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“Competitiveness based on logistic management: a real case study”

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Competitiveness based on logistic management: a real case study

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Abstract An efficient and effective logistic system is a strategic objective in any productive business. This paper presents a real case study of a routing problem in a food industry firm. This problem is solved as a Vehicle Routing Problem (VRP) using the Neural Network (NN) and Tabu Search (TS) algorithms. A customer selection based on a profitability analysis was carried out. The aforementioned algorithms were then applied, leading to a considerable reduction in the total logistic costs. This resulted in an improvement in the company's competitiveness and profit.

Keywords Logistic management · Tabu search · Neural network · Vehicle routing problem

1 Introduction

Logistics management is of particular relevance in highly competitive industries such as the food industry. Logistic costs constitute an important percentage of the total costs in this industry, and the product must be supplied with extreme punctuality (Tarantilis and Kiranoudis 2002). The industry in question is interested in reducing transport costs while maintaining quality, particularly when dealing with fresh and perishable products. This is because each delay may have negative consequences as regards product quality. An inefficient distribution system signifies that products will not reach their destinations on time, and the volume ordered reduces storage space and raises costs considerably. This results from the fact many

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products are returned by traders, which complicates the process of making the optimal logistic decision (Tarantilis and Kiranoudis 2001). It is therefore essential to determine optimal routes with the principal objective of minimizing the distance, costs and time, whilst maintaining the quality of products (Faulin et al. 2011).

This work is focused on reducing logistic costs, i.e. transport, commercial, administration and packing, in a food industry company, in order to maximize profits. The following phases were involved in this process:

- (a) A customer profitability analysis (CPA) was used for customer portfolio redefining. CPA refers to the allocation of revenues and costs to customer segments or individual customers. This allows the profitability of these segments and/or individual customers to be calculated (Van Raaij et al. 2003). A Pareto analysis has been shown to be an effective measurement tool with applications in this type of analysis, and can identify a profitable customer. This type of analysis has been used in previous empirical studies (Zeithaml et al. 2001; Horngren et al. 2001; Reinaldo et al. 2008).
- (b) It was necessary to minimize the principal logistic costs: transport costs. The use of computerized methods in distribution processes often results in a reduction in transport costs of between 5 % and 20 % (Toth and Vigo 2002). For example, given a set of customers with known geographical locations and demands, the problem consists of designing an optimal number of routes that will minimize the total distance traveled. Since this is a traveling salesman problem (TSP) each route starts and ends at the depot, and each customer is visited exactly once. In this work, this TSP is expanded to a VRP since there are different demand requirements at each node.

The food industry has already been considered in an empirical manner (i.e. Tarantilis and Kiranoudis 2002; Faulin 2003; Hsu and Feng 2003; Prindeviz et al. 2003; Prins 2004 and Ma et al. 2012). However, the authors of this paper have not found any research work in literature that can solve the problem presented herein as regards the purchase volume, frequency of orders, or type and prices of the products demanded by customers. One important contribution of the work presented in this paper is, therefore, that its application permits several increases in profits as regards total sales of 75 %, based on several logistic cost reductions. This empirical evidence supports the theory basis of CPA and the optimal routes design in order to reduce logistic costs and increase profits.

2 Company descriptions

This case study was conducted in an important firm in the fresh food industry with a large commercial structure, including a logistics department that has expanded and become consolidated in the Spanish market and has a relevant presence in the EU market, Portugal, Italy and France. In Spain, the firm has segmented the market in the following areas in order to maximize its control of operations: Central Area, Northern Andalucía, Western Andalucía, Eastern Andalucía, Extremadura and Castilla y León. This research is focused on a case study in the region of Extremadura.

The route design is initially carried out by experienced workers, who do not use any formal mathematical methods or specific software. The firm chooses new customers without using any logistical or economical criteria, except that of maximizing sales. The result is that a large number of customers are based on a policy of maximizing sales. This, however, generates a significant growth in logistic costs.

Fig. 1 Company's sales distribution

Fig. 2 Characteristics of the customers selected and not selected

2.1 Customer analysis

In a competitive context, as a food industry, information about customers is increasing. More specifically, information about customers' profitability is considered to be one of the most important pieces of information in logistics management for logistic cost reduction. Profitability depends on sales and whether these sales allow the cost of serving customers to be recovered. It is therefore necessary to know the most important factors that influence this cost of serving (Decoene and Bruggeman 2006).

