# The Eco-Friendly Intermodal Delivery Network

## Optimization of an mTSP by Using K-Means and a Genetic Algorithm

Sergio Mourelo

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John Vadnal, Ph.D.
Thesis Chair

Robert Keith Rich, M.S.
Committee Member

David Schweitzer, Ph.D.
Committee Member

Brenda Ayres, Ph.D.
Honors Director

Date

Abstract

The design of the distribution process is a strategic issue for almost every company. As the use of advanced technology and automation increases in manufacturing and logistics, the implementation of autonomous and electrical transportation, such as driverless vehicles and electric trucks, has become an interesting topic of study within the last few years, with the main objective of minimizing distribution costs and delivery times. The purpose of this research is to prove that intermodal delivery networks, which may combine a train and several electric vehicles, are more efficient and environmentally friendly than unimodal networks for high volume and long haul transportation, regardless of the customers' distribution. This is only applicable if demand does not fall within the capacity restriction of road transportation vehicles. To do so, this paper utilizes an optimization algorithm that consists of a feedback mechanism between K-means and a genetic algorithm, which finds the optimal routes between distribution centers and surrounding customers as a multiple traveling salesman problem (mTSP).

# The Eco-Friendly Intermodal Delivery Network

Currently, logistics is one of the most important areas in business management for almost every company because it covers the management, planning, and delivery of products at the lowest cost. It is an indispensable part of success in business operations as it is a strategic tool for efficient deliveries and the proper functioning and growth of the commercial and marketing departments of many companies. In other words, logistics brings together both supply and sales, and aims to achieve greater efficiency by controlling the flow of customer information, distribution centers, warehouses, and inventory. By doing this, companies intend to minimize response time, optimize storage costs, reduce inventory, and integrate transportation.

In order to achieve success in the implementation of an optimal logistics network in an organization, it is necessary to develop certain functionalities in different areas such as evaluation of types of transportation, analysis of productivity and capacity, quality control, demand forecasting, route planning, and map configuration with delivery network. Thus, logistics management in general is one of the basic elements to improve profitability and competitive performance of a company as a whole.

Besides finding the optimal design of the distribution that minimizes delivery times and distribution costs, many companies look for systems of transportation that bring other advantages associated with them such as increasing the public's safety, reducing energy consumption, and contributing to improved air quality and environmental conditions. The choice of a transportation mode, combined or not, depends on factors such as the need for specific infrastructure, serviced distance, transport capacity, safety, weight, and volume constraints, associated costs including equipment and infrastructure, weather conditions, the urgency and the response time, the enforceable environmental restrictions, saturation of transportation networks, the conditions of the elements that need to be transported, geographic characteristics, and many others. The decision to opt for certain transportation modes or the combination of at least two of them depends on the weights assigned to the different factors and priorities of the decision maker. However, holding paramount the safety, health, and welfare of the public as well as promoting the sustainability of the environment and minimizing delivery times and distribution costs should be the primary objectives for any industrial and systems engineer. Having this in mind, a quick comparison of the different types of transportation available is summarized in Table 1.

*Table 1: Types of Transportation Comparison (U.S. DOT FHA, 1998)*

| **Transportation Comparison** | | | | | |
|---|---|---|---|---|---|
| **Types of Transportation** | **Speed** | **Capacity** | **Safety** | **Costs** | **Type of Merchandise** |
| **Road** | High | Low | Medium | Low | All |
| **Rail** | Medium | High | High | Medium | Bulks and Containers |
| **Maritime** | Low | Very High | High | Low | Bulks and Containers |
| **Air** | Very High | Low | Very High | High | High value, perishable |
| **Intermodal** | High | Medium | Medium | Medium | All |

On one hand, by looking at the different factors such as speed, capacity, safety, and costs, the road transportation is the best option when it comes to high speed and low costs. However, safety and capacity are very low compared to other transportation modes, which would require a higher number of vehicles in order to meet high demands. Moreover, one of the biggest challenges with the current road transportation is roadway congestion. As stated by Schrank, Eisele, Lomax, and Bak (2015), “the data from 1982 to 2014 show that, short of major economic problems, congestion will continue to increase if projects, programs, and policies are not expanded” (p. 1). In 2014, congestion caused trucks to lose $28 billion on wasted time and fuel. Also, the Travel Time Index has increased from 1.09 in 1982 to 1.22 in 2014 and the total congestion cost in billions of dollars has increased from $42 in 1982 to $160 in 2014 (Shrank et al., 2015, p. 3).

On the other hand, air and maritime transportation would not be ideal due to high costs and low speed, respectively. When it comes to air transportation, new disruptive technologies are rising in the last few years such as the use of drones to deliver light packages to the end-users, which could be an efficient solution for short-distances. However, some of the limitations are the capacity and battery-life as drones can only carry one package at a time, with a maximum weight of 5 lbs., for less than 30 minutes (Wang, 2015). Finally, rail transportation could be a feasible solution due to high capacity and safety. However, it is not one of the fastest transportation modes and it could only become an optimal choice if combined with at least another transportation mode due to high investments associated with infrastructure and difficulties to find free space in urban areas in order to reach clients or customers.

