieve the best compromise between the setup and storage costs at the plant. The subsequent local search phase is based on changing the following for each customer in one day: the quantity delivered; the production day; the delivery date; the delivery trip; the position in this trip. The proposed GRASP becomes reactive by allowing the algorithm to find the best value on the restricted candidate list (RCL) in a small set of allowed values. Moreover, a path relinking method is proposed to improve the basic GRASP. The benchmark instances from Boudia et al. (2005) are used to compare the results obtained by the basic GRASP, the reactive version and the two versions with the path relinking procedure with the decomposition heuristics proposed in Boudia et al. (2008). The four GRASP methods obtain better results in total costs terms despite the increase noted as far as computational times are concerned, which both depend on the number of customers of the problem instances. The savings obtained through integration increase with the instance size (18.5% on average if compared with the basic heuristics two-phase decomposition method), while running times range from approximately 2 minutes (for instances with 50 customers) to 35 minutes (for instances with 200 customers). Bard and Nananukul (2009a) develop a two-phase approach to design a reactive TS algorithm to solve a production routing problem. In the first part of phase 1, an initial solution is found by solving an allocation model which determines customer delivery quantities. In the second part, these values become the demand for T independent routing problems, where T is the number of periods in the planning horizon. An efficient CVRP subroutine, also based on TS (Carlton & Barnes, 1996), is called to find the solutions. In phase 2, a neighbourhood search is performed to improve the allocations and routing assignments found in phase 1. The results obtained by performing computational experiments using the benchmark instances by Boudia et al. (2005) show improvements in all cases which range from 10% to 20% if compared to those obtained by the previous GRASP procedure of Boudia et al. (2007). However, the increase of between 3 and 5 times in running times is emphasized.

Later, Boudia and Prins (2009) address the same production routing problem by proposing an MA which creates an initial solution in 3 steps. In step 1, a production plan is determined without considering production capacities limitations. It is assumed in this step that the total amount to produce equals the total customer demand throughout the planning horizon minus the initial plant inventory. In step 2, the savings algorithm of Clarke and Wright (1964) is applied to determine the vehicle trips. Finally, the production plan is adjusted and repaired by applying a modified version of the Wagner and Whitin (1958) algorithm. Next, selection and crossover are performed to generate new solutions, which are improved with the local search procedure proposed in Boudia et al. (2007) before being selected by population management mechanisms. Computational tests are carried out with the dataset of instances in Boudia et al. (2007). Hence results obtained by the MA are compared to those obtained by the GRASP procedures and the decomposition heuristics proposed by the same authors. The experiments show that the MA can tackle the biggest instances (200 customers and 20 periods) in an average CPU time of 68 minutes, and that it obtains 23% more savings if compared to a classical decoupled approach.

Other TS applications are found in Shiguemoto and Armentano (2010) and in Armentano et al. (2011). A TS algorithm with a relaxation mechanism that allows the evaluation of infeasible solutions to guide a solution search is proposed in Shiguemoto and Armentano (2010). This algorithm constructs an initial solution by setting equal amounts to deliver to the demand levels by applying the Clarke and Wright (1964) algorithm to determine not only the routes per period, but also the production plan using an implementation of the Wagner and Whitin (1958) algorithm. A composite move is examined for each item, each customer and all the periods, and the move that leads to the smallest total cost is executed and stored in the short-term memory as a tabu. The composite move is based on three components: (1) transferring the maximum quantity from one period to another without violating inventory bounds; (2) inserting this quantity into one route; and (3) determining a new production plan based on a Wagner and Whitin (1958) algorithm by taking into account the shift of the transferred amount. Finally, a diversification strategy is performed. This TS procedure is applied to the sets of single item instances generated by Bertazzi et al. (2005), whose results, which were obtained by their heuristics for the order-up-to level inventory policy, are compared to those obtained by the TS algorithm for a maximum level policy at the customer warehouses. The computational results indicate that TS provides an average total cost reduction of 48-50% if compared to the decomposition heuristic algorithm by Bertazzi et al. (2005), while the average computational time required by the TS procedure is approximately the same as that required by the previous heuristics with properly set stopping criteria values. A set of generated instances has also been used to evaluate the performance of the proposed TS procedure for multi-item production routing problems if compared to a decoupled approach. For a set of instances of 5 and 10 items, 12 and 24 time periods, and 30, 50 and 100 customers, the proposed TS algorithm achieves 58.97% total savings on average, while the overall computational time mean is more than 6 times longer than that of the decoupled approach. Armentano et al. (2011) present two TS variants for the production routing problem: one with two phases, namely, construction and short-term memory, and one that also incorporates longer term memory to be used in a path relinking procedure. This approach also allows some infeasible solutions in the TS and path relinking procedures, which renders it easier to proceed to good solutions. Construction and short-term memory are determined in the same way as in Shiguemoto and Armentano (2010), but by considering the additional capacity constraints (production and trip length). Finally, a path relinking procedure is proposed to integrate intensification and diversification strategies into the solution method. All these solution procedures are tested in instances with multiple items generated by the authors, and also in the single item instances by Boudia et al. (2005). The two variants of the proposed TS algorithm yield good tradeoffs between the obtained savings and computational time. Moreover, these approaches outperform the MA developed by Boudia and Prins (2009) and the reactive TS proposed by Bard and Nananukul (2009a) in all the single item instances considered. The best results are obtained by the path relinking version, which achieves improvements in relation to up 8.57% for instances with 200 customers if compared to the reactive TS algorithm, although the increased computational time is an average of 46.82%.