Customer profitability varies greatly in a typical company, but in general the most profitable twenty percent of customers generate eighty percent of the company's profits (Kaplan and Cooper 2000). This is the Pareto rule, also known as the "80:20 rule". Pareto observed that a small number of causes are responsible for a great number of results (Dorota and Michal 2007).

An analysis of company's sales distribution confirms Pareto's rule, showing that approximately 20 % of the total customers demand 80 % of the total (Fig. 1).

The next step is to determine the differences between customers as regards their consumption of resources. The size and number of orders, the number of sales visits, the use of helpdesks and various other services may be very different for each customer. Information technology makes it possible to record and analyze more customer data (number of orders, number of sales visits, number of service calls) in order to calculate customer profitability (Van Raaij et al. 2003; Van Raaij 2005).

A new scenario has been defined based on only 20 % of customers (Fig. 2) distributed on three routes. The characteristics of the customers selected are:

- (i) large volume of product demanded;
- (ii) orders take place with the same frequency (twice a week);

Fig. 3 Customer distribution (Badajoz)

Fig. 4 Customer distribution (Cáceres)

- (iii) large orders for the same type of products, and
- (iv) less salesman visits needed

The types of customer are: 71 % wholesale, 21 % retailers and 8 % manufacturers. These percentages suppose an increase in wholesale customers (11 %) and a reduction in retailer customers (10 %).

An emplacement analysis of the customers was carried out in order to optimize the routes defined by the firm. The cities, denoted in this paper as nodes, and the percentage of customers in these cities are shown in Figs. 3 and 4.

3 The model

The route design consists of finding a route covering the shortest distance that visits all the nodes (cities). The simplest case is referred to as the TSP. Given a set of cities and the cost of travel or distance between each possible pair, the TSP is to find the best possible way of visiting all the cities (only once for each) and returning to the starting point, that will minimize the travel cost or distance.

The VRP expands the TSP to include different service requirements at each node and different capacities for vehicles in the fleet. The VRP is one of the combinatorial optimization problems most frequently studied owing to both to its practical relevance and its considerable difficulty (Toth and Vigo 2002). A VRP problem is proposed in order to find a collection of K simple circuits (corresponding to vehicle routes) with the minimum cost, defined as the sum of the costs of the arcs belonging to the circuits, and such that:

- (i) each circuit visits the depot vertex.
- (ii) each city is visited by exactly one circuit.
- (iii) each city has a specific demand.

The problem is formulated as a Hamiltonian cycle, i.e., the problem is defined by the graph $G = (V, E)$, where $V \in R^2$ is a set of n cities and E is a set of arcs connecting these cities. Under these conditions, the problem can be formulated as:

$$\text{Minimize: } \sum_{i < k} c_{ij} x_{ij}, \quad (1)$$

where x_{ij} is the binary decision variable, which in the case of $i < j$ has the following values:

$$x_{ij} \begin{cases} 1 & \text{if the arc joining cities } i \text{ and } j \text{ is used in solution} \\ 0 & \text{otherwise} \end{cases},$$

subject to the constraints:

$$\sum_{i < k} x_{ik} + \sum_{j < k} x_{kj} = 2, \quad (1a)$$

$$k = 1, 2, \dots, n, \quad (1b)$$

$$\sum_{i, j \in S} x_{ij} \leq |S| - 1, \quad (1c)$$

$$S \subset V, \quad 3 \leq |S| \leq n - 3, \quad x_{ij} \in \{0, 1\}, \quad (1d)$$

$$i, j = 1, 2, \dots, n, \quad i < j,$$

where c is the associated cost matrix of E , composed of the elements c_{ij} which represent the “distance” (expressed as physical distance, cost, time, etc.) between the cities i and j , where the Euclidean conditions signify that $c_{ij} \leq c_{ik} + c_{kj}$ for all $i, j \in V$. The constraints ensure that:

- (i) All the cities are connected to each other.
- (ii) Subpath S is eliminated, since the subpath should not be defined for $|S| = 2$ and $|n - 2|$, because restrictions (1c) and (1d) ensure that no subpath is generated between two cities.

