

# Development of programming models for analysis and solution of logistic problems

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Logistics is the aspect of the supply chain which is responsible of the efficient flow and delivery of goods or services from suppliers to customers. Because a logistic system involves specialized operations such as inventory control, facility location and distribution planning, the logistic professional requires mathematical, technological and managerial skills and tools to design, adapt and improve these operations. On the technological side, main research is focused on modeling and solving logistic problems by means of integer programming and meta-heuristics methods. However, in practice, the application of these methods for specific and large scale problems is restricted by the required knowledge and/or skills (e.g., programming proficiency, background in operations research, platform use). Also, the availability of test instances with specific features is limited. In this context, the present work describes the development of programming models to address the following aspects for research in the logistic and supply chain management fields: (1) development of test instances for routing and facility location problems with real geographical coordinates, (2) implementation of Euclidean, Manhattan and geographical arc length distance metrics for solving routing and facility location problems, (3) simulation of non-deterministic inventory control models, (4) importing/exporting and plotting of input data and solutions for analysis and visualization by third-party platforms, and (5) development of a nearest-neighbor meta-heuristic to provide very suitable solutions for vehicle routing and facility location problems, which are frequently studied for improvement of logistic systems. These developments can be used by the academic researcher or professional to get additional programming skills to solve supply chain problems.

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## ABSTRACT

Logistics is the aspect of the supply chain which is responsible of the efficient flow and delivery of goods or services from suppliers to customers. Because a logistic system involves specialized operations such as inventory control, facility location and distribution planning, the logistic professional requires mathematical, technological and managerial skills and tools to design, adapt and improve these operations. On the technological side, main research is focused on modeling and solving logistic problems by means of integer programming and meta-heuristics methods. However, in practice, the application of these methods for specific and large scale problems is restricted by the required knowledge and/or skills (e.g., programming proficiency, background in operations research, platform use). Also, the availability of test instances with specific features is limited. In this context, the present work describes the development of programming models to address the following aspects for research in the logistic and supply chain management fields: (1) development of test instances for routing and facility location problems with real geographical coordinates, (2) implementation of Euclidean, Manhattan and geographical arc length distance metrics for solving routing and facility location problems, (3) simulation of non-deterministic inventory control models, (4) importing/exporting and plotting of input data and solutions for analysis and visualization by third-party platforms, and (5) development of a nearest-neighbor meta-heuristic to provide very suitable solutions for vehicle routing and facility location problems, which are frequently studied for improvement of logistic systems. These developments can be used by the academic researcher or professional to get additional programming skills to solve supply chain problems.

## INTRODUCTION

Research on supply chain management (SCM) and logistics has been performed following quantitative (simulation, mathematical modeling and optimization) and qualitative (case study, interviews, empirical studies) approaches (Sachan A and Datta S, 2005). These approaches have been performed on the different logistic processes of the SC such as inventory control, transportation, production and distribution (Lloyd C et al., 2013; Kuczyńska-Chalada M et al., 2018). Transportation has been reported as the largest research topic in logistics (Daugherty P et al., 2017).

With the rise of Industry 4.0 (which is associated to “Internet of Things” or “SMART systems”) logistics faces the challenge to control the entirety of logistic activities of enterprises cooperating in supply and logistic chains (Kuczyńska-Chalada M et al., 2018). In this context, the use of (a) embedded systems and (b) intelligent systems are considered as vital resources to achieve smart and autonomous flow of raw materials, work-in-process, and distribution of end products throughout the SC in accordance to human planning (Lloyd C et al., 2013; Kuczyńska-Chalada M et al., 2018).

The development of intelligent systems is based on quantitative research as it involves optimization, mathematical modeling, simulation and statistical assessment. A key resource for these tasks is the availability of specialized data for analysis and testing. Thus, research on state-of-the-art systems for transportation planning is supported by available databases of test sets (instances) such as TSPLIB (Reinelt G, 1991, 1997) for the Traveling Salesman Problem,

CVRPLIB (Uchoa E et al., 2017; Oliveira D et al., 2019) for the Vehicle Routing Problem, and SJC/p3038 sets (Chaves AA and Nogueira-Lorena LA, 2010; Nogueira-Lorena LA, 2007) for Facility Location Problems.

However, not all databases consider the different aspects of real logistics problems such as specific demand/location patterns and/or distance metrics. Also, in practice, the development and implementation of specific resources and solving methods is restricted by the required technical knowledge or skills associated to programming platforms and mathematical modeling. As presented in (Rao K et al., 1998) the use of software programs, computer programming and spreadsheet modeling, are effective problem-solving tools within logistic education. Hence, universities have revised their programs to provide qualified logistic professionals with these tools (Erturgut R, 2011).

Among the extensive educational resources for the logistic professional, few of them provide detailed examples of implementation. While the methodological steps are frequently described, source data such as software models, programming code, and test sets, are not explicitly available for sharing. Also, license restrictions regarding the implementation software avoids the use of some simulation models for commercial purposes. The high costs of some of these licenses restrict their use by freelance professionals, micro, small and medium enterprises, which have limited economic resources.

In this context, the present work describes the development of open source programming code for the researcher and professional in logistics and supply chain management. Particularly, the following aspects are addressed:

- development of test instances for routing and facility location problems with real geographical coordinates;
- implementation of Euclidean, Manhattan and geographical arc length distance metrics for solving routing and facility location problems (symmetric and asymmetric metrics are considered);
- importing/exporting and plotting of input data and solutions for analysis and visualization by third-party platforms;
- simulation of non-deterministic inventory control models for assessment of supply strategies;
- development of a nearest-neighbor meta-heuristic to provide very suitable solutions for vehicle routing and facility location problems.

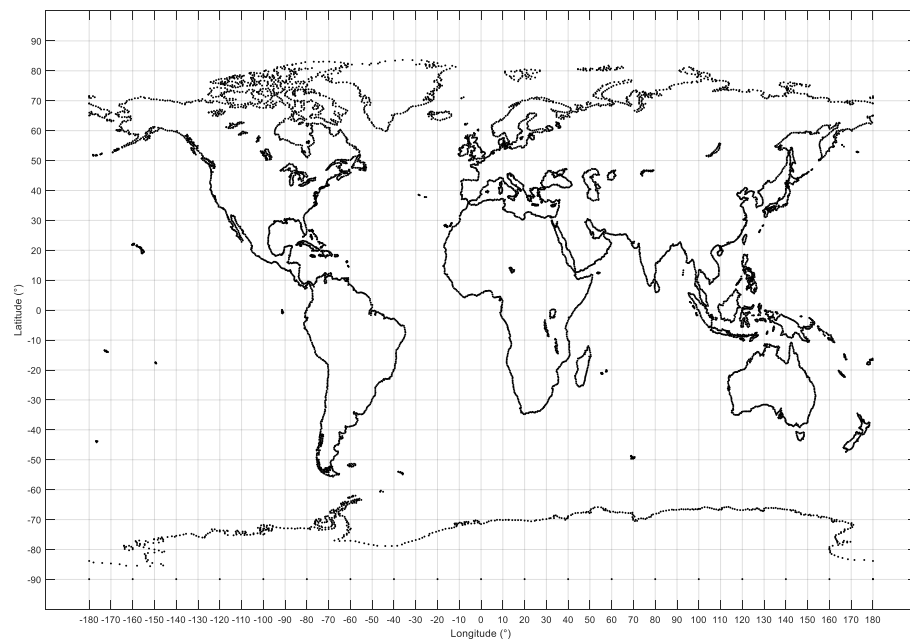
As complementary material, two problems are studied and solved with these resources: (a) an integrated inventory – vehicle routing problem, and (b) a multi-facility location problem with inventory management. Implementation of the codes was performed through the open source programming software GNU Octave (Eaton JW et al., 2018). The advantage of this software is that it runs on GNU/Linux, macOS, BSD, and Windows, and it is compatible with many MATLAB scripts. Also, its language syntax makes it easily adaptable to other languages such as C++.

## DEVELOPMENT OF TEST INSTANCES

The development of location data is important to test solving methods or algorithms for facility location and vehicle routing problems. To generate location data associated to real geographical coordinates the first step is to understand the coordinate system of the real world. Figure 1 presents the ranges for longitude and latitude coordinates ( $\lambda$  and  $\phi$  respectively) of the world map.

With these ranges the second step consists on generating location data within specific regions. In example, consider the region delimited by  $\lambda \in [-102, -100]$  and  $\phi \in [20, 22]$ . A set of locations within this region can be generated through two approaches:

- First, by adapting an already existing set of locations (standard test instance). There are available different sets of test instances for research within the distribution field. However,



**Figure 1.** World map displaying the range for longitude ( $\lambda$ ) and latitude ( $\phi$ ) coordinates in degrees.

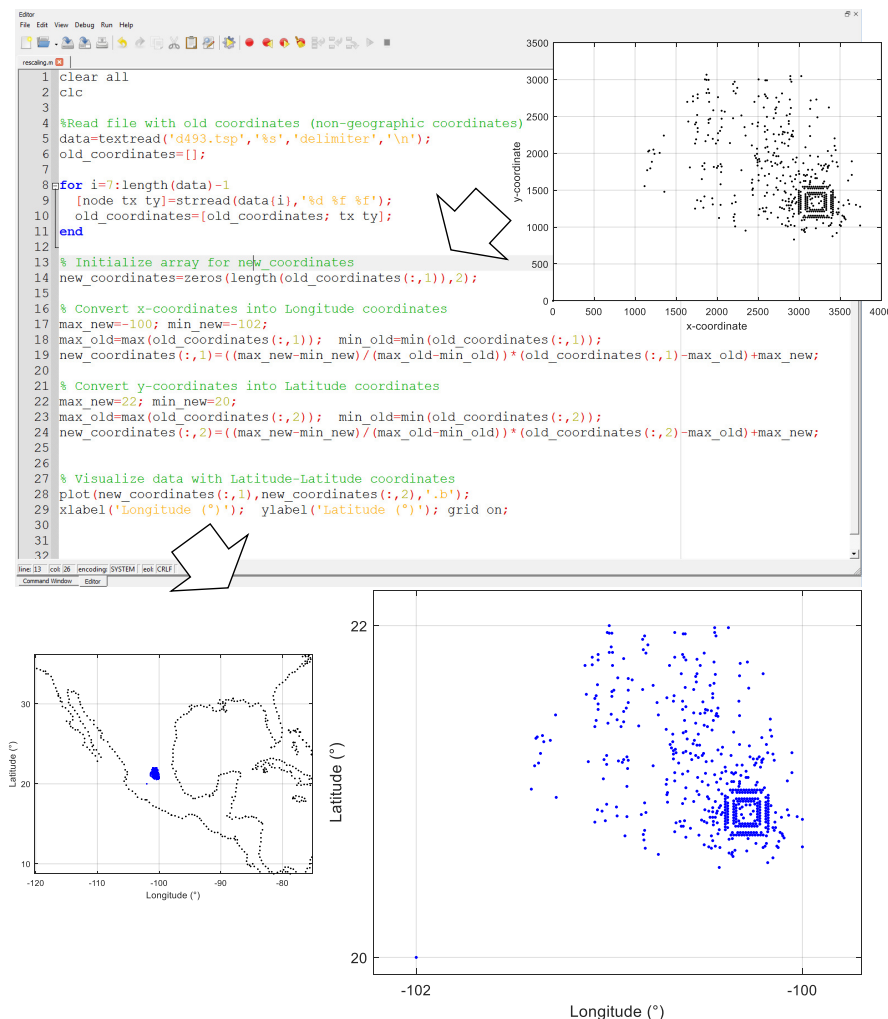
many of them are not adjusted to geographic coordinates. This can affect the process to estimate distance metrics in kilometers. Figure 2 presents the visualization of coordinates from the instance *d493* of the database TSPLIB (Reinelt G, 1997). As presented, the range of the  $x$  and  $y$  axes are different from those presented in Figure 1. These non-geographical coordinates can be converted by using the following equation:

$$v' = \left( \frac{max_{new} - min_{new}}{max_{old} - min_{old}} \right) \times (v - max_{old}) + max_{new}. \quad (1)$$

Where  $v$  is the value within the old range and  $v'$  is the converted value within the new range. Figure 2 presents the programming code developed to convert the coordinates of *d493.tsp* into geographic coordinates.

- Second, by using a probability function. In this case, random coordinates can be generated by using distributions such as the *uniform* distribution with parameters  $a$  and  $b$  which represent the minimum and maximum values for the generation range, or the *normal* distribution where  $a$  and  $b$  represent the mean and standard deviation values within the generation range. Figure 3 presents the code developed to generate  $N=493$  geographic coordinates considering these distributions. Note that a set of specific  $N$  coordinates cannot solely be generated by adaptation of existing data. In such case, a mixture of the codes presented in Figure 2 and 3 can provide a required set of  $N$  coordinates.

In addition to coordinate data, information regarding demands of locations and capacities of vehicles and warehouses must be generated for routing and coverage problems. By assuming a homogeneous fleet / set of warehouses a unique value is assigned to each of these elements. However, this does not necessarily apply to the demands of the locations to be served. Some instances have considered homogeneous demand (same value for all locations). However, in practice, this is not considered. Figure 4 presents an additional code to generate random demand for each location. Note that, within the demand context, the first location is considered to be the central depot or warehouse, thus, demand is equal to zero.