Adulyasak et al. (2012) propose an ALNS framework based on reducing the complexity of the production routing problem by decomposing it into several subproblems, which are easier to solve. The initial solution is obtained by solving a production-distribution problem with a fix-and-optimize approach and a routing problem by using the Clarke and Wright (1964) heuristics. In additional, an initial solution is generated by applying a setup move procedure based on iteratively adding the inequalities by Fischetti and Lodi (2003) for local branching. These initial solutions are then improved in the next phase by applying ALNS. Binary variables are handled by the selection and transformation operators in the ALNS algorithm, whereas the optimal value of the remaining continuous variables is determined by a minimum cost network flow algorithm with an exact optimization algorithm. In order to evaluate the efficiency of the proposed solution method, computational experiments are performed with the benchmark instances proposed by Archetti et al. (2011) and Boudia et al. (2005). For the first dataset, the results obtained by the ALNS method are compared to those generated by the heuristic algorithm proposed by Archetti et al. (2011). For the second dataset, this comparison is made with the GRASP by Boudia et al. (2007), the reactive TS by Bard and Nananukul (2009a), the MA by

Boudia and Prins (2009) and the reactive TS with path relinking by Armentano et al. (2011). The proposed ALNS solution approach outperforms all the previous heuristics approaches as it provides high quality solutions. Thus, the improvements prove more relevant for the larger instances of the Boudia et al. (2005) datasets as the savings in total costs obtained is 7.8% versus the reactive TS with path relinking by Armentano et al. (2011) and the best previous solution method evaluated with this benchmark's instances. However, the additional computational time required by ALNS is an average of 96.56 minutes, which is 47.58% longer than that used by the TS with path relinking.

Table 4. Modelling aspects of the reviewed papers

	Modelling of objective function structure									
	Production costs	Setup costs	Inventory costs	Transport costs between nodes	Transport time costs	Fixed cost per vehicle	Fixed cost per empty vehicle	Variable cost per product transported	Fixed cost per delivery made to a customer	Acquiring and unloading cost
Chandra and Fisher (1994)		●	●	●		●				
Metters (1996)	●					●				
Fumero and Vercellis (1999)		●	●			●	●	●		
Van Buer et al. (1999)					●	●				
Bertazzi et al. (2005)	●	●	●	●		●				
Lei et al. (2006)	●		●	●	●					
Boudia et al. (2007)		●	●	●						
Boudia et al. (2008)		●	●	●						
Bard and Nananukul (2009a)		●	●	●						
Bard and Nananukul (2009b)		●	●	●				●	●	
Boudia and Prins (2009)		●	●	●						
Chen et al. (2009)	●				●					
Çetinkaya et al. (2009)			●	●		●				
Bard and Nananukul (2010)		●	●	●						
Shiguemoto and Armentano (2010)	●	●	●	●		●				
Calvete et al. (2011)	●			●						●
Archetti et al. (2011)	●	●	●	●						
Armentano et al. (2011)	●	●	●	●		●				
Kuhn and Liske (2011)		●	●	●						
Adulyasak et al. (2012)	●	●	●	●						
Adulyasak et al. (2013)	●	●	●	●						
Amorim et al. (2013)	●	●		●		●				