Model (1) contains $n(n - 1)$ binary variables, with $2n$ constraints and $2^n - 2(n - 1)$ subpaths constraints that need to be removed, making it highly complex and costly from a computational point of view. This work considers the restrictions proposed by Miller et al. (1960), which can reduce the number of subpaths (Gouveia and Pires 1999), also referred to as disposal restrictions. In these new restrictions it is necessary to consider the new variables u_i ($i = 2, \dots, n$) given by:

$$u_i - u_j + (n - 1)x_{ij} \leq n - 2, \quad i, j = 2, \dots, n, \quad i \neq j, \quad (1e)$$

$$1 \leq u_i \leq n - 1, \quad i = 2, \dots, n. \quad (1f)$$

The restriction (1e) indicates that the solution does not contain a subpath in all cities $S \subseteq V$ and that all the subpaths contain more than n cities. The restriction (1f) ensures that the u_i variables are defined only for each subpath.

A number of algorithms can be used to find optimal tours, but none are feasible for large instances since they all grow exponentially in terms of computational cost (Ganesh et al. 2007). The practical importance of the VRP provides the motivation for the effort involved in the development of metaheuristics algorithms (Baldacci et al. 2007). Several metaheuristics

have been proposed for the VRP in recent years. The six main types of metaheuristic that have been applied to the VRP are: Simulated Annealing (SA), Deterministic Annealing (DA), Tabu Search (TS), Genetic Algorithms (GA), Ant Systems (AS), and Neural Networks (NN) (Gendreau et al. 2002). In this paper, the problem has been solved by using TS and NN algorithms.

3.1 Neural network algorithm

The (NN) algorithm originated in the 50s, and was used for optimization by Hopfield and Tank (1985). NN is usually employed in combinatorial optimization problems to calculate routes for the structure and characteristics of the case study presented in this paper (Peterson 1990; Potvin and Robillard 1995; Abdolhamid et al. 1997; Leung et al. 2004). NN algorithm is based on concepts related to the human brain mechanism, and they are inspired by the neuron system.

NN consists of processing units, called artificial neurons, which are organized in layers. One of the advantages of NN is that it requires a minimum computational cost in comparison to that required by exact algorithms and other heuristics algorithms. NN can learn from a reference solution set. This process takes place in an adaptive manner in which the connection between neurons is adjusted in order to implement the desired behavior (which in this research work will be to minimize the total distance covered). New advantages have been found in self organization, in which NN organizes the information received during training time, and it can work online, i.e., the computational operations are carried out in parallel, thus minimizing the information lost during the process, etc. (Sivanandam et al. 2006).

The NN can be single layered, with an input and output layer, or multiple layered, i.e. with an input, hidden and output layer-net (Sivanandam et al. 2006). A multiple NN is employed in this paper because it allows consistent results to be obtained and solves this type of problems efficiently (Fig. 5).

After an NN has been developed and trained in a learning phase, NN will provide new results by itself. The number of neurons in the input and output is determined automatically. However, the number of hidden layers and neurons in each hidden layer has been defined by multiple combinations tested for NN. The NN approach in this paper is based on the following functions (see Fig. 6):

Fig. 5 Neural Network with three layers

Fig. 6 Main functions of the NN approach

Fig. 7 Neighborhood solution obtained by swapping the order of visiting cities 5 and 2

- (i) *Pdv Function*: This function creates a weight matrix, which gives an importance weight to the entries. It also creates a route pattern, generating a vector path or solution.
- (ii) *Geper Function*: This generates the permutations necessary for the *pdv* function.
- (iii) *Dpdv Function*: This finds the path, starting from the vector map generated by a function called *pos*.
- (iv) *Fc Function*: *Fc* does the learning in order to obtain the reference optimal solutions.

The function command is $fc(N, A)$, where N is the number of nodes and A represents the matrix of distances between the different nodes.

3.2 Tabu search algorithm

The TS algorithm is based on artificial intelligence using the concept of memory. It has been implemented through the use of simple structures. TS is considered to be a metaheuristic algorithm and was developed by Fred Glover in 1986 as an alternative with which to solve the principal problems confronted by classical search algorithms. TS is one of the most frequently used algorithms in empirical research in VRP, with excellent results (Gendreau et al. 1994; Lee et al. 2008; Derigs and Reuter 2009). In this respect Courdeau and Laporte (2004) noted that:

“While the success of any particular method is related to its implementation features, it is fair to say that tabu search clearly outperforms competing approaches”.