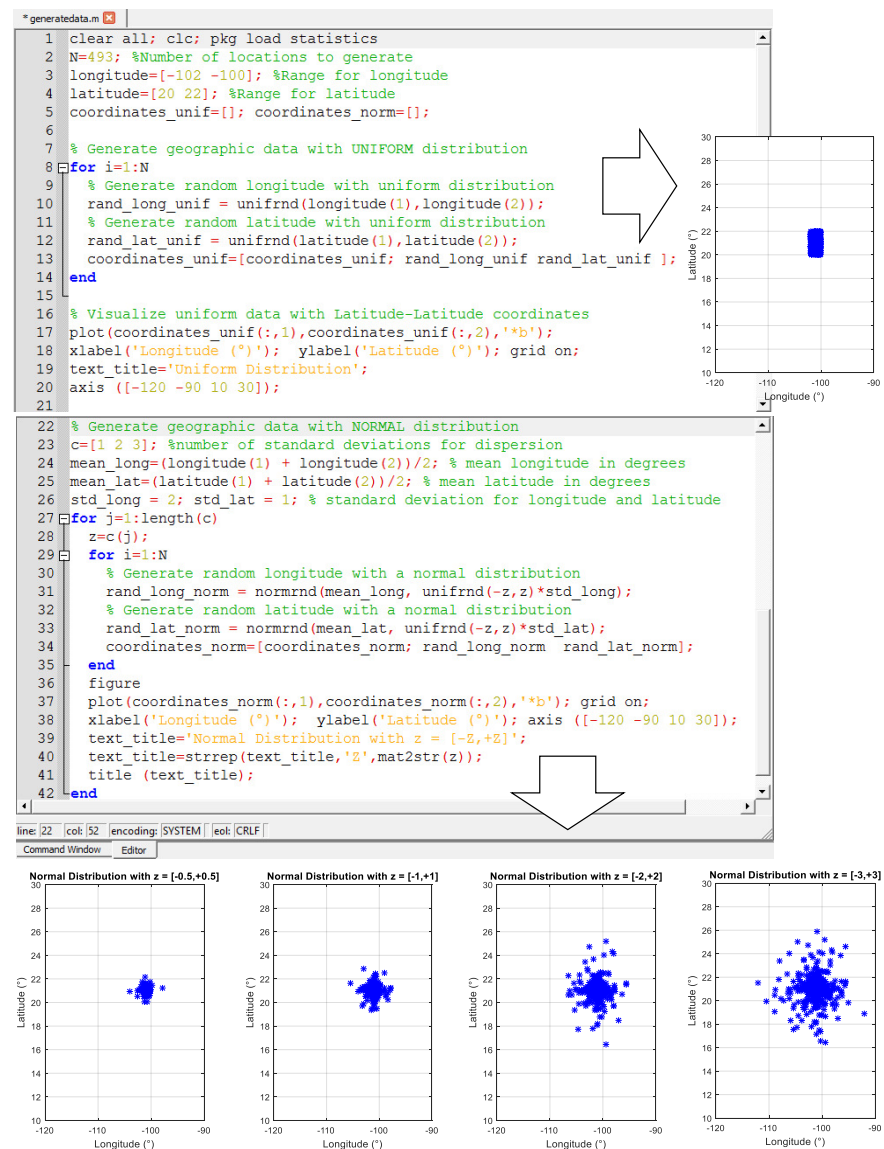
**Figure 2.** Programming Model 1: Re-scaling and plotting of existing location data.

## DISTANCE METRICS

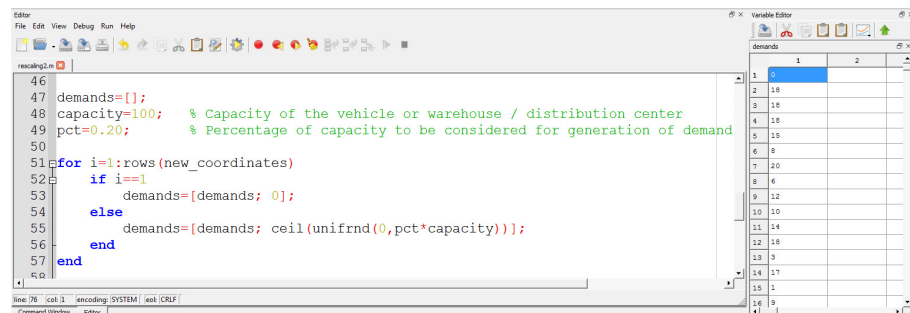
Within distribution problems, a metric to determine the suitability of a route over other routes is required. The most common criteria to optimize distributions problems is to minimize the metric of distance which is positively associated to transportation costs. There is a wide set of distance metrics, being the *Euclidean* distance the most commonly used. Other metrics, such as *Manhattan* distance or *arc length* are more closely associated to real-world contexts (Reinelt G, 1997). Figure 5 shows the details of these distance metrics together with their implementation code. It is important to remember that distance is estimated between two points  $i$  and  $j$ , thus, the  $x$  and  $y$  coordinates, or longitude ( $\lambda$ ) and latitude ( $\phi$ ) coordinates, must be known in advance.

An important resource for any distribution problem is known as the distance matrix  $A$  which stores all distances between each location  $i$  and  $j$  within the distribution network. Thus, this matrix, of dimension  $N \times N$  (where  $N$  is the number of locations, including the central depot) stores each  $d_{ij}$  data where  $i, j = 1, \dots, N$  and  $d_{ii} = d_{jj} = 0$  (the distance between each point and itself is zero). The code presented in Figure 5 estimates also the symmetric distance matrix ( $d_{ij} = d_{ji}$ ) for each type of metric.

By considering the converted coordinates into longitude and latitude degrees, the *Euclidean* and *Manhattan* distances provide similar values. In this regard, these values do not represent kilometers. In order to obtain a distance in kilometers, the *arc length* metric is considered. This metric considers the spherical model of the Earth's surface which has a radius of 6371 kilometers.

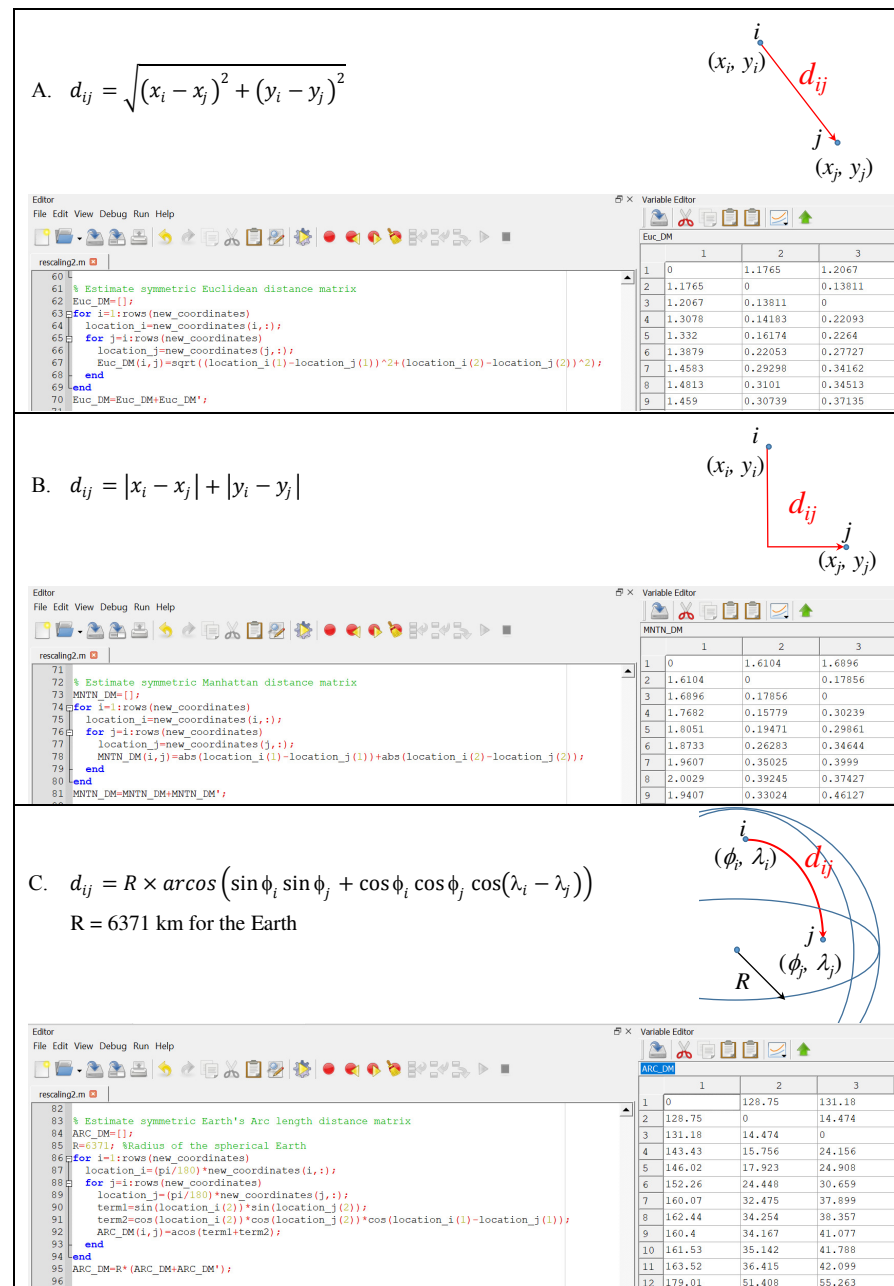


**Figure 3.** Programming Model 2: Generation of  $N$  uniform and normal random geographic coordinates and plotting.



**Figure 4.** Programming Model 3: Generation of  $N$  random demand data.

133 For this, the coordinates in latitude and longitude degrees are converted into radians by a factor  
134 of  $\pi/180^\circ$ . This leads to a symmetrical distance matrix in kilometers.



**Figure 5.** Programming Model 4: (A) Euclidean, (B) Manhattan, and (C) Arc length distances.

It is important to note that an approximation of the *Manhattan* distance can be estimated in terms of the *arc length* or *Euclidean* distance by considering trigonometry and right triangles theory. By knowing the angle  $\theta$  between the hypotenuse and one of the catheti, and the length or magnitude of the hypotenuse (i.e., *Euclidean* or *arc length*  $d_{ij}$ ), the length of both catheti can be estimated as:

$$c_1 = d_{ij} \times \sin(\theta), \quad (2)$$

$$c_2 = d_{ij} \times \cos(\theta). \quad (3)$$

Thus, if the *Euclidean* or *arc length* metric is available, then the *Manhattan* distance can be estimated as  $c_1 + c_2$ . Different estimates can be obtained based on the assumed value for  $\theta$ .

137 Finally, an asymmetric distance matrix ( $d_{ij} \neq d_{ji}$ ) can be constructed by adjusting the code  
 138 described in Figure 5 to represent  $d_{ji} = d_{ij} + \text{unifrnd}(0, \text{mean}(d_{ij}))$ . Note that this operation  
 139 modifies  $d_{ji}$  by adding to  $d_{ij}$  a random uniform value within the range from 0 to the mean value  
 140 of all distances within  $A$  (although a different random value can be added).

## 141 INVENTORY CONTROL

142 Inventory management is an important aspect of distribution as proper inventory levels are  
 143 required to ensure the constant supply of goods. This however must comply with restrictions to  
 144 avoid unnecessary costs associated to inventory supply processes.

145 The concept of an “economic order quantity” (EOQ) has been widely used to define the  
 146 optimal lot size required to minimize operational costs associated to ordering and keeping goods  
 147 through the supply chain. Defining this lot size is a complex task due to the different variables  
 148 involved in the inventory supply processes such as costs, delivery times, planning horizon, cycle  
 149 time, stock-out costs and probabilities, service levels, demand patterns (Thinakaran N et al.,  
 150 2019).

151 Thus, different mathematical models have been developed to determine the EOQ considering  
 152 these multiple variables (Thinakaran N et al., 2019; Braglia M et al., 2019; De SK and Sana SS,  
 153 2015; Hovelaque V and Bironneau L, 2015). Two of the most useful models for inventory control  
 154 are the continuous and periodic review models with non-deterministic demand. These models,  
 155 also known as the  $(Q, R)$  (Hariga M, 2009; Adamu I, 2017) and  $P$  (Lieberman G and Hillier F,  
 156 2000) models respectively, are analyzed in the following sections.

### 157 Continuous Review Model

158 The  $(Q, R)$  model considers the costs and variables described in Table 1.

**Table 1.** Parameters and variables of the  $(Q, R)$  inventory control model.

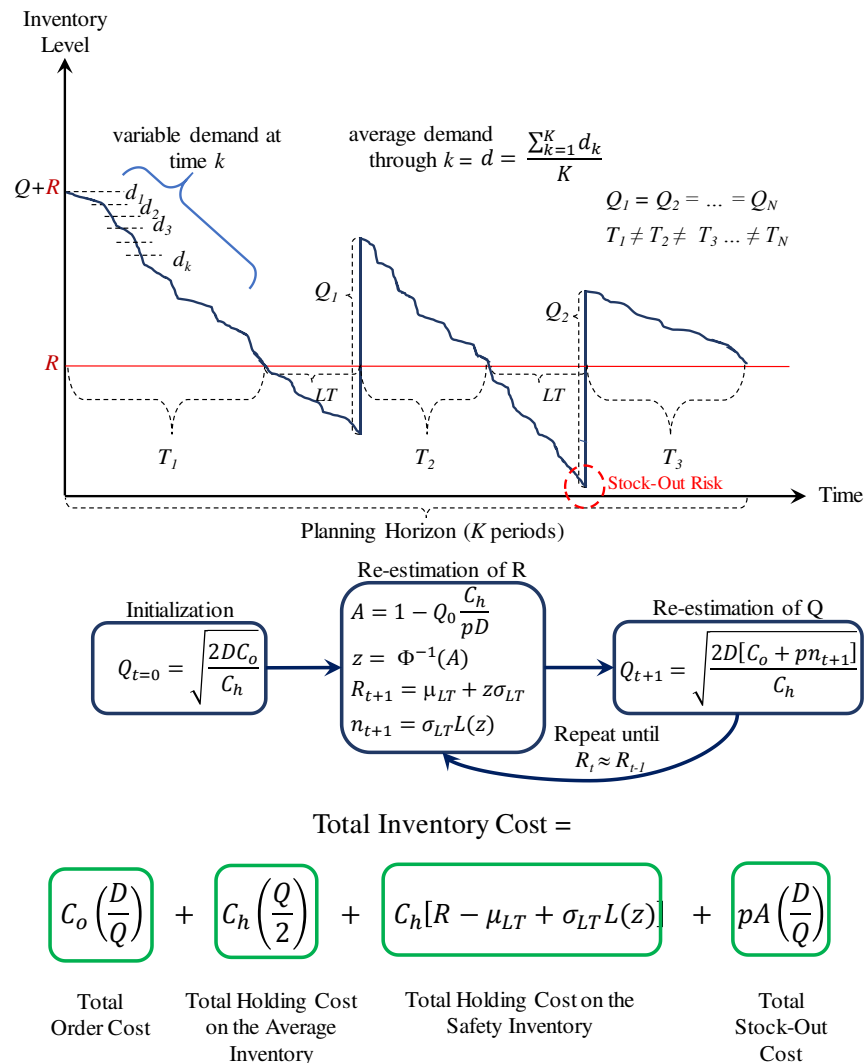
Parameter or Variable	Description
$C_o$	Order cost per lot $Q$ .
$C_h$	Holding cost per unit of product in inventory.
$p$	Stock-out cost per unit of product.
$Q$	Economic order quantity (EOQ)
$R$	Reorder point (level of inventory at which a lot of size $Q$ must be ordered to avoid stock-out).
$LT$	Lead time
$d$	Average daily demand of products, or average demand of products on the smallest unit of time.
$\sigma$	Standard deviation of the average daily demand of products (it must be estimated on the same unit of time as $d$ ).
$\mu_{LT}$	Average demand of products through the $LT$ . It can be estimated as $d \times LT$ if both are under the same unit of time.
$\sigma_{LT}$	Standard deviation of products through the $LT$ . It can be estimated as $\sigma \times \sqrt{LT}$ if both are under the same unit of time.
$D$	Cumulative demand through the planning horizon. Note that if $d$ is a weekly demand, then $D = K \times d$ where $K$ is the number of weeks within the planning horizon.
$L(z)$	Loss function associated to $R$ .
$C$	Purchase cost per unit of product.