Table 5. Solution approaches of the reviewed papers

	Mathematical programming-based approaches				*Lagrangian heuristics*	*Decomposition heuristics*	*Metaheuristics*						*Other heuristics*
	EX	B&P	B&C	MP-H	LR		TS	SA	GRASP	MA	ACS	ALNS	ε-exact
Chandra and Fisher (1994)						●							
Metters (1996)	●												
Fumero and Vercellis (1999)					●								
Van Buer et al. (1999)							●	●					
Bertazzi et al. (2005)						●							
Lei et al. (2006)						●							
Boudia et al. (2007)									●				
Boudia et al. (2008)						●							
Bard and Nananukul (2009a)							●						
Bard and Nananukul (2009b)		●											
Boudia and Prins (2009)										●			
Chen et al. (2009)						●							
Çetinkaya et al. (2009)						●							
Bard and Nananukul (2010)		●											
Shiguemoto and Armentano (2010)							●						
Calvete et al. (2011)											●		
Archetti et al. (2011)			●	●									
Armentano et al. (2011)							●						
Kuhn and Liske (2011)													●
Adulyasak et al. (2012)												●	
Adulyasak et al. (2013)			●										
Amorim et al. (2013)	●												

5 Discussion and further research directions

Although production lot-sizing and VRP problems have been traditionally classified as mid-term problems by Karimi et al. (2003) and Crainic and Laporte (1997), respectively, most of the reviewed articles do not explicitly state their correspondence to the tactical decision level. Moreover, different nomenclatures for the names of the periods into which the planning horizon is divided are identified according to the particular issues dealt with by the addressed problems. For those multiperiod models oriented to mid-term problems, the authors opt to use generic periods or to contemplate a planning horizon divided into several days. Obviously, the vehicle routing and the distribution of final products to customers can strongly impact on production planning and scheduling, especially where perishable goods are concerned. In this context, in which operational issues are prevalent, the time periods correspond to short frames, e.g., hours, or the planning horizon reduces to include a single period. This kind of production routing problem is found less frequently in the literature; indeed we have identified three papers that deal with the operational decision level (Amorim et al., 2013; Chen et al., 2009; Van Buer et al., 1999). The main difference between tactical and operational production and the routing problem lies in the fact that, at the tactical level, distribution activities start at the end of each period, after production has been completed, while at operational level, the delivery process may start once customers' orders have been completed to more accurately and better synchronize the two planning processes (Amorim et al., 2013). Moreover in this operational decision level context, with products that have a very short lifespan, no inventory is carried from one planning horizon to the next. Hence the inventories equations at the production plant and customer warehouses are not included in the problem.

The majority of the reviewed papers assume that a single global manager coordinates the decisions made on production, inventories and routing with a centralized approach (Perea-López, Ydstie, & Grossmann, 2003). Accordingly, this decision maker has total visibility and control over the production plants and retailers, and can individually manage the inventory levels at his/her customer warehouses, as in a VMI system enriched with production and routing decisions. Along these lines, some of the reviewed papers focus on evaluating different inventory policies (maximum level, order-up to level and fill-fill dump) for the replenishment of capacitated retailer warehouses.

On the other hand, the modelling of the production system is done in a general way without considering typical lot-sizing extensions, such as back-orders, setup carry-overs, sequencing, and parallel machines, which relate more to operational issues, but most of the analyzed papers consider warehouses with limited capacity in production facilities. Moreover, the considered production-distribution systems are always composed of only one production plant (except in Calvete et al., 2011 and Lei et al., 2006) and several customers, whose number may vary. In fact, the number of customers has a much stronger impact on problem complexity than the number of production sites because of the exponential growth of problem size when determining transport routes. All the reviewed papers contemplate a routing problem with multiple capacitated vehicles, which implies solving another bin packing problem. However, classical VRP assumptions are frequently considered, such as a homogenous and limited fleet of vehicles that only can perform one trip per period and can only visit each node at least once. In this sense, these assumptions oversimplify the routing problem as far as real-world distribution networks are concerned which, under dynamic conditions, can render these problems unfeasible. Additionally, neither are the trade-offs between several conflicting criteria managed by decision makers in such environments contemplated because all the reviewed papers opt for single-objective models, which generally offer a minimized total costs function, including the production, setups, inventory and transport costs relating to total travelled distances and less frequently fixed costs per used vehicles. Given all these assumptions, solutions for real production routing problems and practical applications in industrial environments are scarce, hence the proposed models are validated mainly with numerical randomly generated datasets.