TS explores the solutions by moving in each iteration from a reference solution to the best solution in its neighborhood. A neighborhood to a reference solution is defined as any solution that is obtained by a pair wise exchange of any two nodes in the solution. This always guarantees that any neighborhood to a feasible solution is a feasible solution (Fig. 7).

The new solution may deteriorate when it is moved from one iteration to another (Ganesh et al. 2007), as opposed to the classical local descent search methods. This can be avoided by using a list that contains recent modifications that have occurred during the transformation from the current solution, called a tabu list. The tabu list only permits new solutions if the method improves the best solution obtained.

The TS approach used in this paper has the following two primary functions:

Table 1 Distances and runtimes (NN) and (TS) algorithm

	Route 1		Route 2		Route 3	
	Distance (km)/ time (h)	Runtime (s)	Distance (km)/ time (h)	Runtime (s)	Distance (km)/ time (h)	Runtime (s)
Before	1237.3/20.15	–	1353.5/21.23	–	1442.6/20.56	–
Neural network	922/15.45	1.875	804/13.55	14.25	874.5/12.45	5.219
Tabu search	925.8/14.54	0.187	804/13.55	0.125	874.5/12.45	0.110

- (i) *Tabu Function*: This function will generate all the possible permutations with which to discover the minimum route.
- (ii) *List Function*: This function contains the tabu list which includes the solutions that have been explored, such that these solutions will not be considered.

TS also employs the *tabu* function (A , path), in which path is a vector composed of the initial solutions, and A represents the matrix of distances.

3.3 Results

Table 1 shows the reduction in the distances between the routes initially implemented by the firm and the routes obtained with the NN and TS algorithms when applied to the selected customers.

As discussed in previous sections, these algorithms solve problems of NP-hard computational complexity. As will be noted, the solutions generated by both methods (Table 2) are almost the same, but if the travel order is analyzed, then the solution obtained by NN is better than that obtained by the TS, based on the location of populations.

However, the variable algorithm ‘execution time of use’ varies considerably between algorithms. This is because NN considers a learning process and requires more time to find the solution.

The NN algorithm is more useful than the TS algorithm when there are more nodes, because in the NN algorithm the number of possible solutions is equal to the number of nodes elevated to log (2), whereas in the TS method the number of possible solutions is equal to the number of nodes elevated to 2.

4 Logistic cost analysis

An important proportion of costs in a typical business is provided by logistic decisions (Christopher 2011). Logistic cost analysis is one the main references when managing the logistic operations. The authors of this paper have used the state-of-the-art (i.e. Lysons and Gillingham 2005) as a basis to consider logistic costs as being: transport, administration, commercial and packing costs. This section will compare logistic costs from the reference scenario with the new scenario designed in this paper given by a selection of customers and the implementation of the VPR solution.

4.1 Transport costs

Giblin (2001) observed that transportation is the greatest single cost category in logistic costs. The transportation costs take into account the distance traveled, the vehicle capacity