159 With these parameters and variables, lots of size  $Q$  are ordered through a planning horizon  
 160 to serve a cumulative demand. Figure 6 presents an overview of the supply patterns considered  
 161 by this model and its mathematical formulation to determine  $Q$ ,  $R$ , and the *Total Inventory*  
 162 *Costs* associated to it. As presented, at the beginning of the planning horizon, the inventory level  
 163 starts at  $R + Q$ . This is decreased by the daily or weekly demand estimated as  $d$ . If historical



164 demand data is available, their use can provide a better estimate for  $d$ . As soon as the inventory  
 165 level reaches  $R$ , the inventory manager must request an order of size  $Q$  because there is only  
 166 stock to supply  $LT$  days or weeks. Here, it is important to observe that the inventory must  
 167 be continuously reviewed or checked to accurately detect the re-order point  $R$  and reduce the  
 168 stock-out risk during the  $LT$ .

169 Because uncertain demand is assumed, the inventory consumption rate is different throughout  
 170 the planning horizon. Hence,  $R$  can be reached at different times. This is the reason to obtain  
 171 different periods between inventory reviews.



**Figure 6.** Inventory Supply Pattern under the Continuous Review ( $Q, R$ ) Model.

For this model, Figure 7 presents the code to estimate the lot size  $Q$ , the reorder point  $R$ , and the *Total Inventory Cost*. How these parameters perform under a dynamic demand scenario is addressed through the visualization (plotting) algorithm also presented in Figure 7. This algorithm generates random demand test data ( $d_{test}$ ) by the expression:

$$d_{test} = d \pm z\sigma, \quad (4)$$

172 where  $z$  is the number of standard deviations and is randomly generated within a specific range.  
 173 Figure 8 presents examples considering  $z \in [-3, +3]$ ,  $z \in [-5, +5]$ , and  $z \in [-7, +7]$ . As presented,  
 174 in all cases through the planning horizon there are no stock-out events. As variability increases

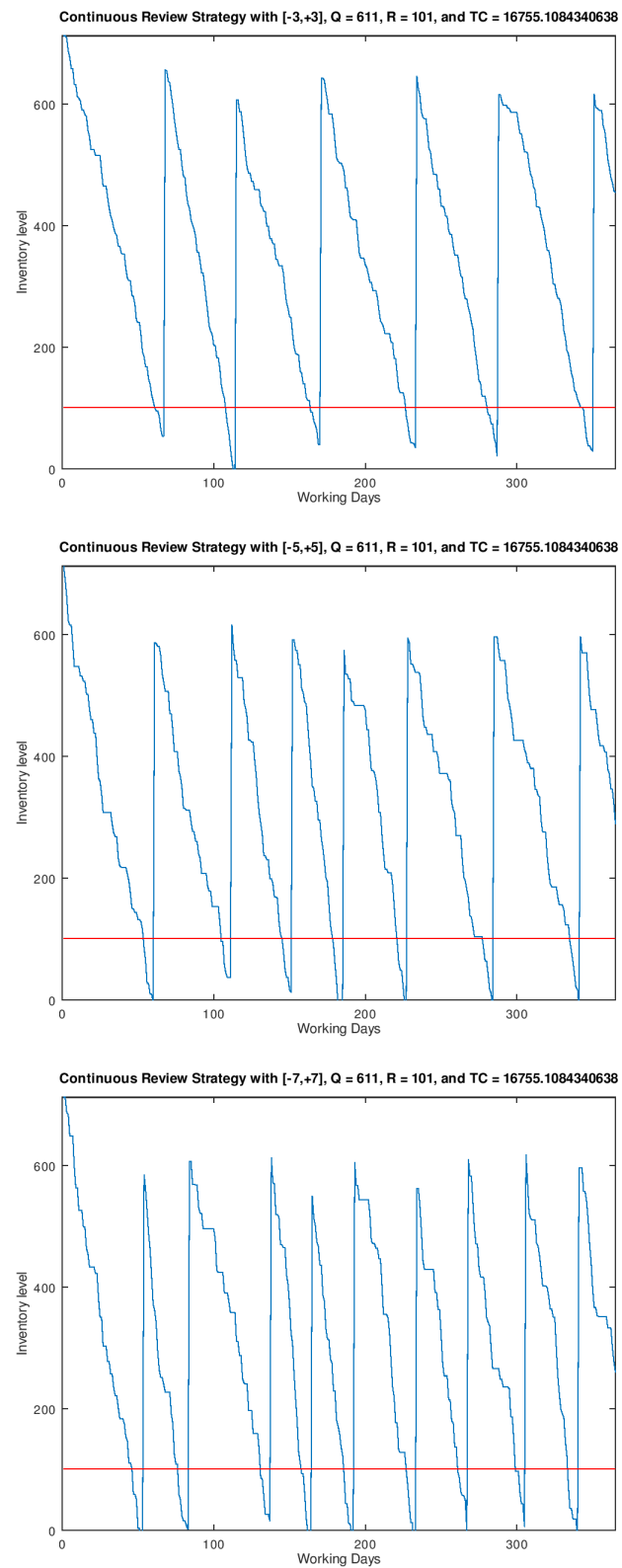
the consumption rate is faster, thus more orders must be requested. Thus, for  $z \in [-3, +3]$  six orders were needed while for  $z \in [-5, +5]$  seven orders were needed. Finally, for  $z \in [-7, +7]$  nine orders were needed to avoid stock-out. This corroborates the validity of this method for inventory control under uncertain demand.

```
clear all; clc; pkg load statistics
d = 10; std = 6; %units per day of average demand and standard deviation
z = 3; %standard deviations for demand variability
K = 365; %working days through the planning horizon
D = K*d; %cumulative demand
% C Co Ch p
Costs = [250.0 1250.0 25.0 150.0]; % Inventory Associated Costs
LT = 7; T = 21; %days of lead time and days between reviews
% ===== Determine parameters for (Q,R) model =====
for i=1:20 %Number of iterations
    if i==1 % Initial Value for Q
        Q = sqrt((2*D*Costs(2))/Costs(3));
    else
        Q = sqrt((2*D*(Costs(2) + Costs(4)*n))/Costs(3));
    end
    A=1-Q*(Costs(3)/(Costs(4)*D)); Z=norminv(A); % Z for Continuous Review Model
    R = d*LT + Z*std*sqrt(LT);
    L = stdnormal_pdf(Z)-Z*(1-stdnormal_cdf(Z)); % Loss function
    n = L*std*sqrt(LT);
end
Q=ceil(Q); R=ceil(R); % round final values towards positive infinity
% ===== Determine Associated Total Inventory Cost =====
TOC = (Costs(2)*D)/Q; % Total Order Cost
THC = (Costs(3)*Q)/2; % Total Holding Cost
TSS = Costs(3)*(R - d*LT + std*sqrt(LT)*L); % Total Holding Cost of Safety Stock
TSK = Costs(4)*A*(D/Q); % Total Stock-Out Cost
TC = TOC +THC +TSS +TSK ;
% ===== Test (Q,R) Parameters =====
Inventory = Q+R; count_LT=0; inv_consumption = []; % Initialization
for i=1:K
    inv_consumption = [inv_consumption ; Inventory];
    dt=d+unifrnd(-z,z)*std; % Random daily demand within [-z, +z] std
    if dt<0
        dt = 0;
    end
    if Inventory - dt > R
        Inventory =Inventory - dt;
    else
        Inventory =Inventory - dt;
        count_LT=count_LT+1;
    end
    if count_LT == LT+1
        Inventory=Inventory+Q; count_LT=0;
    end
end
% ===== Visualization Code =====
vect_R=ones(length(inv_consumption),1)*R;
plot(inv_consumption); hold on; plot(vect_R,'-r'); axis([0 K 0 Q+R]);
xlabel('Working Days'); ylabel('Inventory level');
text_title='Continuous Review Strategy with [-z,+z], Q = QX, R = RX, and TC = TCX';
text_title=strrep(text_title,'z',mat2str(z));
text_title=strrep(text_title,'QX',mat2str(Q));
text_title=strrep(text_title,'RX',mat2str(R));
text_title=strrep(text_title,'TCX',mat2str(TC));
title(text_title);
```

**Figure 7.** Programming Model 5: Continuous Review ( $Q, R$ ) Model and Visualization Code.

## 179 Periodic Review Model

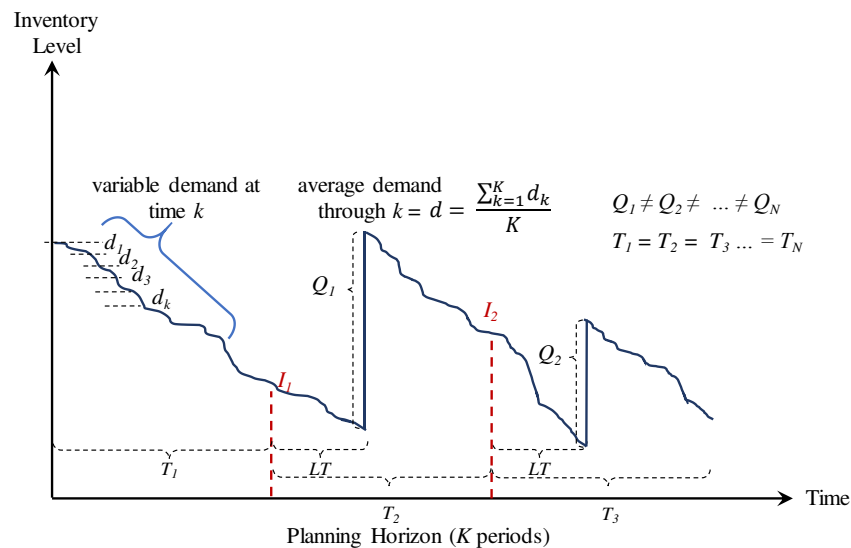
180 The  $P$  model considers the costs and variables described in Table 2. Figure 9 presents an overview  
 181 of the supply patterns considered by this model and its mathematical formulation to determine  $Q$   
 182 and the *Total Inventory Costs* associated to it. In contrast to the  $(Q, R)$  model, in the  $P$  model  
 183 the inventory review is performed at fixed intervals of length  $T$  and  $Q$  is estimated considering  
 184 the available inventory  $I$  at that moment. Thus, different lots of size  $Q$  are ordered depending  
 185 of the available inventory at the end of the review period  $T$ . Figure 10 presents the code to  
 186 estimate the lot size  $Q$ , the *Total Inventory Cost*, and the consumption and supply patterns for  
 187 the  $P$  model.



**Figure 8.** Performance of the Continuous Review ( $Q, R$ ) Strategy with Different Variability Conditions.

**Table 2.** Main parameters and variables of the  $(Q, R)$  and  $P$  models

Variable	Description
$C_o$	Order cost per lot $Q$ .
$C_h$	Holding cost per unit of product in inventory.
$Q$	Economic order quantity (EOQ)
$LT$	Lead time
$T$	Time between inventory reviews and $T > LT$
$d$	Average daily demand of products, or average demand of products on the smallest unit of time.
$D$	Cumulative demand through the planning horizon. Note that if $d$ is a weekly demand, then $D = K \times d$ where $K$ is the number of weeks within the planning horizon.
$\sigma$	Standard deviation of the average daily demand of products (it must be estimated on the same unit of time as $d$ ).
$z$	Number of standard deviations associated to a service level.



$$Q_T = d(T + LT) + z\sigma\sqrt{T + LT} - I_T$$

Total Inventory Cost =

$$C_h \left( \frac{dT}{2} \right) + C_o \left( \frac{D}{dT} \right) + C_h z \sigma \sqrt{T + LT}$$

Total Holding Cost on the Average Inventory      Total Order Cost      Total Holding Cost on the Safety Inventory