The main efforts made by the authors centre more on developing efficient solution methods for these production and distribution environments, despite their artificiality. The formidable complexity of the considered problem, formed by a combination of a lot-sizing problem and a capacitated multiperiod vehicle routing problem, indicates a common pattern for solving such problems. In general, most of the reviewed articles opt for decoupling production and routing decision,s and for solving the corresponding problems separately with proper solution methods. For example, production planning problem is frequently solved to optimality by applying the Wagner and Whitin (1958) algorithm, or its variations, or by using the exact methods embedded in MIP solvers, while vehicle routing is overcome with several well-known heuristic algorithms (e.g., Clarke and Wright, 1964). This approach can also be used as a starting point or an initial solution for constructive search heuristics and metaheuristics, which are used as post-processing solution improvement methods. Therefore, these solution procedures attempt to interconnect both problems in order to preserve the coordination of production and routing planning decisions and the corresponding savings. The impossibility of obtaining optimal solutions given the heuristic nature of the solution methods proposed is reflected in the progressive evolution made by the level of sophistication of the solution methods to obtain better results, despite the longer computational times required if compared to previous solution approaches. In this sense, a current trend in developing exact algorithms to solve the production routing problem has been identified in the works of Bard and Nananukul (2010); Archetti et al. (2011) and Adulyasak et al. (2013).

Apart from the representative seminal works of Chandra and Fisher (1994) and Fumero and Vercellis (1999), to the best of our knowledge, there is a core of researchers (Boudia and Prins; Bard and Nananukul; Armentano and Shiguemoto; Adulyasak, Cordeau and Jans and Archetti and Bertazzi) who offer 12 of the 22 reviewed papers to address production routing problems. They can be considered reference authors given their continuous work in this area. Despite their shared point of view, in this group of papers, only Armentano et al. (2011) consider a multiproduct production routing problem with production capacity constraints, while Shiguemoto and Armentano (2010) address a multiproduct, but uncapacitated, problem. On occasion, this group of reference papers compares the proposed solution methods with decoupled approaches (Chandra and Fisher, 1994; Fumero and Vercellis, 1999) and the optimal results obtained by MIP solvers for only small instances (Amorim et al., 2013). Nonetheless, a comparison of the performance of the proposed solution methods is generally made with their previously published solution methods and by using the typical benchmark instances available in the literature (Archetti et al., 2011; Boudia et al., 2005) in accordance with the problem parameters considered. For example, the instances of Archetti et al. (2011) take into account aspects such as inventory costs at customer warehouses, initial inventory at customer warehouses, and varying transportation and production costs, but not production and inventory capacity limitations. However, the datasets of Boudia et al. (2005) contemplate only one product, zero inventory costs at the customer warehouses, and problem sizes are generally larger. One of the drawbacks of both datasets is oversized available capacities.

According to the drawbacks detected in the reviewed papers, a set of future research lines can be identified to improve current production and routing models:

5.1 *More realistic models*

Firms in industrial sectors need models that provide solutions to their current production and routing challenges. Some commercial software suites are able to provide solutions to supply chain design and transport planning such as Supply Chain Guru (Llamasoft, 2015), CAPS Logistics (Infor, 2015), Insight (Insight, 2015) and JDA Supply Chain Planning (JDA, 2015), However, in the production and routing research field, there is room for improvement by developing models which incorporate more realistic planning issues on production, inventory and routing aspects. In this sense, the consideration of more accurately modelled production systems (e.g., including setup times, several production lines, overtimes, subcontrating production, etc.) and other routing problems like the configuration of time windows at customer warehouses, backhauling or open routes without having to return to the central depot, among others, can enrich production and routing models, and can also facilitate their practical application in real-world industries. Accordingly, the additional complexity of the resulting models which incorporate these additional and more realistic issues must necessarily be accompanied by solution approaches which provide good quality solutions in reasonable computational times for industrial and logistics managers or for decision makers in these firms.