Table 2 Routes

Route 1	Route 2	Route 3
<i>Neural network</i>		
(a) Valdepeñas	(a) Valdepeñas	(a) Valdepeñas
(b) Talayuela	(b) Talarrubias	(b) Mérida
(c) Navalmoral de la Mata	(c) Villanueva de la Serena	(c) Calamonte
(d) Casatejada	(d) Don Benito	(d) Montijo
(e) Jaraiz de la Vera	(e) Santa Amalia	(e) Talavera la Real
(f) Plasencia	(f) Almoharín	(f) Campo Maior
(g) Torrejoncillo	(g) Miajadas	(g) Elvas
(h) Coria	(h) Trujillo	(h) Badajoz
(i) Moraleja	(i) Cáceres	(i) Corte de Peleas
(j) Alagón del Caudillo	(j) Arroyo de la Luz	(j) Almendralejo
(k) Cuacos de Yuste	(k) Malpartida de Cáceres	(k) Zafra
(l) Villanueva de la Vera	(l) Aldea Moret	(l) Puebla de Sancho Pérez
(m) Candeleda.	(m) Valdepeñas	(m) Valdepeñas
(n) Valdepeñas		
<i>Tabu search</i>		
(a) Valdepeñas	(a) Valdepeñas	(a) Valdepeñas
(b) Navalmoral de la Mata	(b) Talarrubias	(b) Mérida
(c) Moraleja	(c) Villanueva de la Serena	(c) Calamonte
(d) Coria	(d) Don Benito	(d) Montijo
(e) Torrejoncillo	(e) Santa Amalia	(e) Badajoz
(f) Alagón del Caudillo	(f) Almoharín	(f) Elvas
(g) Plasencia	(g) Miajadas	(g) Campo Maior
(h) Cuacos de Yuste	(h) Trujillo	(h) Talavera la Real
(i) Jaraiz de la Vera	(i) Cáceres	(i) Corte de Peleas
(j) Casatejada	(j) Arroyo de la Luz	(j) Almendralejo
(k) Talayuela	(k) Malpartida de Cáceres	(k) Zafra
(l) Villanueva de la Vera	(l) Aldea Moret	(l) Puebla de Sancho Pérez
(m) Candeleda	(m) Valdepeñas	(m) Valdepeñas
(n) Valdepeñas		

and the duration of the tour (Rentizelas et al. 2009). In this work, the transport cost is set per kilometer (€/km). This cost will depend on the vehicle capacity, the price of fuel, and the drivers' salaries.

4.2 Commercial costs

Commercial costs are basically composed of the sellers' salaries. In the reference scenario, there were four sellers and a sales manager. The new scenario will require a seller and a sales manager for each of the 3 routes selected.

4.3 Administration cost

The administration costs include the costs of indirect personnel and support staff, the central distribution personnel, inventory planning analysis personnel, and the personnel related to administrative management, among which is the cost of receiving, processing and verifying orders, and finally the billing and other department costs. An allocation rule is used as an indirect cost, concretely cost per invoice.

4.4 Packing cost

The packing costs include the cost of retrieving a pallet, carton or item from its storage location and transporting it to the staging area to be packed and prepared for its transportation. The packing costs depend on the type of product. Table 3 shows the percentages of the main products over the average.

Table 4 shows a comparison between the initial situation and the new scenario. Costs are a % of total sales.

The most relevant result is that logistic costs have been reduced from 12 % to 6 % of total sales, and the profits have increased from 5 % of total sales to more than 9 %. A comparison of the logistic costs is shown in Fig. 8 below.

Finally, the aforementioned analysis that was carried out in the region of Extremadura could be extrapolated to the remaining national regions and to the international distribution areas.

Table 3 Packing cost percentages over the average

Product	(%) Average
Pork channel	37.84
Cutting-packing pork	157.66
Frozen pork	37.84
Beef channels	44.14
Cutting-packaging beef	217.57
Lamb	126.13
Processed	78.83

Table 4 Comparison of analytical result accounts

	New proposal	Before
Sales	100.00 %	100.00 %
Atypical cost	(0.38 %)	(0.31 %)
Net sales	99.62 %	99.69 %
Cost of sales	(83.74 %)	(83.09 %)
Industrial margin	15.88 %	16.61 %
Transport cost	(2.99 %)	(6.47 %)
Commercial costs	(1.60 %)	(3.05 %)
Picking cost costs	(1.20 %)	(1.15 %)
Administration costs	(0.82 %)	(0.63 %)
Profit	9.26 %	5.31 %

Fig. 8 Percentages of logistic costs over sales

5 Conclusions

This case study has shown that an appropriate logistics management can significantly reduce logistic costs by more than 60 %, and increase profits by more than 75 %, based on the fact that:

- An uncontrolled growth of customers causes an important increase in logistics costs, thus reducing a company's profits. The inclusion of customer profitability represents a substantial change in the way in which organizations think about their logistics activities. The elimination of the non-value adding customer has limited effects on sales, but commercial and transport costs have been reduced. Commercial management must be consistent with the company's logistics management. Logistic cost analysis systems tend to generalize the total cost of route assigning as being the same as a rate per unit of sales to all customers. This work demonstrates that the inclusion or removal of customers in a logistic model may significantly alter the total costs of the route. A company's commercial department must not only be interested in selling its products but also in knowing what the associated costs are if an increase in sales and an improvement in profitability are to be attained.
- This paper shows that implementing algorithms in order to solve various instances of VRP can significantly reduce the transportation costs that occur during the delivery process. The computational performance of these algorithms produces good results in a short computational time. The company's management was satisfied with the performance of the algorithm and decided to use it in their weekly distribution.