**Figure 9.** Inventory Supply Pattern under the Periodic Review ( $P$ ) Model.

As in the case of the  $(Q, R)$  model, Figure 11 presents examples considering  $z \in [-3, +3]$ ,  $z \in [-5, +5]$ , and  $z \in [-7, +7]$  for the variable demand rate. Here, the advantages of the  $(Q, R)$  model are evident for demand with high variability. At the moment of review (at the end of  $T$ ), the lot size  $Q - I$  is estimated based on the historical data modeled through  $d$  and  $\sigma$ . This lot size must be able to cover the demand for the next period  $T + LT$ . However, this increases

```

clear all; clc; pkg load statistics
d = 10; std = 6; %units per day of average demand and standard deviation
z = 3;          %standard deviations for demand variability
K = 365;        %working days through the planning horizon
D = K*d;        %cumulative demand
SL = 0.985;     %service level of 98.5%
% Inventory associated costs
%      C      Co      Ch      p
Costs = [250.0 1250.0 25.0 150.0]; % Inventory Associated Costs
LT = 7; T = 21; % days of lead time and days between reviews
Z = norminv(SL); % Z-value for Periodic Review Model
% ===== Determine parameters for P model =====
I = 0; Q=d*(T+LT)+Z*std*sqrt(T+LT)-I; Inventory=Q; count_T=0; count_LT=0;
% ===== Determine Associated Total Inventory Cost =====
TOC = (Costs(2)*D)/(d*T); % Total Order Cost
THC = (Costs(3)*(d*T))/2; % Total Holding Cost
TSS = Costs(3)*Z*std*sqrt(T+LT); % Total Holding Cost of Safety Stock
TC = TOC +THC +TSS;
% ===== Test P Parameters =====
inv_consumption = [];
for i=1:K
    inv_consumption = [inv_consumption ; Inventory];
    dt=d+unifrnd(-z,z)*std; % Random daily demand within [-z, +z] std
    if dt<0
        dt = 0;
    end
    Inventory=Inventory-dt; count_T=count_T+1;
    if count_T == T
        I= Inventory; count_T=0; count_LT=LT+1;
    end
    if count_LT>0
        count_LT=count_LT-1;
        if count_LT == 0
            Inventory = Inventory+(Q-I);
        end
    end
end
% ===== Visualization Code =====
plot(inv_consumption); hold on; axis([0 K 0 Q]);
xlabel('Working Days'); ylabel('Inventory level');
text_title='Periodic Review Strategy with [-z,+z], Q = QX and TC = TCX';
text_title=strrep(text_title,'z',mat2str(z));
text_title=strrep(text_title,'QX',mat2str(Q));
text_title=strrep(text_title,'TCX',mat2str(TC));
title(text_title);

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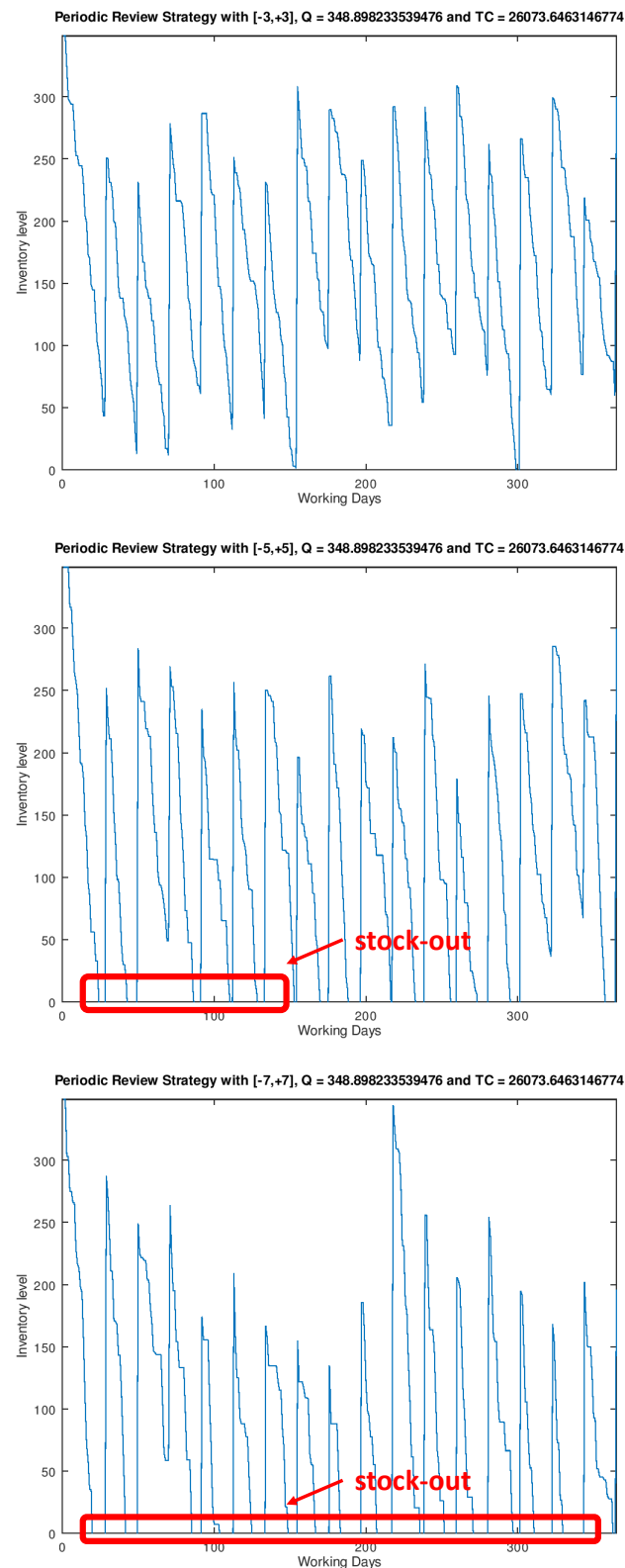
**Figure 10.** Programming Model 6: Periodic Review *P* Model and Visualization Code.

the stock out risk because ordering is restricted to be performed just at the end of  $T$ . Thus, if during that period the demand significantly increases (more than that modeled by  $\sigma$ ), inventory can be consumed at a higher rate. For the considered example, the required service level was set to 98.5%. By assuming normality, the  $z$ -value associated to this probability is approximately 2.17. Thus, for demand with  $z \in [-3, +3]$  standard deviations, the  $Q$  estimated by the  $P$  model is marginally able to keep the supply without stock-out. As presented in Figure 11, with higher variability there are stock-out events. Thus, it is recommended to re-estimate the  $Q$  parameter considering the updated demand patterns during the previous  $T + LT$  (i.e., update  $d$  and  $\sigma$ ). These observations are important while evaluating inventory supply strategies.

## 202 SOLVING METHODS FOR ROUTING AND FACILITY LOCATION PROBLEMS 203

Standard approaches of Operations Research (OR) such as Mixed Integer Linear Programming (MILP) or Dynamic Programming (DP) are often of limited use for large problems due to excessive computation time (Zäpfel G et al., 2010). Thus, meta-heuristics have been developed to provide near-optimal solutions in reasonable time for large production and logistic problems.

As introductory meta-heuristic, this work is considering two integrated local search algorithms with the fundamentals of GRASP (Greedy Randomized Adaptive Search Procedure) and Nearest-Neighbor Search (NNS). A complete review of more complex meta-heuristics and solving methods



**Figure 11.** Performance of the Periodic Review  $P$  Strategy with Different Variability Conditions.

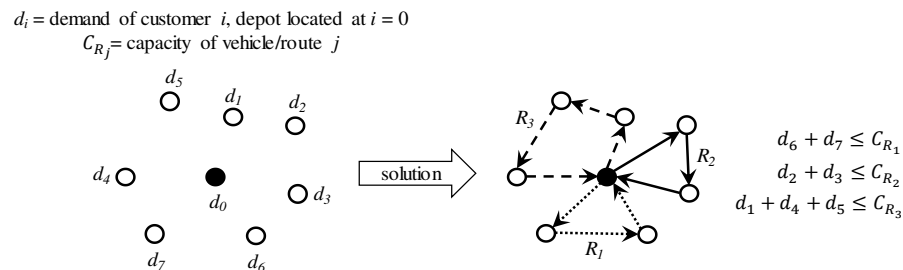
for different vehicle routing / facility location problems can be found in (Basu S et al., 2015; Prodhon C and Prins C, 2014; Bräysy O and Gendreau M, 2005a,b).

For the development of the integrated local search algorithms it is important to identify the characteristics of the vehicle routing / facility location problems and their solutions. This is discussed in the following sections.

### Vehicle Routing Problem (VRP)

In this problem, a vehicle or set of vehicles departs from a single location where a depot or distribution center is established. These vehicles serve a set of locations associated to customers/suppliers to deliver/collect items.

If each vehicle has finite capacity then the vehicle's route can only visit those customer/supplier locations whose requirements do not exceed its capacity. This leads to define multiple routes to serve unique sets of customer/supplier locations where each location can only be visited once. Optimization is focused on determining the required routes and the visiting sequence to minimize traveling distance and/or costs. Figure 12 presents an overview of the capacitated VRP (also known as CVRP).



**Figure 12.** Characteristics of the capacitated vehicle routing problem (CVRP)

For the CVRP, two main features are required to provide a solution: partitioning and sequencing of minimum distance. Partitioning can be applied over a single total route to obtain sub-routes served by vehicles of finite capacity. Sequencing then can be applied over a set of customer locations to determine the most suitable order to reduce traveling time/distance. This can be applied on the single total route and on each sub-route.

In this work, a nearest neighbor search (NNS) approach is considered for the sequencing and partitioning algorithm. Figure 13 presents the sequencing code for the symmetric CVRPLIB instance *X-n219-k73.vrp* considering Euclidean distance. The instance consists of 219 nodes (i.e., 218 customer/demand locations and one central depot location) and homogeneous fleet with capacity of 3.

As presented, the algorithm performs a sequencing through the nearest or closest candidate nodes within a distance threshold given by the minimum distances plus the weighted standard deviation of the distances between all nodes or locations. Once that the total partial route of nearest nodes is obtained, it is partitioned through the function *partitioning2* whose code is presented in Figure 14. The result of the partitioning process leads to 73 sub-routes which is the optimal number as stated in the file name of the instance. Observe that another function, called *random\_improvement* (see Figure 15) is performed on the total route and within the function *partitioning2* for each sub-route. This function consists of exchange and flip operators which are applied on sequences of nodes to improve the sequence obtained either by the nearest neighbor approach or by the partitioning process. Finally, Figure 16 presents the plotting code for the total route and the CVRP sub-routes.

An important aspect of any solving method, particularly meta-heuristics, is the assessment of its accuracy. The most frequently used metric for assessment is the % error gap, which is computed as:

$$\%e = \left( \frac{a-b}{b} \right) \times 100.0, \quad (5)$$

```

clear all; clc; pkg load statistics;
coords=[]; demands=[];

%===== Read File of Coordinate and Demand Data =====
data=textread('X-n219-k73.vrp','%s','delimiter','\n');
[s_1 s_2 nodes]=strread(data{4},'%s %s %d');
[s_1 s_2 capacity]=strread(data{6},'%s %s %d');
for i=8:nodes-1 % Lines of File with Coordinates Data
    [node tx ty]=strread(data{i},'%d %f %f'); coords=[coords; tx ty];
end
for i=8:nodes+1:length(data)-4 % Lines of File with Demand Data
    [node d]=strread(data{i},'%d %f'); demands=[demands; d];
end

% ===== Compute Euclidean Symmetric Distance Matrix =====
Euc_DM=[]; Euc_DM0=[];
for i=1:length(coords(:,1))
    loc_i=coords(i,:);
    for j=1:length(coords(:,1))
        loc_j=coords(j,:);
        Euc_DM(i,j)=sqrt((loc_i(1)-loc_j(1))^2+(loc_i(2)-loc_j(2))^2);
    end
end

% ===== Compute Distance Statistics for Sequencing =====
tp_0=sort(reshape(Euc_DM,1,nodes*nodes)); %Re-arrange into vector and sort
tp_1=tp_0(nodes+1:length(tp_0)); %Eliminate distance data of i=j
mn_dst=mean(tp_1); std_dst=std(tp_1); %Mean and standard deviation of Euc_DM
% =====

absolute=Inf;
for max_iteras=1:500
    % ===== Nearest-Neighbor NN sequencing to obtain total single route =====
    % different weights for the standard deviation
    w_std=[0.00001, 0.00005 0.0001 0.0005 0.001 0.005 0.01 0.05];
    cont_lim=1; % counter for selection of weights
    members=2:1:nodes; % vector with all remaining customer locations
    partial_route=[]; all_nodes_inserted=0;
    current_node=1; % The partial route starts at the "current" node "1"
    while all_nodes_inserted==0
        threshold= std_dst*w_std(cont_lim); cont_lim=cont_lim+1;
        if cont_lim>length(w_std) cont_lim=1; end
        distances=[];
        for j=1:length(members) % Compute distances from "current" node to remaining nodes
            distances(j)=Euc_DM(current_node,members(j));
        end
        if isempty(distances)==0 % There are remaining nodes to be inserted if distances is
            % not empty. Candidate remaining nodes are those within a distance threshold
            ind_temp=find(distances<=(min(distances))+threshold);
            % The "closest" node is randomly selected from the candidate remaining nodes
            closest_node=members(ind_temp(ceil(unifrnd(0,length(ind_temp)))));
            ind_ref=find(members==closest_node);
            % (1)"closest" node is removed from the remaining nodes, (2)"current" node is inserted
            % into the "partial" route, (3)"current" node is updated with the "closest" node
            members(ind_ref)=[];partial_route=[partial_route current_node];current_node=closest_node;
        else
            all_nodes_inserted=1; partial_route=[partial_route current_node]; %All nodes inserted
        end
    end
    partial_route(1)=[]; %Node "1" is removed from partial route
    [total_route distance_improved_route]=random_improvement(partial_route, Euc_DM);
    [CVRP_distance CVRP_routes]=partitioning2(total_route,capacity,demands,Euc_DM);

    if CVRP_distance< absolute
        best_absolute=[];
        best_absolute=CVRP_routes; %Updates best absolute CVRP solution
        absolute=CVRP_distance; %Updates distance value of the best absolute CVRP solution
        fprintf('%d CVRP distance = %1.4f \n',max_iteras, absolute);
        best_partial_route=[];
        best_partial_route=total_route;
    end
end
end

```

**Figure 13.** Programming Model 7: Nearest-neighbor algorithm for node sequencing.

247 where  $a$  is the result obtained with the considered solving method and  $b$  is the best-known  
 248 solution. For the present example, the best-known solution is 117595.0 while the described NNS  
 249 algorithm achieved a solution of  $a = 119162.6799$ . Hence, the error gap is estimated as 1.33%,  
 250 which is very close to the best-known solution. Also, this result was obtained within reasonable  
 251 time (117.046165 seconds).

## 252 Facility Location Problem (FLP)

253 In this problem, it is required to determine the most suitable location for a facility or set of  
 254 facilities to serve a set of customers/suppliers. As in the CVRP, if capacity is considered for the  
 255 facilities, multiple facilities are required to serve unique sets of customer/supplier locations where  
 256 each location can only be served by a unique facility. If facilities are located at the location  
 257 of minimum distance to all customers/suppliers, the FLP is known as the capacitated Weber  
 258 problem (Aras N et al., 2007). However, if facilities are located at the average locations between



```
function [CVRP_distance matrix_CVRP_routes_nodes]=partitioning2(total_route, capacity, demands, Euc_DM)
    remaining_capacity=capacity; matrix_CVRP_routes_nodes=[];
    row=1; % number of sub-routes is initialized as "1"
    column=1; remaining_nodes=length(total_route);
    % ===== Partitioning Process =====
    for uu=1:length(total_route)
        node=total_route(uu); d=demands(node);
        if d<=remaining_capacity
            matrix_CVRP_routes_nodes(row,column)=node; remaining_capacity=remaining_capacity-d; column=column+1;
        else
            remaining_capacity=capacity; row = row+1; column=1; % number of sub-routes is increased
            matrix_CVRP_routes_nodes(row,column)=node; remaining_capacity=remaining_capacity-d; column=column+1;
        end
    end
    % ===== Estimate Total Distance of All Sub-routes = CVRP Distance =====
    CVRP_routes=[]; CVRP_distance=0;
    for k=1:length(matrix_CVRP_routes_nodes(:,1))
        sub_route_0=[]; sub_route_0=matrix_CVRP_routes_nodes(k,:); top=find(sub_route_0>0);
        sub_route=[]; sub_route=sub_route_0(1:top(length(top))); CVRP_routes=[CVRP_routes sub_route];
        [sub_route dist_sub_route]=random_improvement(sub_route, Euc_DM);
        for p=1:length(sub_route)
            matrix_CVRP_routes_nodes(k,p)=sub_route(p);
        end
        CVRP_distance=CVRP_distance+dist_sub_route;
    end
end
```

**Figure 14.** Programming Model 8: Partitioning algorithm for sequence of nodes.