5.2 *Consideration of uncertainty*

Production routing problem environments can be subjected to the influence of uncertainties that relate to procurement, manufacturing and transportation activities, and also to customer preferences or market conditions. However of the reviewed papers, only Chen et al. (2009) consider uncertainty conditions relating to demand levels. According to Mula et al. (2006) and to Peidro et al. (2009), the literature provides several approaches to address these uncertainty conditions, such as the analytical approaches, simulation approaches and hybrid approaches (based on the integration of analytical and simulation models) that represent uncertainties based on probability distributions, which are generally based on historic data. However, when statistical data are unreliable or are not available, models based on probability distributions are not the best choice (Wang & Shu, 2005). In this context, fuzzy mathematical programming can be an alternative approach to model and integrate all the different types of uncertainty inherent to production and routing planning processes to help develop robust models that can give flexible, valid plans in these uncertainty environments.

5.3 *Focus on inbound vehicle routing*

The production and transport routing problem is defined by the consideration of simultaneously planning production amounts and routes to serve manufactured final products to the respective customers. However, the consideration of vehicle routing planning for inbound logistic processes that perform the procurement of parts and raw materials in a material requirement planning industrial system can be most challenging. In line with this, vehicles would travel among multiple suppliers to collect the components required to manufacture finished goods according to the bill of materials, and also to the corresponding stock levels at the production plants. To address this new problem, procurement vehicle routes can be better synchronized with production processes, thus obtaining savings in logistic, production and inventory costs, especially in those industries with complex bills of materials, such as automobile and aeronautic firms, which are generally responsible for their procurement transport processes.

5.4 *Globalization and different transport modes*

The increase in worldwide commercial transactions corresponding to the procurement of components and raw materials in countries with lower labour costs made by western companies and their corresponding sales in different countries or continents implies developing production and routing models that explicitly consider long-distance transportation issues and different transport modes (e.g., truck, railway, ship, plane) with their corresponding travel transit times, costs and inherent routing constraints. Moreover for both short- and long-distance transport processes in production routing problems, the simultaneous consideration of different collection and delivery strategies, such as direct deliveries, milk runs, grouping and cross-docking consolidation, can also improve the flow of products among partners, cut transport delays and, hence, lower larger inventory levels at warehouses that go against them.

5.5 *Environmental and social responsible constraints*

Current production and distribution logistics strategies are not sustainable in the long term because of their negative impact on environmental and social aspects despite being economically feasible. For example, relocation of manufacturing activities in countries with lower costs can increase the carbon footprint associated with the production and delivery of products, as well as destruction of employment in countries of origin. Hence, a new perspective that focuses on evaluating plans from not only the economic cost viewpoint, but also from an ecological and social perspective, have to be taken into account when modelling production routing problems. In this sense, the new constraints relating to waste management, emission of dangerous gases and noises produced by production (Chaabane, Ramudhin, & Paquet, 2012; Deif, 2011; Elhedhli & Merrick, 2012) and transport processes (Demir, Bektaş, & Laporte, 2014; C. Lin, Choy, Ho, Chung, & Lam, 2014; Park & Chae, 2014), and improved worker conditions, among others, can be added to current production routing problem models to tackle environmental and social requirements.

5.6 *Better benchmarks*

In order to validate proposed production and transport routing problems, and examine the effectiveness of solution methods, a set of benchmarks inspired in real industrial and logistics environments is required. To the best of our knowledge, current available dataset instances in the literature are artificially generated and are oversized if compared with available capacities. In this sense, the development of a new group of instances which contains parameters deriving from a rich description of constraints related to realistic production routing problems would be interesting. The consideration of the above future research lines in designing this new dataset would also be valuable, as would their publication on the Internet where they would be available for researchers in this field.

6 Conclusions

This work reviews the optimization models for integrated production and transport routing planning decisions given the recent interest shown in this field, and also the increase in the number of publications on production routing problems. To examine the selected papers, a classification based on the analysis of the following criteria has been proposed: production; inventory and routing aspects; modelling aspects of the objective function structure and solution approach. Moreover, a discussion of the findings and the proposal of future research lines have been provided in accordance with the detected trends and drawbacks. The reviewed papers dealing with production and routing planning decisions present models with simple production and transport issues and single objective approaches. Real applications in industrial environments are not common because researchers centre more on developing efficient solution methods that are validated with artificially generated datasets. In our opinion, the production routing problem is extremely challenging. Therefore, effective methods that can obtain good quality solutions in a reasonable running time for highly realistic models which consider uncertain conditions, inbound logistic processes and different transport modes is a path left open to conduct new research works given their possible impact on industrial applications.

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