According to these results, the first conclusion is to consider a new customer portfolio based on the profitability criterion. Secondly, it is possible to optimize the transport costs by minimizing the distance covered using the NN and TS algorithms.

The results of this study should be interpreted with caution owing to certain limitations. One important limitation is the elimination of non-value adding customers. This is likely to have negative consequences: (a) it could lead to the loss of remaining customers that the abandoning firm would like to retain, and (b) it could influence potential customers not to join the focal company but rather one of its competitors (Haenlein and Kaplan 2011). This depends on the use of two types of abandonment approaches. The first of these is a direct approach in which the company explicitly states to the customer that it wishes to terminate the relationship. The second is an indirect approach in which no explicit statement of the goal is provided. In this case, the company uses an indirect abandonment strategy, such as increases in prices based on higher logistics cost. Mittal et al. (2008) state that indirect abandonment strategies are associated with less severe negative consequences than direct ones. The same authors also stress that eliminating unprofitable customers can generate benefits beyond a

pure increase in profitability. These include improved employee productivity, reduced capacity constraints, and better strategic alignment between the customer base and business objectives. Secondly, this case study has additionally revealed quite a large proportion of unprofitable customers for the company, which is worthy of a further specific and in-depth study. Thirdly, this work does not include the constraints related to priority orders, and the time constraints are not implemented in the delivery centers. Finally, although a single case study does not allow the results to be generalized to other settings, the combination of prior studies and empirical data presented in this study provides a strong indication that customer profitability analysis and effective route design are useful.

References

- Abdolhamid, T., Somhon, S., & Enkawa, T. (1997). A competitive neural network algorithm for solving vehicle routing problem. *Computers & Operations Research*, 33, 473–476.
- Baldacci, R., Toth, P., & Vigo, D. (2007). Recent advances in vehicle routing exact algorithms. *4OR: A Quarterly Journal of Operations Research*, 5, 269–298.
- Christopher, M. (2011). *Logistics and supply chain management: creating value-adding networks*. Edinburg: Pearson Education.
- Decoene, V., & Bruggeman, W. (2006). Strategic alignment and middle-level managers' motivation in a balanced scorecard setting. *International Journal of Operations & Production Management*, 26, 429–448.
- Derigs, U., & Reuter, K. (2009). A simple and efficient tabu search heuristic for solving the open vehicle routing problem. *Journal of the Operational Research Society*, 60, 1658–1669.
- Dorota, K., & Michal, K. (2007). Activity-based costing and customer profitability. *Cost and Management*, 21, 18–25.
- Faulin, J. (2003). Applying MIXALG procedure in a routing problem to optimize food product delivery. *Omega*, 31, 387–395.
- Faulin, J., Juan, A., Lera, F., & Grasman, C. (2011). Solving the capacitated vehicle routing problem with environmental criteria based on real estimations in road transportation: a case study. *Procedia - Social and Behavioral Sciences*, 20, 323–334.
- Ganesh, K., Nallathambi, A. S., & Narendran, T. T. (2007). Variants, solution approaches and applications for vehicle routing problems in supply chain: agile framework and comprehensive review. *International Journal of Agile Systems and Management*, 2, 50–75.
- Gendreau, M., Hertz, A., & Laporte, G. (1994). A tabu search heuristic for the vehicle routing problem. *Management Science*, 40, 1276–1290.
- Gendreau, M., Laporte, G., & Potvin, J. Y. (2002). Metaheuristics for the VRP. In P. Toth & D. Vigo (Eds.), *SIAM monographs on discrete mathematics and applications. The vehicle routing problem* (pp. 129–154). Philadelphia: SIAM.
- Giblin, J. (2001). Transportation: the forgotten link in the supply chain. <http://www.ascet.com/html>.
- Gouveia, L., & Pires, J. M. (1999). The asymmetric travelling salesman problem and a reformulation of the Miller–Tucker–Zemlin constraints. *European Journal of Operational Research*, 112, 134–146.
- Haenlein, M., & Kaplan, A. M. (2011). Evaluating the consequences of abandoning unprofitable customers: a comparison of direct and indirect abandonment strategies. *Zeitschrift für Betriebswirtschaft*, 81, 77–94.
- Hopfield, J. J., & Tank, D. W. (1985). 'Neural' computation of decisions in optimization problems. *Biological Cybernetics*, 52, 141–152.
- Horngren, C. T., Foster, G., & Datar, S. M. (2001). *Cost accounting: a managerial emphasis*. Upper Saddle River: Prentice Hall.
- Hsu, C. L., & Feng, S. (2003). Vehicle routing problem for distributing refrigerated food. *Journal of the Eastern Asia Society for Transportation Studies*, 5, 2261–2272.
- Kaplan, R. S., & Cooper, R. (2000). *Cost & effect: using integrated cost systems to drive profitability and performance*. Boston: Harvard Business School Press.
- Lee, B. K., Kang, K. H., & Lee, Y. H. (2008). Decomposition heuristic to minimize total cost in a multi-level supply chain network. *Computers & Industrial Engineering*, 54, 945–959.
- Lysons, K., & Gillingham, M. (2005). *Purchasing and supply chain management*. London: Prentice Hall.
- Leung, K. S., Jin, H. D., & Xu, Z. B. (2004). An expanding self-organizing neural network for the traveling salesman problem. *Neurocomputing*, 62, 267–292.