```
function [partial_route ref_distance]=random_improvement(partial_route, Euc_DM)
    % reference distance to evaluate improvements
    ref_partial_route=[1 partial_route 1]; % inserts node "1" at start/end to compute total distance
    ref_distance=0;
    for j=1:length(ref_partial_route)-1
        ref_distance=ref_distance+Euc_DM(ref_partial_route(j), ref_partial_route(j+1));
    end
    if length(partial_route)>1
        ref_distance=-
        it=150; % iterations to improve the partial route
        for iterations=1:it
            % Inversion/Flip Operator
            inv_partial_route=partial_route; inv_distance=0;
            pA=ceil(unifrnd(0.0*length(partial_route),length(partial_route)));
            pB=ceil(unifrnd(0.0*length(partial_route),length(partial_route)));
            while pA==pB pB=ceil(unifrnd(0.0*length(partial_route),length(partial_route))); end
            % Flip segment within positions pA and pB
            if pA<pB
                inv_partial_route(pA:pB)=flip(partial_route(pA:pB));
            else
                inv_partial_route(pB:pA)=flip(partial_route(pB:pA));
            end
            inv_partial_route=[1 inv_partial_route 1]; % inserts node "1" at start/end to compute total distance
            for j=1:length(inv_partial_route)-1
                inv_distance=inv_distance+Euc_DM(inv_partial_route(j),inv_partial_route(j+1));
            end
            % Exchange Operator
            exc_partial_route=partial_route; exc_distance=0;
            exc_partial_route(pA)=partial_route(pB); exc_partial_route(pB)=partial_route(pA);
            exc_partial_route=[1 exc_partial_route 1];
            for j=1:length(exc_partial_route)-1
                exc_distance=exc_distance+Euc_DM(exc_partial_route(j),exc_partial_route(j+1));
            end
            % Decision process to evaluate improvement
            if inv_distance <= exc_distance
                candidate_route=inv_partial_route; candidate_distance=inv_distance;
            else
                candidate_route=exc_partial_route; candidate_distance=exc_distance;
            end
            if candidate_distance <= ref_distance % new solution is better than current solution
                partial_route=candidate_route; partial_route(1)=[]; partial_route(length(partial_route))=[];
                ref_distance=candidate_distance;
            end
        end
    end
end
```

**Figure 15.** Programming Model 9: Random algorithm to improve sequencing of nodes.

all customers/suppliers (i.e., at the centroids), the FLP is known as the capacitated centered clustering problem (CCCP) (Negreiros M and Palhano A, 2006). Finally, if facilities are located at already defined median locations, the FLP is known as the capacitated p-median problem (CPMP) (Stefanello F et al., 2015). Figure 17 presents an overview of these variations of the FLP. It is important to observe that the feature of the locations has a direct effect on the solution.

Facility location problems are frequently solved through clustering or classification methods. Within this context, a nearest neighbor search (NNS) approach with an appropriate capacity-restricted assignment algorithm can provide very suitable solutions. Figure 18 presents the main code of the NNS algorithm for the CCCP instance *SJC1.dat* considering Euclidean distance. The instance consists of 100 nodes (i.e., 100 customer/demand locations), 10 centroids (i.e., 10 facilities to be located) and homogeneous capacity of 720.

The main code generates a feasible initial solution through the function *random\_assignment* which is described in Figure 19. Randomness is considered when two or more nodes are located at the same distance from a centroid, and on the initial location of the centroids. This adds

```

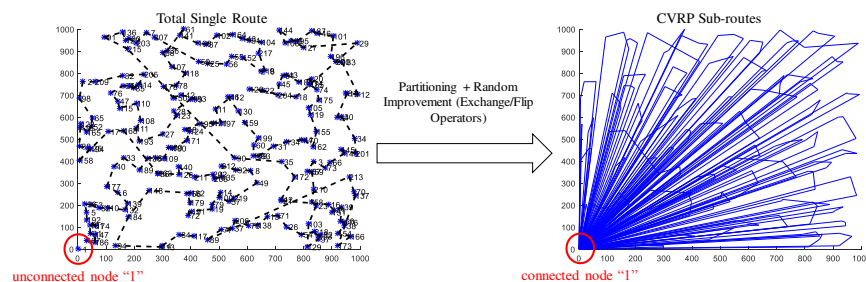
%Plot routine to draw the partial route, the labels of each node, and the
%CVRP sub-routes
figure
hold on
label_nodes= 1:1:nodes; label_text = cellstr(num2str(label_nodes));
for i=1:nodes
    plot(coords(i,1),coords(i,2),'*b');
    text(coords(i,1),coords(i,2),label_text(i),'FontSize',10);
end

for i=1:length(best_partial_route)-1
    xx=[coords(best_partial_route(i),1) coords(best_partial_route(i+1),1)];
    yy=[coords(best_partial_route(i),2) coords(best_partial_route(i+1),2)];
    plot(xx,yy,'-k','LineWidth',2);
end

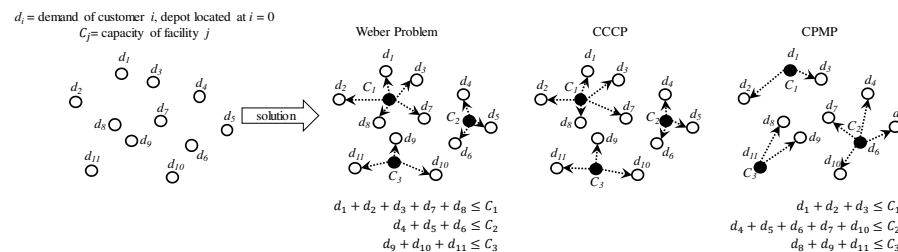
figure
hold on

for k=1:length(best_absolute(:,1))
    sub_route=[]; sub_route=[1 best_absolute(k,:) 1];
    %Eliminate zeros from sub_route
    find_zeros=find(sub_route==0); sub_route(find_zeros)=[];
    for i=1:length(sub_route)-1
        xx=[coords(sub_route(i),1) coords(sub_route(i+1),1)];
        yy=[coords(sub_route(i),2) coords(sub_route(i+1),2)];
        plot(xx,yy,'-b');
    end
end
end

```



**Figure 16.** Programming Model 10: Plotting algorithm for visualization of routes.



**Figure 17.** Characteristics of the capacitated facility location problem (CFLP)

flexibility to the assignment task and to the search mechanism of the NNS algorithm.

Then, this initial solution is improved through the function *update\_centroids\_assignment* which is described in Figure 20. As presented in the main code (see Figure 18) if the solution generated by *update\_centroids\_assignment* complies with all restrictions and its objective function's value is better than the reference value (*total distance* < *REF*), then it is stored in the arrays *best\_assignments* and *best\_centroids*.

When solving combinatorial problems, it is always recommended to verify the correctness of the solution. It is also recommended to know the convergence patterns of the solving algorithm. Both aspects provide insights regarding hidden mistakes in the programming code and deficiencies in the search mechanisms of the solving algorithm (e.g., fast or slow convergence to local optima). As presented in the main code (see Figure 18), at each iteration of the NNS the reference value is stored in the array *convergence*. Then, a verification routine is performed on the best solution which was found by the NNS algorithm. If the verification is successful the main code proceeds to plot the best found solution and the *convergence* data. Both plots for the CCCP instance *SJC1.dat* are presented in Figure 21.

```

clear all; clc; pkg load statistics;

%Load set of coordinates of nodes from test instance file:
data=textread('SJCL.dat','%s','delimiter','\n'); coordinates=[]; demands=[];

for i=2:length(data)
    [coorx coor y capacity dem]=strread(data(i),'%f %f %d %d');
    coordinates=[coordinates;coorx coor y]; demands=[demands;dem];
end

P = 10; % Number of centroids - facilities
N = length(coordinates(:,1)); % Number of clients - nodes

% Generate random solution
[centroids assignments total_distance] = random_assignment(N,P,capacity, demands, coordinates);
REF = total_distance; % Initial reference value for assessment of convergence
fprintf('Iteration 0 with REF = %1.5f \n',REF);

ITERATIONS=50; convergence=[];

% Local Search Metaheuristic for Improvement
for i=1:ITERATIONS
    [centroids assignments total_distance] = update_centroids_assignment(N,P,capacity, demands, coordinates, assignments);
    if total_distance < REF
        best_assignments=assignments; best_centroids=centroids; REF=total_distance;
        fprintf('Iteration %d with REF = %1.5f \n', i, REF);
    else
        if total_distance == Inf
            [centroids assignments total_distance] = random_assignment(N,P,capacity, demands, coordinates);
        end
    end
    convergence=[convergence;REF];
end

% Verification Routine
dems=[]; dists=[];
for i=1:P
    dem_ac=0; coords=[];
    for j=1:N
        if best_assignments(j)==i
            coords=[coords;coordinates(j,:)]; dem_ac=dem_ac+demands(j);
        end
    end
    dems=[dems;dem_ac]; dist=0; cx=best_centroids(i,:);
    for j=1:length(coords(:,1))
        dist=dist+ sqrt ( (cx(1)-coords(j,1))^2 + (cx(2)-coords(j,2))^2);
    end
    dists=[dists; dist];
end
dists=sum(dists);
if length(find(dems>capacity))>0
    fprintf('Error \n');
else
    if dists == REF fprintf('Full Success \n'); else fprintf('Partial Success \n'); end
end

figure; hold on;
for i=1:P
    coords=[];
    % Identify nodes assigned to facility i
    for j=1:N
        if best_assignments(j)==i
            coorx=[best_centroids(i,1) coordinates(j,1)]; coor y=[best_centroids(i,2) coordinates(j,2)];
            plot(coorx,coor y,'-b');
        end
    end
end

title('Assignments of Clients to Facilities','FontSize',12);
xlabel('X-Coordinates'); ylabel('Y-Coordinates');

figure; hold on;
title('Convergence of Local Search Metaheuristic','FontSize',12);
plot(1:ITERATIONS, convergence, 'ob');
xlabel('Iterations'); ylabel('Total Distance of Solution');

```

**Figure 18.** Programming Model 11: Local Search algorithm for CCCP.

Finally, the accuracy of this solution is assessed through Eq. (5). The NNS solution, which is plotted in Figure 21, leads to a total distance value of  $a = 18043.76066$  while the best-known solution leads to  $b = 17359.75$ . Then, the error gap is estimated as 3.94% which is within the limit of 5.0% for the CCCP.

The consideration of randomness within the search mechanism of the NNS algorithm is common to most meta-heuristic solving methods. Convergence is dependent of this aspect, thus, assessment of meta-heuristics is performed considering different CCCP instances and multiple executions. If the coefficient of variability of results through multiple executions is within 0.20 it can be assumed that the meta-heuristic is stable. Figure 22 presents an example of this extended assessment scheme considering instances from the well-known SJC and DONI databases. After 20 executions of the meta-heuristic (as performed in (Chaves AA and Nogueira-Lorena LA, 2010, 2011)), the coefficient of variability (CV), the best, worst and average results are obtained to estimate their associated error gaps from the best-known (BK) solutions of the test instances. As observed, the CV is very small, less than 3.0% for all instances, hence the algorithm is stable. Thus, a very suitable solution can be obtained within a few executions of the algorithm, which for all instances (except *doni2*) is within the error gap of 5.0%.

Other assessment schemes can consider the execution time, time to best solution, and average computational times. This is specific for the assessment of new solving methods. Logistic research

```

function [centroids assignments total_distance] = random_assignment(N,P,capacity, demands, coordinates)
% P = number of facilities, N = number of nodes
% Generate random solution
x_min=min(coordinates(:,1)); x_max=max(coordinates(:,1));
y_min=min(coordinates(:,2)); y_max=max(coordinates(:,2));

% Random centroids within the range of the nodes' coordinates
centroids=[];
for i=1:P
    centroids=[centroids; unifrnd(x_min,x_max) unifrnd(y_min,y_max)];
end

% Initialization of arrays
distance_matrix = zeros(P,N); % Distance matrix PxN
assignments = zeros(1,N); % Assignment vector for each node within N
capacities = zeros(1,P); % Cumulative capacity vector for each facility within P
distances = zeros(1,P); % Cumulative distance vector for each facility within P

% Compute distance matrix PxN
for i=1:P
    pA=centroids(i,:);
    for j=1:N
        pB=coordinates(j,:); distance_matrix(i,j) = sqrt((pA(1)-pB(1))^2+(pA(2)-pB(2))^2);
    end
end

clients=1:N; % List of all nodes to be assigned to each facility within P (unassigned nodes)
% Perform assignment while there are unassigned nodes
while length(clients)>0
    a=min(min(distance_matrix));
    [row,col]=find(distance_matrix==a); % location of the minimum value within the distance matrix
    if length(row)>1
        % random selection if more than one node has the same minimum distance to a facility
        c=ceil(unifrnd(0,length(row)));
    else
        c=1;
    end
    % Identification of the node with the minimum distance to a facility
    facility = row(c); node = col(c);
    % Perform assignment if the node is within the list of unassigned nodes
    % and there is available capacity within the facility
    if length(find(clients==node))>0 % capacities(facility)+demands(node)<=capacity
        assignments(node)=facility; % Perform assignment of the node to the facility
        capacities(facility)=capacities(facility)+demands(node); % Update capacity of the facility
        d=find(clients==node); clients(d)=[]; % Locate and remove assigned node from the list of unassigned nodes
        distance_matrix(facility,node)=Inf; % Remove the minimum value of the assigned node from the distance matrix
    else
        % If assignment cannot be performed, then remove the minimum value
        % for future assignment to a different facility
        distance_matrix(facility,node)=Inf; % Remove the current minimum value for future assignment
    end
end

% Compute total distance from current centroids to assigned nodes
for i=1:P
    dist=0; coords=[];
    % Identify nodes assigned to facility i
    for j=1:N
        if assignments(j)==i coords=[coords;coordinates(j,:)]; end
    end
    if length(coords)>0
        cx=centroids(i,1);
        % Compute cumulative distance from centroid to all its assigned nodes
        for j=1:length(coords(:,1))
            cy=coords(j,2); dist=dist+sqrt((cx(1)-cy(1))^2+(cx(2)-cy(2))^2);
        end
        distances(i)=dist;
    else
        % If no nodes are assigned to the facility, remove facility by making its distance equal to Inf.
        % This also marks this solution as not valid but suitable for improvement.
        distances(i)=Inf;
    end
end
total_distance=sum(distances);

```

**Figure 19.** Programming Model 12: Nearest-neighbor algorithm for initial assignment of nodes to closer centroids (CCCP instances).

is continuously extended in both important fields: (a) mathematical modeling of problems, and (b) adaptation and development of new solving methods. As presented, this work can provide the basis and resources for these research fields. In the following section, the application of the proposed programming models for two examples is described.

## APPLICATION EXAMPLES

### Example 1: Capacitated Vehicle Routing

The present example consists on developing a distribution scheme for 550 points within a city. The product to be distributed is insulin, which is important for people with diabetes or pancreatic dysfunction. Because people have different prescriptions for insulin use, and sometimes more than one person within a region needs insulin, the demand patterns may vary significantly from one point to another.

Due to the characteristics of the product, the distribution vehicle must have specific characteristics which involve costs. This restricts the frequency of distribution. Because there are only seven vehicles, the distribution must ensure fast response to the variable demand patterns without exceeding costs associated to inventory supply. In general, Figure 23 presents the methodological steps to solve this distribution problem. Initially, data regarding the capacity of the vehicles in terms of units of product must be estimated. For this case, the unit of product consists of a