- Ma, H., Cheang, B., Lim, A., Zhan, L., & Zhu, Y. (2012). An investigation into the vehicle routing problem with time windows and link capacity constraints. *Omega*, 40, 336–347.
- Miller, C. E., Tucker, A. W., & Zemlin, R. A. (1960). Integer programming formulation of traveling salesman problems. *Journal of the Association for Computing Machinery*, 7, 326–329.
- Mittal, V., Sarkees, M., & Murshed, F. (2008). The right way to manage unprofitable customers. *Harvard Business Review*, 86, 95–102.
- Peterson, C. (1990). Parallel distributed approaches to combinatorial optimization: benchmark studies on travelling salesman problem. *Neural Computation*, 2, 261–269.
- Potvin, J. Y., & Robillard, C. (1995). Clustering for vehicle routing with a competitive neural network. *Neurocomputing*, 8, 125–139.
- Prindezis, N., Kiranoudis, C. T., & Kouris, D. M. (2003). A business-to-business fleet management service provider for central food market enterprises. *Journal of Food Engineering*, 60, 203–210.
- Prins, C. (2004). A simple and effective evolutionary algorithm for the vehicle routing problem. *Computers & Operations Research*, 31, 1985–2002.
- Reinaldo, S., Rodrigues, B., & Vázquez, E. (2008). Cost-to-serve measurement and customer profitability analysis. *International Journal of Logistics Management*, 19, 389–407.
- Rentizelas, A. A., Tolis, A. J., & Tatsiopoulos, I. P. (2009). Logistics issues of biomass: the storage problem and the multi-biomass supply chain. *Renewable & Sustainable Energy Reviews*, 13, 887–894.
- Sivanandam, S. N., Dumathi, S., & Deepa, S. N. (2006). *Introduction to neural networks using MATLAB 6.0*. Delhi: McGraw Hill.
- Tarantilis, C. D., & Kiranoudis, C. T. (2001). A meta-heuristic algorithm for the efficient distribution of perishable foods. *Journal of Food Engineering*, 50, 1–9.
- Tarantilis, C. D., & Kiranoudis, C. T. (2002). Distribution of fresh meat. *Journal of Food Engineering*, 51, 85–91.
- Toth, P., & Vigo, D. (2002). Models, relaxations and exact approaches for the capacitated vehicle routing problem. *Discrete Applied Mathematics*, 123, 487–512.
- Van Raaij, E. M. (2005). The strategic value of customer profitability analysis. *Marketing Intelligence & Planning*, 23, 372–381.
- Van Raaij, E. M., Vernooij, J. A., & van Triest, S. (2003). The implementation of customer profitability analysis: a case study. *Industrial Marketing Management*, 32, 573–583.
- Zeithaml, V. A., Rust, R. T., & Lemon, K. N. (2001). The customer pyramid: creating and serving profitable customers. *California Management Review*, 43, 118–142.