```
function [centroids assignments total_distance] = update_centroids_assignment(N,P,capacity, demands, coordinates, assignments)
% P = number of facilities, N = number of nodes / clients
% Initialization of arrays
distance_matrix = zeros(P,N); % Distance matrix PxN
capacities = zeros(1,P); % Cumulative capacity vector for each facility within P
distances = zeros(1,P); % Cumulative distance vector for each facility within P

%Backup of initial assignments
original_assignments = assignments;

%Compute centroids from current assignments
centroids=[];
for i=1:P
    coords=[];
    for j=1:N
        if assignments(j)==i coords=[coords;coordinates(j,:)]; end
    end
    if length(coords)>0
        if length(coords(:,1))==1
            cx=coords; % If only one node is assigned, then this is the centroid's location
        else
            % If more than one node is assigned, their average coordinates are the centroid's location
            if length(coords(:,1))>1 cx=mean(coords); end
        end
    else
        % If no nodes are assigned to the facility, compute the centroid's
        % location as the average of all coordinates
        cx=mean(coordinates);
    end
    centroids=[centroids;cx]; % Update centroids
end

% Compute distance matrix with updated centroids
for i=1:P
    pA=centroids(i,:);
    for j=1:N pB=coordinates(j,:); distance_matrix(i,j)= sqrt((pA(1)-pB(1))^2+(pA(2)-pB(2))^2); end
end

clients=1:1:N; % List of all nodes to be assigned to each facility within P (unassigned nodes)
% Initialization for update of assignments with updated centroids
assignments = zeros(1,N); alarm=0;

while length(clients)>0 % alarm == 0
    a=min(min(distance_matrix));
    if min(min(distance_matrix))==Inf
        alarm = 1;
    else
        [row,col]=find(distance_matrix==a); % location of the minimum value within the distance matrix
        % random selection if more than one node has the same minimum distance to a facility
        if length(row)>1 c=ceil(unifrnd(0,length(row))); else c=1; end
        % Identification of the node with the minimum distance to a facility
        facility = row(c); node = col(c);
        % Perform assignment if the node is within the list of unassigned nodes
        % and there is available capacity within the facility
        if length(find(clients==node))>0 && capacities(facility)+demands(node)<=capacity
            assignments(node)=facility; % Perform assignment of the node to the facility
            capacities(facility)=capacities(facility)+demands(node); % Update capacity of the facility
            % Locate and remove assigned node from the list of unassigned nodes
            d=find(clients==node); clients(d)=[];
            distance_matrix(facility,node)=Inf; % Completely remove assigned node from the distance matrix
        else
            % If assignment cannot be performed, then remove the minimum value
            % for future assignment to a different facility
            distance_matrix(facility,node)=Inf; % Remove the current minimum value for future assignment
        end
    end
end

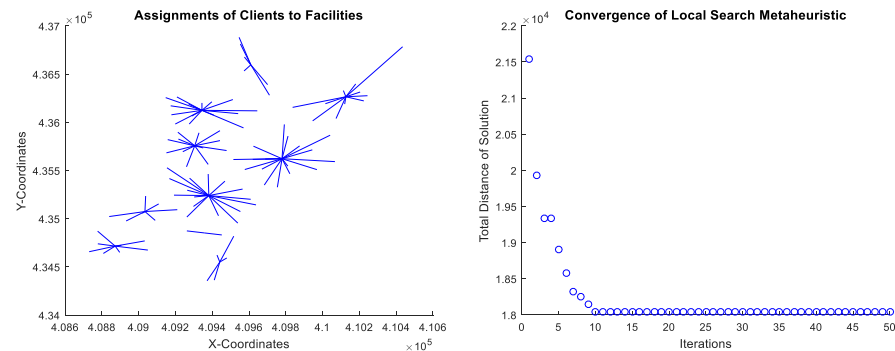
if alarm==0
    distances=zeros(1,P);
    % Compute total distance from current centroids to assigned nodes
    for i=1:P
        dist=0; coords=[];
        % Identify nodes assigned to facility i
        for j=1:N
            if assignments(j)==i coords=[coords;coordinates(j,:)]; end
        end
        if length(coords)>0
            cx=[]; cx=centroids(i,:);
            % Compute cumulative distance from centroid to all its assigned nodes
            for j=1:length(coords(:,1))
                cy=[]; cy=coords(j,:); dist=dist+sqrt((cx(1)-cy(1))^2+(cx(2)-cy(2))^2);
            end
            distances(i)=dist;
        else
            % If no nodes are assigned to the facility, remove facility by making its distance equal to Inf.
            % This also marks this solution as not valid but suitable for improvement.
            distances(i)=Inf;
        end
    end
    total_distance=sum(distances);
else
    total_distance=Inf;
end

if total_distance==Inf
    fprintf('unfeasible solution - initialize with random centroids \n');
    assignments=original_assignments; centroids=[];
    x_min=min(coordinates(:,1)); x_max=max(coordinates(:,1));
    y_min=min(coordinates(:,2)); y_max=max(coordinates(:,2));
    for i=1:P centroids=[centroids; unifrnd(x_min,x_max) unifrnd(y_min,y_max)]; end
    total_distance=Inf;
end
```

**Figure 20.** Programming Model 13: Nearest-neighbor algorithm for improvement of the assignment of nodes to closer centroids (CCCP instances).

323 pre-filled injection pen of 3 ml with 100 UI/ml (300 insulin units per pen) at an approximate  
 324 cost of  $C = 20$  USD. The vehicles' containers for transportation of this product has a capacity  
 325 of  $1.0 \text{ m}^3$ . Based on the dimensions of the product's package, estimated as  $0.10 \times 0.20 \times 0.085$   
 326  $= 0.0016 \text{ m}^3$ , the capacity is approximated as  $1.0 / 0.0016 = 625$  units.

327 Then, data regarding the demand patterns must be estimated to formulate the inventory  
 328 supply strategy. Figure 24 presents the gathered information from each of the delivery points

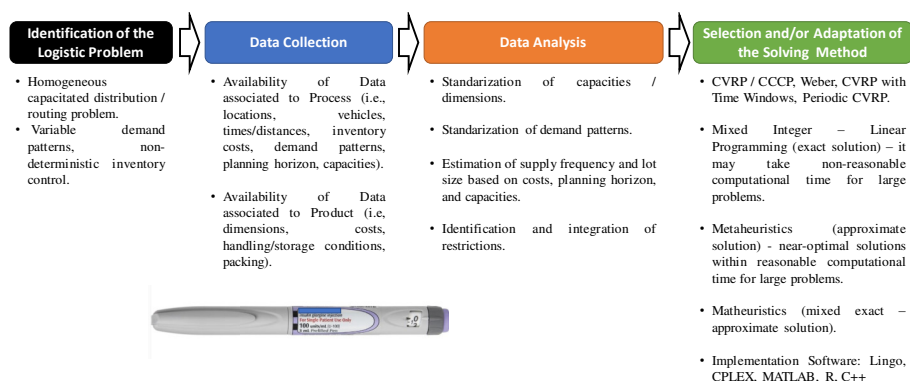


**Figure 21.** Results of the plotting algorithm: (A) assignments to centroids, (B) convergence of the search algorithm.

Instance	N	P	BK	Executions of the NNS Algorithm										CV	Error Gap (%)		
				1	2	3	4	5	6	7	8	9	10		Average	Best	Worst
SJC1	100	10	17359.75	19108.27	19233.84	19143.14	18031.42	19123.88	19393.45	18290.98	18174.94	18208.74	19200.32	0.02	8.00	3.87	11.72
SJC2	200	15	33181.65	34453.55	34263.04	33790.98	35184.40	34532.35	33966.42	34046.24	35374.06	35105.41	34846.92	0.02	3.81	0.72	7.21
SJC3a	300	25	45366.35	51494.75	47372.43	50184.63	47203.20	48262.37	48935.47	46790.16	48520.69	51850.40	49161.28	0.03	8.50	3.14	14.29
SJC3b	300	30	40695.46	44615.34	45297.04	45737.66	42897.90	43961.01	43714.43	44092.16	44020.33	42566.97	44201.15	0.02	8.14	4.60	13.34
SJC4a	402	30	61944.85	65574.16	66041.85	67444.02	65048.20	66532.38	65065.30	63879.09	65608.26	66293.10	64655.21	0.01	6.09	3.12	8.88
SJC4b	402	40	52214.55	54734.18	56138.30	54767.02	55450.18	56601.05	56984.65	56187.81	55050.67	55194.70	57268.72	0.01	6.96	4.83	9.68
don1	1000	6	3021.41	3183.97	3184.49	3193.70	3200.12	3096.33	3228.53	3315.32	3254.76	3185.43	3184.49	0.02	6.35	2.45	9.73
don2	2000	6	6080.70	6450.75	6771.04	6457.37	6520.50	6565.59	6943.25	6812.66	6604.67	6890.82	6462.06	0.02	9.00	6.02	14.19
don3	3000	8	8446.08	9386.09	9164.45	9046.35	9210.88	9222.20	9284.65	9046.58	9078.15	9521.70	8764.82	0.02	9.05	3.77	12.76
don4	4000	10	10854.48	11343.30	11554.67	12569.50	11727.37	12145.86	12228.30	11591.12	11749.20	12064.27	11900.86	0.03	9.52	4.50	15.80
don5	5000	12	11134.94	12134.10	11826.50	12239.01	11795.63	11778.82	12228.90	11756.23	11630.03	11991.76	11688.43	0.02	7.46	4.45	13.58

Instance	N	P	BK	Executions of the NNS Algorithm													
				11	12	13	14	15	16	17	18	19	20				
SJC1	100	10	17359.75	18414.13	18771.68	18980.26	18920.01	18238.01	18801.80	19309.07	19110.21	18456.53	18044.67				
SJC2	200	15	33181.65	33984.90	34244.03	34194.04	33933.64	33419.28	35572.49	34591.19	34987.62	34192.40	34202.39				
SJC3a	300	25	45366.35	49957.54	50486.07	49110.78	49326.85	49819.80	50118.63	49121.94	49122.90	48504.67	49125.72				
SJC3b	300	30	40695.46	42757.81	43491.62	43258.93	45979.48	46123.80	44577.86	43476.13	42845.84	43770.52	42757.56				
SJC4a	402	30	61944.85	64684.17	66330.04	66942.44	64252.03	65602.74	66930.28	64881.96	66203.34	66084.76	66330.83				
SJC4b	402	40	52214.55	56098.36	55717.76	55381.78	55560.09	56688.00	56007.38	55433.25	57244.58	55346.98	55156.16				
don1	1000	6	3021.41	3178.30	3289.38	3280.55	3255.53	3222.71	3285.68	3272.36	3209.67	3095.41	3150.72				
don2	2000	6	6080.70	6716.37	6523.83	6587.83	6514.85	6514.85	6757.51	6769.05	6450.75	6446.69	6792.99				
don3	3000	8	8446.08	9460.70	9121.97	9488.05	8788.67	9107.96	9004.30	9324.03	9316.03	9523.56	9352.43				
don4	4000	10	10854.48	11446.71	11908.09	12536.06	11531.49	12016.75	12263.57	11809.81	11522.08	11916.93	11938.64				
don5	5000	12	11134.94	12647.01	11733.33	11695.76	12072.83	11774.91	11937.90	11931.33	11879.98	12157.47	12410.48				

**Figure 22.** Extended Data for Assessment of NNS Algorithm for CCCP.



**Figure 23.** General methodological steps to address logistic problems - Example 1.

regarding demand patterns and locations through a planning horizon of two weeks. The main distribution center is located at  $\lambda = -98.245678$  and  $\phi = 19.056784$ .

Because most of the demands' CVs are bigger than 0.20, it is considered that variability is significant. Due to this, the non-deterministic periodic review ( $P$ ) model is considered to estimate the net requirements for  $T =$  one period of two-weeks (15 days), and  $LT =$  one day ( $1/15 = 0.07$  of one period of two-weeks). Note that under this assumption,  $d = \mu$  from Figure 24 for the ( $P$ ) model, and  $z = 2.1700904$  for a service level of 98.5%.

Regarding costs,  $C_o$  and  $C_h$  are estimated from the point of view of the ordering entity, in

Demand Data										Location Data									
i	j	μ	σ	CV	i	j	μ	σ	CV	i	j	μ	σ	CV	i	j	μ	σ	CV
1	3	1	0.33	111	3	1	0.33	221	3	1	0.33	331	3	2	0.67	441	3	2	0.67
2	1	0.25	112	7	2	0.29	222	3	1	0.33	332	3	2	0.67	442	3	2	0.67	
3	3	2	0.67	113	2	1	0.30	223	7	2	0.29	333	3	2	0.67	443	2	1	0.50
4	3	1	0.33	114	4	1	0.25	224	2	1	0.50	334	4	1	0.25	444	4	2	0.50
5	2	1	0.50	115	6	2	0.33	225	3	1	0.33	335	4	2	0.50	445	4	2	0.50
6	2	1	0.50	116	5	1	0.20	226	2	1	0.50	336	4	2	0.50	446	3	2	0.67
7	2	1	0.50	117	3	2	0.67	227	2	1	0.30	337	2	1	0.50	447	4	2	0.50
8	3	1	0.33	118	3	2	0.67	228	3	2	0.67	338	4	2	0.50	448	3	2	0.67
9	4	1	0.25	119	2	1	0.50	229	3	1	0.33	339	4	1	0.25	449	3	1	0.33
10	4	2	0.50	120	3	1	0.33	230	2	1	0.50	340	2	1	0.50	450	2	1	0.50
11	2	1	0.50	121	2	1	0.50	231	4	2	0.50	341	4	2	0.50	451	4	2	0.50
12	5	2	0.40	122	4	2	0.50	232	3	2	0.67	342	3	1	0.33	452	2	1	0.50
13	4	1	0.25	123	4	2	0.50	233	3	2	0.67	343	3	2	0.67	453	4	2	0.50
14	2	1	0.33	124	2	1	0.50	234	6	2	0.33	344	4	1	0.25	454	3	2	0.67
15	3	1	0.33	125	4	2	0.50	235	3	2	0.67	345	2	1	0.50	455	4	2	0.50
16	4	1	0.25	126	7	2	0.29	236	2	1	0.50	346	3	1	0.33	456	3	1	0.33
17	2	1	0.50	127	9	2	0.22	237	3	2	0.67	347	2	1	0.50	457	2	1	0.50
18	3	2	0.67	128	3	1	0.33	238	3	1	0.33	348	3	1	0.33	458	5	2	0.40
19	2	1	0.50	129	3	2	0.67	239	5	2	0.40	349	3	1	0.33	459	4	2	0.50
20	4	2	0.50	130	3	2	0.67	240	2	1	0.50	350	2	1	0.50	460	3	2	0.67
21	6	2	0.33	131	4	2	0.50	241	2	1	0.50	351	4	2	0.50	461	2	1	0.50
22	4	1	0.25	132	2	1	0.50	242	3	1	0.33	352	3	2	0.67	462	3	2	0.67
23	3	1	0.33	133	2	1	0.50	243	2	1	0.50	353	4	2	0.50	463	4	2	0.50
24	5	2	0.40	134	3	1	0.33	244	4	2	0.50	354	6	2	0.33	464	4	2	0.50
25	4	2	0.50	135	5	2	0.40	245	4	2	0.50	355	2	1	0.50	465	3	2	0.67
26	2	1	0.50	136	4	2	0.50	246	3	2	0.67	356	2	1	0.50	466	2	1	0.50
27	3	1	0.33	137	3	2	0.67	247	2	1	0.50	357	2	1	0.50	467	3	2	0.67
28	3	1	0.33	138	5	2	0.40	248	2	1	0.50	358	2	1	0.50	468	3	1	0.33
29	2	1	0.50	139	2	1	0.50	249	4	2	0.50	359	3	1	0.33	469	3	1	0.33
30	3	1	0.33	140	3	2	0.67	250	4	1	0.25	360	3	2	0.67	470	2	1	0.50
31	3	2	0.67	141	4	1	0.25	251	2	1	0.50	361	2	1	0.50	471	4	2	0.50
32	4	1	0.25	142	2	1	0.50	252	3	1	0.33	362	2	1	0.50	472	4	2	0.50
33	4	1	0.25	143	2	1	0.50	253	7	2	0.29	363	4	2	0.50	473	3	1	0.33
34	2	1	0.50	144	2	1	0.50	254	3	2	0.67	364	5	2	0.40	474	3	1	0.33
35	2	1	0.50	145	3	2	0.67	255	3	1	0.33	365	5	2	0.40	475	3	1	0.33
36	4	2	0.50	146	4	2	0.50	256	3	1	0.33	366	2	1	0.50	476	3	1	0.33
37	3	2	0.67	147	4	1	0.25	257	2	1	0.50	367	3	1	0.33	477	2	1	0.50
38	7	2	0.29	148	2	1	0.50	258	4	1	0.25	368	3	1	0.33	478	4	2	0.50
39	2	1	0.50	149	4	2	0.50	259	4	2	0.50	369	2	1	0.50	479	3	2	0.67
40	3	2	0.67	150	5	2	0.40	260	4	1	0.50	370	2	1	0.50	480	3	1	0.33
41	3	1	0.33	151	4	2	0.50	261	4	2	0.50	371	3	2	0.67	481	4	2	0.50
42	3	2	0.67	152	4	2	0.50	262	4	2	0.50	372	3	2	0.67	482	3	2	0.67
43	2	1	0.50	153	3	2	0.67	263	3	1	0.33	373	4	2	0.50	483	3	1	0.33
44	6	1	0.17	154	2	1	0.50	264	5	2	0.40	374	4	2	0.50	484	4	2	0.50
45	2	1	0.50	155	3	2	0.67	265	3	2	0.67	375	3	1	0.33	485	3	1	0.33
46	3	2	0.67	156	3	1	0.33	266	4	2	0.50	376	3	2	0.67	486	4	2	0.50
47	3	2	0.67	157	4	2	0.50	267	4	2	0.50	377	2	1	0.50	487	3	1	0.33
48	3	1	0.33	158	4	1	0.25	268	4	2	0.50	378	4	2	0.50	488	3	1	0.33
49	3	1	0.33	159	2	1	0.50	269	2	1	0.50	379	6	2	0.33	489	2	1	0.50
50	3	2	0.67	160	3	1	0.33	270	2	1	0.50	380	3	2	0.67	490	2	1	0.50
51	3	1	0.33	161	4	2	0.50	271	4	2	0.50	381	2	1	0.50	491	3	1	0.33
52	3	2	0.67	162	4	2	0.50	272	4	1	0.25	382	4	2	0.50	492	4	2	0.50
53	4	1	0.25	163	4	2	0.50	273	3	1	0.33	383	3	1	0.33	493	3	1	0.33
54	4	2	0.50	164	3	2	0.67	274	3	2	0.67	384	2	1	0.50	494	4	2	0.50
55	5	1	0.20	165	7	2	0.29	275	2	1	0.50	385	4	1	0.25	495	2	1	0.50
56	4	1	0.25	166	3	1	0.33	276	3	2	0.67	386	3	1	0.33	496	2	1	0.50
57	3	1	0.33	167	4	1	0.25	277	4	2	0.50	387	3	1	0.33	497	4	2	0.50
58	3	1	0.33	168	4	2	0.50	278	3	1	0.33	388	2	1	0.50	498	5	2	0.40
59	5	2	0.40	169	4	2	0.50	279	4	2	0.50	389	5	2	0.40	499	3	2	0.67
60	4	2	0.50	170	4	2	0.50	280	2	1	0.50	390	3	2	0.67	500	4	2	0.50
61	2	1	0.50	171	4	2	0.50	281	2	1	0.50	391	4	2	0.50	501	2	1	0.50
62	2	1	0.50	172	3	1	0.33	282	5	2	0.40	392	4	2	0.50	502	4	2	0.50
63	4	2	0.50	173	3	2	0.67	283	2	1	0.50	393	4	2	0.50	503	6	2	0.33
64	4	2	0.50	174	3	1	0.33	284	3	2	0.67	394	4	2	0.50	504	2	1	0.50
65	5	1	0.25	175	3	2	0.67	285	5	2	0.20	395	4	2	0.50	505	2	1	0.50
66	2	1	0.50	176	3	1	0.33	286	4	1	0.25	396	3	2	0.67	506	3	2	0.67
67	2	1	0.50	177	4	2	0.50	287	4	1	0.25	397	3	2	0.67	507	2	1	0.50
68	5	1	0.20	178	2	1	0.50	288	3	2	0.67	398	2	1	0.50	508	4	1	0.25
69	4	1	0.25	179	2	1	0.50	289	3	1	0.33	399	4	2	0.50	509	4	2	0.50
70	4	1	0.25	180	3	1	0.33	290	2	1	0.50	400	4	1	0.25	510	4	2	0.50
71	5	2	0.40	181	3	2	0.67	291	5	1	0.20	401	4	2	0.50	511	6	2	0.33
72	5	2	0.40	182	3	1	0.33	292	3	2	0.67	402	4	2	0.50	512	3	1	0.33
73	3	1	0.33	183	4	2	0.50	293	3	2	0.67	403	4	2	0.50	513	4	2	0.50
74	3	1	0.33	184	4	1	0.25	294	4	1	0.25	404	4	1	0.25	514	5	2	0.40
75	3	1																	

the efficiency of the vehicle (kilometers per liter), and  $d_j$  is the cumulative distance up to the delivery point  $j$ . For a standard vehicle  $d_e$  is estimated as 12 kilometers per liter and  $d_s$  as 1.10 USD per liter (based on regional costs). Because  $d_j$  is directly associated to the traveled distance, its minimization can be achieved through the application of an appropriate distribution planning model as the CVRP (*Programming Models 4(c), 7-10*).

Figure 25 presents the net requirements (lot size  $Q$ ) per location based on the  $P$  model considering a period between reviews of two weeks. These results represent the demand data for the CVRP model. As minimization of the inventory management costs is the main objective of the distribution scheme, the total cost for the  $P$  model with the integrated  $C_o$  cost is considered as the objective function. Thus, Figure 25 also presents the distribution planning obtained by the CVRP and the associated  $C_o$  and total inventory costs for each delivery location.

The sum of all total costs associated to inventory management is estimated as 1016.5939 USD, where the total order cost is estimated as 470.5898 USD. This represents a significant investment even if appropriate inventory control and distribution planning is performed. A key aspect to improve these results is to extend on the availability of other distribution centers. This is to be addressed in the following example.

## Example 2: Facility Location

From the previous analysis, the task of finding an alternative location for the distribution center was explored. As presented in Figure 26, the new location estimated at  $\lambda = -98.2266$  and  $\phi = 19.0369$  by the NNS approach (*Programming Models 11-13*), can lead to a total inventory management cost of approximately 905.1940 USD with a total order cost of 355.1493. This represents a reduction of  $(1 - 905.1940/1016.5939) \times 100.0\% = 10.958\%$  and  $(1 - 355.1493/470.5898) \times 100.0\% = 24.531\%$  respectively.

Figure 27 presents the results considering two distribution centers, with four and three vehicles respectively. This was achieved by changing the *capacity* variable in *Programming Models 11-13* from a single constant value (homogeneous capacity) to a vector with different capacity values for each distribution center (heterogeneous capacity). Under this scheme, the routes of the first distribution center can lead to a total inventory management cost of approximately 517.4791 USD with a total order cost of 180.7032 USD. On the other hand, the routes of the second distribution center can lead to a total inventory management cost of approximately 350.7018 USD with a total order cost of 137.4330 USD. In total, this strategy leads to a reduction of  $(1 - (517.4791 + 350.7018)/905.1940) \times 100.0\% = 4.09\%$  and  $(1 - (180.7032 + 137.4330)/355.1493) \times 100.0\% = 10.42\%$  respectively on the previous costs.

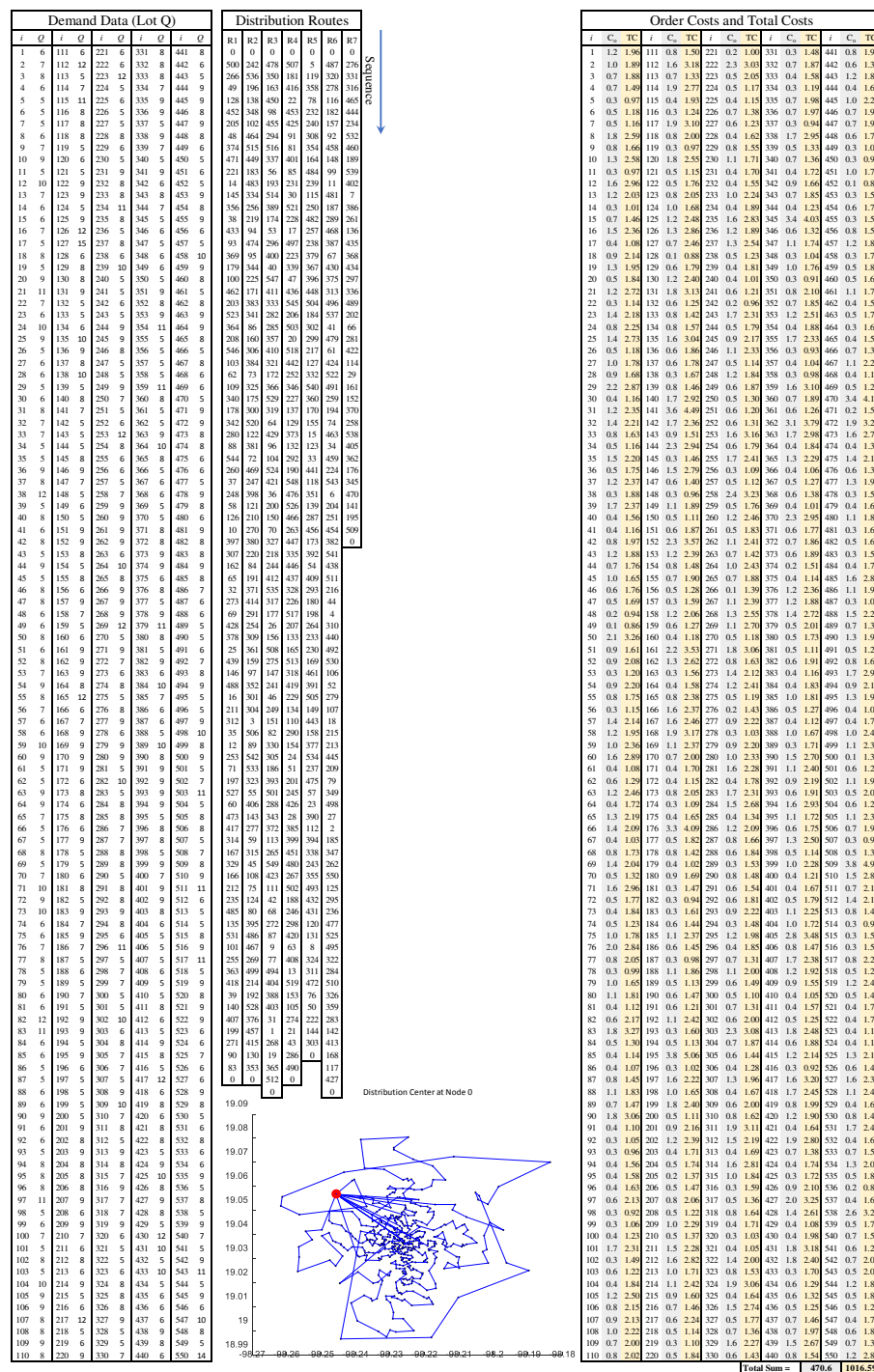
Figure 28 presents the total inventory management cost for the cases with three, four, five, six and seven distribution centers. It can be observed that there is a limit to increase the number of distribution centers to reduce the total inventory costs. A steady reduction is observed for up to five distribution centers. However, a steady increase is observed for six and seven distribution centers (which implies a vehicle per distribution center). Hence, it is important to consider that there is an optimal or near-optimal number of distribution centers to reduce the total costs associated to distance. Also, the achieved savings must compensate the investment required for this additional infrastructure within a suitable period of time.

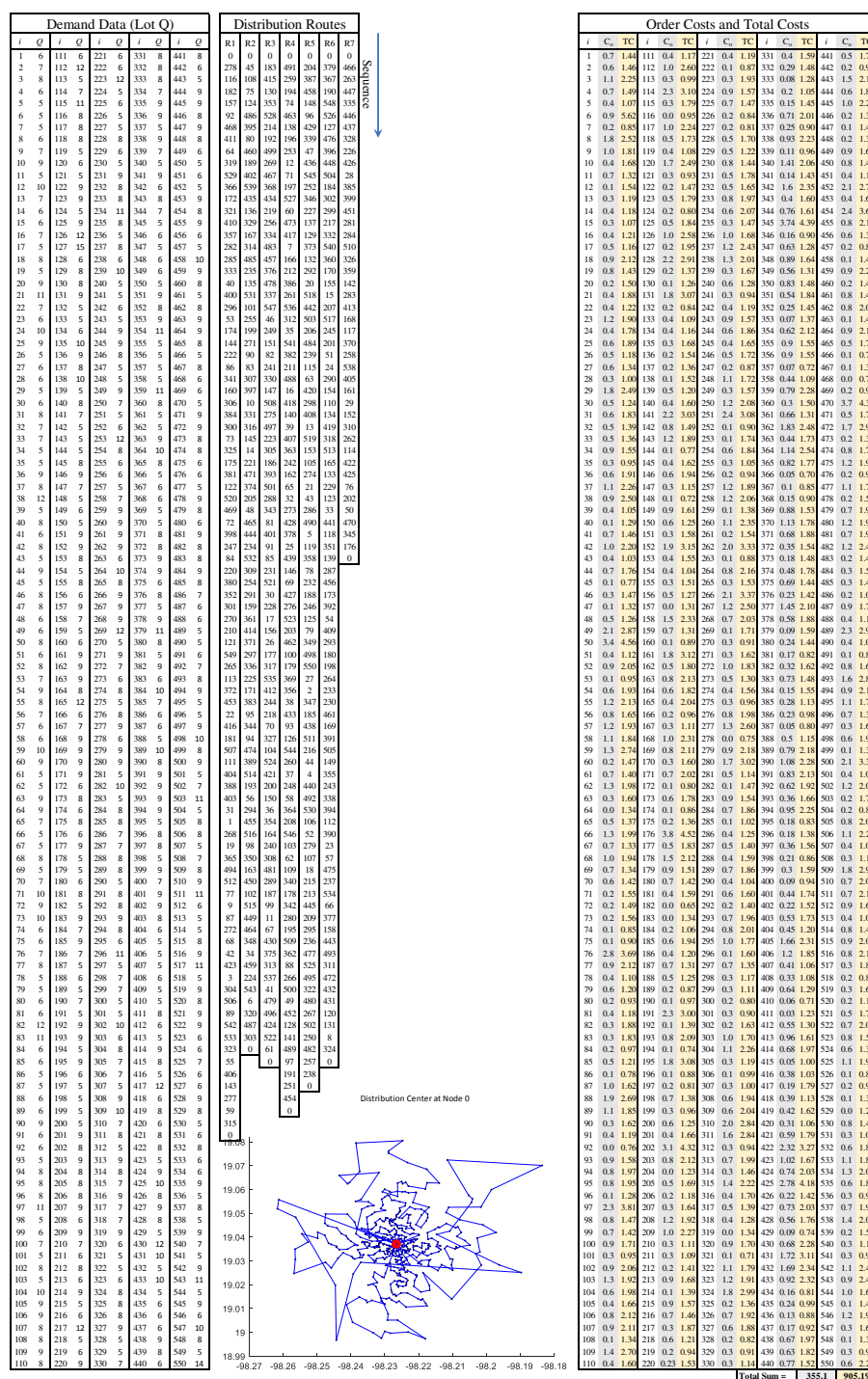
## RESULTS AND CONCLUSIONS

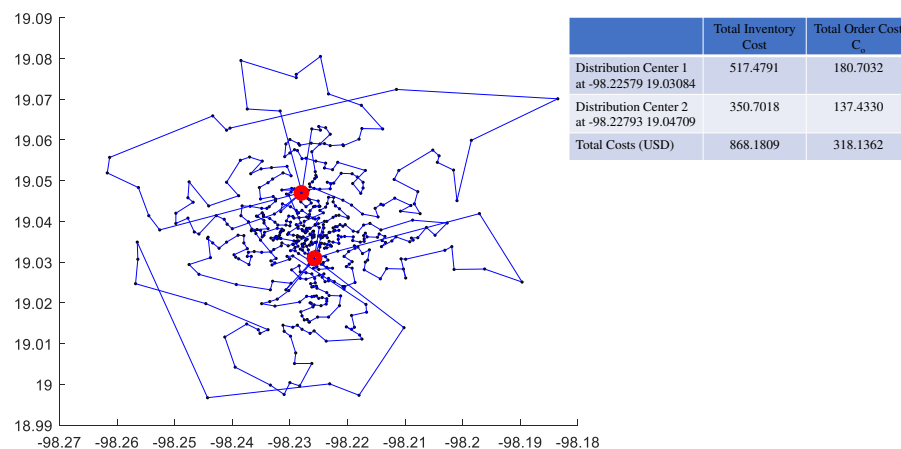
In this work the development of resources for logistic and inventory management research was presented. These resources are complemented with programming code and implementation examples to motivate their learning and application. Specifically, the following aspects are covered by this material:

- development of instances for vehicle – routing/ facility location instances with near-to-real geographical data;
- development of instances with symmetric and asymmetric distance/cost data considering the main distance metrics available for modeling;
- development of exporting and plotting codes for visualization and processing by third-party platforms;









**Figure 27.** Results of Inventory Management Costs for Example 2: Strategy with Two Distribution Centers

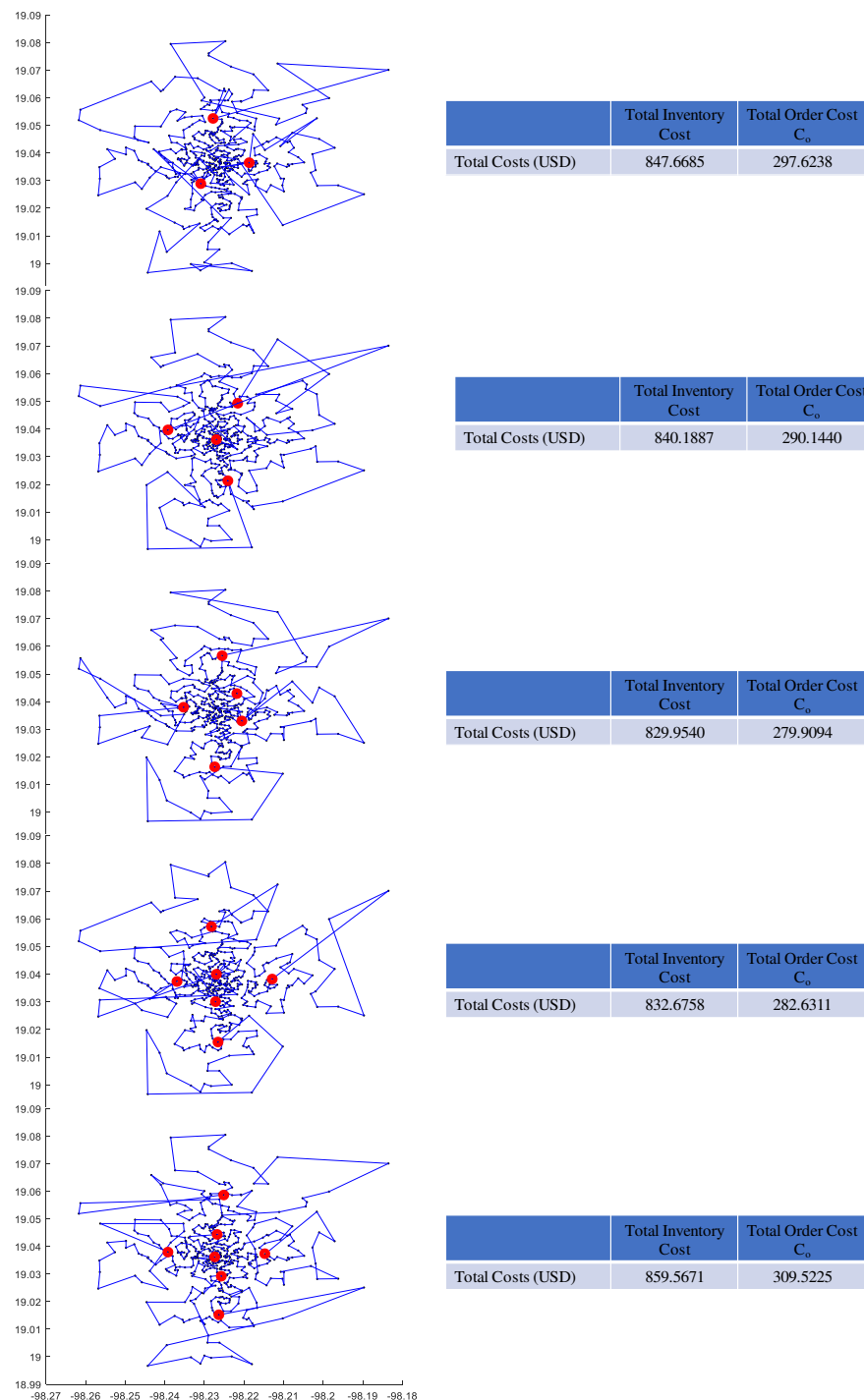
the key aspects and tools to understand most of the associated works reported in the specialized literature.

## STATEMENT

“The author declares that there is no conflict of interest regarding the publication of this paper.”

## REFERENCES

- Adamu I (2017). Reorder quantities for (Q,R) inventory models. *International Mathematical Forum*, 12(11):505–514.
- Aras N, Yumusak S, and Altmel K (2007). Solving the capacitated multi-facility weber problem by simulated annealing, threshold accepting and genetic algorithms. In Doerner, K, Gendreau M, Greistorfer P, Gutjahr W, Hartl R, and Reimann M, editors, *Metaheuristics: Progress in Complex Systems Optimization*, pages 491–112.
- Basu S, Sharma M, and Ghosh P (2015). Metaheuristic applications on discrete facility location problems: a survey. *OPSEARCH*, 52(3):530–561.
- Braglia M, Castellano D, Marrazzini L, and Song D (2019). A continuous review (Q, r) inventory model for a deteriorating item with random demand and positive lead time. *Computers and Operations Research*, 109:102–121.
- Bräysy O and Gendreau M (2005a). Vehicle Routing Problem with Time Windows, Part I: Route Construction and Local Search Algorithms. *Transportation Science*, 39(1):104–118.
- Bräysy O and Gendreau M (2005b). Vehicle Routing Problem with Time Windows, Part II: Metaheuristics. *Transportation Science*, 39(1):119–139.
- Chaves AA and Nogueira-Lorena LA (2010). Clustering search algorithm for the capacitated centered clustering problem. *Computers & Operations Research*, 37(3):552–558.
- Chaves AA and Nogueira-Lorena LA (2011). Hybrid evolutionary algorithm for the capacitated centered clustering problem. *Expert Systems with Applications*, 38:5013–5018.
- Daugherty P, Bolumole Y, and Schwieterman M (2017). Logistics Research: What a Long, Strange Trip It’s Been. *Transportation Journal*, 56(3):213–226.
- De SK and Sana SS (2015). Multi-criterion multi-attribute decision-making for an EOQ model in a hesitant fuzzy environment. *Pacific Science Review A: Natural Science and Engineering*, 17:61–68.
- Eaton JW, Bateman D, Hauberg S, and Wehbring R (2018). *GNU Octave version 4.4.0 manual: a high-level interactive language for numerical computations*.
- Erturgut R (2011). Increasing demand for logistics technician in business world and rising trend of logistics programs in higher vocational schools: Turkey case. *Procedia - Social and Behavioral Sciences*, 15:2776–2780.



**Figure 28.** Results of Inventory Management Costs for Example 2: Strategy with Three to Seven Distribution Centers

- 437 Hariga M (2009). A continuous review (Q,r) model with owned and rented storage facilities. In  
 438 *Proc. of the IEEE International Conference on Computers & Industrial Engineering (CIE*  
 439 *2009)*, pages 1297–1301.  
 440 Hovelaque V and Bironneau L (2015). The carbon-constrained EOQ model with carbon emission  
 441 dependent demand. *International Journal of Production Economics*, 164:285–291.  
 442 Kuczyńska-Chalada M, Furman J, and Poloczek R (2018). The challenges for logistics in the

- 443 aspect of Industry 4.0. *Multidisciplinary Aspects of Production Engineering*, 1(1):553–559.
- 444 Lieberman G and Hillier F (2000). *Introduction to Operations Research (7th ed.)*. McGraw-Hill.
- 445 Lloyd C, Pötsch T, Yi S, Zúñiga R, Safaei M, Issa S, and Rügge I (2013). Resources in logistics
- 446 - a multidisciplinary challenge. In *Proc. of the 6th International Federation of Automatic*
- 447 *Control Conference on Management and Control of Production and Logistics (IFAC 2013)*,
- 448 pages 449–455.
- 449 Negreiros M and Palhano A (2006). The capacitated centred clustering problem. *Computers &*
- 450 *Operations Research*, 33(6):1639—1663.
- 451 Nogueira-Lorena LA (2007). *Problem Instances*. <http://www.lac.inpe.br/~lorena/instancias.html>.
- 452 Oliveira D, Uchoa E, Pecin D, Pessoa A, Poggi M, Vidal T, and Subramanian A (2019). *CVRPLIB*
- 453 *Capacitated Vehicle Routing Problem Library*. <http://vrp.atd-lab.inf.puc-rio.br/index.php/en/>.
- 454 Prodhon C and Prins C (2014). A survey of recent research on location-routing problems.
- 455 *European Journal of Operational Research*, 238(1):1–17.
- 456 Rao K, Stenger A, and Wu HJ (1998). Integrating the use of computers in logistics education.
- 457 *International Journal of Physical Distribution & Logistics Management*, 28(4):302–319.
- 458 Reinelt G (1991). TSPLIB - A Traveling Salesman Problem Library. *ORSA Journal on*
- 459 *Computing*, 3(4):376–384.
- 460 Reinelt G (1997). *TSPLIB*. <http://elib.zib.de/pub/mp-testdata/tsp/tsplib/tsplib.html>.
- 461 Sachan A and Datta S (2005). Review of supply chain management and logistics research.
- 462 *International Journal of Physical Distribution & Logistics Management*, 35(9):664–705.
- 463 Stefanello F, CB-de-Araújo O, and Müller F (2015). Matheuristics for the capacitated p-median
- 464 problem. *International Transactions in Operational Research*, 22(1):149–167.
- 465 Thinakaran N, Jayaprakas J, and Elanchezhian C (2019). Survey on Inventory Model of EOQ &
- 466 EPQ with Partial Backorder Problems. *Materials Today: Proceedings*, 16:629–635.
- 467 Uchoa E, Pecin D, Pessoa A, Poggi M, Vidal T, and Subramanian A (2017). New benchmark
- 468 instances for the Capacitated Vehicle Routing Problem. *European Journal of Operational*
- 469 *Research*, 257(3):845–858.
- 470 Zäpfel G, Braune R, and Bögl M (2010). *Metaheuristic Search Concepts: A Tutorial with*
- 471 *Applications to Production and Logistics*. Springer Heidelberg Dordrecht London New York.