From an economic standpoint, Jean-Paul Rodrigue, Claude Comtois, and Brian Slack (2013) state that “different transportation modes have different cost functions according to the serviced distance. Road, rail, and maritime transport have respectively a T1, T2, and T3 cost functions.”

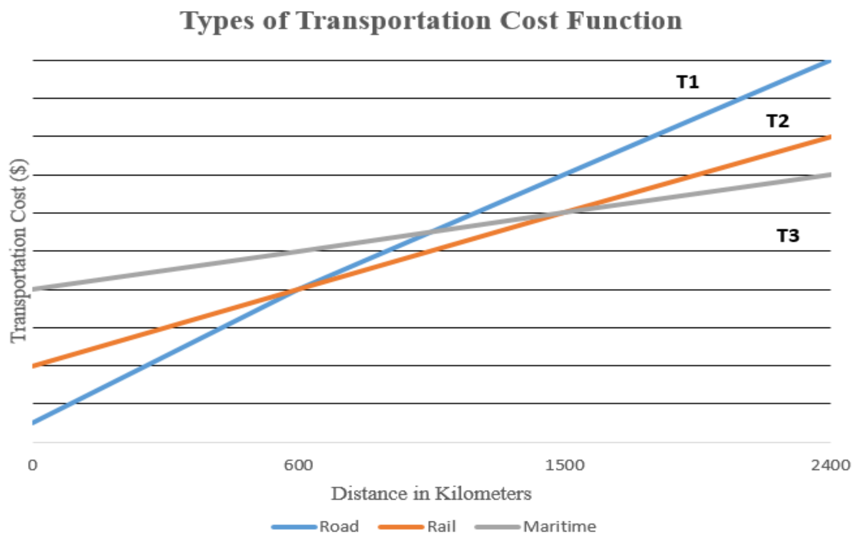


*Figure 1: Types of Transportation Cost Function*

As shown in figure 1, road transportation will be more profitable for shorter distances while rail and maritime transportation will minimize distribution costs per unit in medium and larger distances, respectively. The crossover point where road transportation becomes more expensive than rail transportation is roughly located between 500 and 750 km from the departure point. Secondly, the crossover point where rail and road transportation become more expensive than maritime transportation is generally located around 1,500 km (Rodrigue et al., 2013). However, breakeven distances may change depending on market densities, resources available, and specific transportation characteristics of each region. Thus, this research studies, from an operational perspective, the implementation of an intermodal network that will consist of a train and several electric vehicles.

**Intermodal Network: A Train-EVs in Tandem Delivery System**

Advanced technology and automation are playing a huge role on the production of autonomous and electric vehicles that could revolutionize the automobile industry and current logistics networks in a few years. Given the projections estimated by Vijay Gill, Barrie Kirk, Paul Godsmark, and Brian Flemming (2015), the arrival of automated vehicles (AVs), also known as driverless or self-driving vehicles, is the disruptive technology that is not only on the drawing board, but is actually about to operate, or operating, in many countries of the world. For example, Singapore and the government of the United Kingdom are promoting the testing of AVs on their public highways in 2015 while the European Union is expanding on the CityMobil2 program to help develop and introduce AVs in Europe (Gill, Kirk, Godsmark, & Flemming, 2015, p. 7). Moreover, companies such as Mercedes-Benz, Nissan, Peugeot, Volvo and Tesla are moving toward the development of AVs with electric motors. For example, "Mercedes-Benz already has demonstration vehicles capable of 99 per cent autonomous operation and commercially available vehicles that are 70 per cent autonomous" (Gill et al., 2015, p. 7). For now, the speed of these vehicles vary from 25 km/h, which is the speed of a driverless shuttle, to 40 km/h, which is the speed of a fully automated, electric vehicle that Google is likely to start using for deliveries (UK Department of Transport, 2015). Even though the AVs' average speed is low compared to standard vehicles, this form of transportation will be ideal in urban areas. For high volume and long haul transportation, it is necessary to highlight the development of hybrid-electric trucks (which increase fuel efficiency by combining an electric motor with a conventional combustion engine), battery electric trucks (which have an electric motor powered by batteries), and fuel cell electric trucks (which use fuel cells to convert hydrogen and air into electricity). Currently, companies such as BRUSA, BMW, and Freightliner have already developed electric trucks with capacities varying from 8 tons up to 40. Even though these technologies are still in development due to battery-life limitations, these electric vehicles "have the potential to dramatically reduce fuel consumption, cutting fuel costs for business, improving air quality and public health, and moving America towards cutting its projected oil use in half within the next 20 years" (Union of Concerned Scientists, 2012, p. 6).

When it comes to rail transportation, the U.S. freight rail network is widely considered one of the most dynamic freight systems in the world. It consists of 140,000 rail miles operated by more than 560 railroads and it accounts for approximately 40% of all freight (Federal Railroad Administration, 2012). Also, railroads are the most environmentally friendly transportation mode as trains are four times (on average) more fuel efficient than trucks. In fact, "moving freight by rail instead of truck lowers greenhouse gas emissions by 75%" (Association of American Railroads, 2015). Furthermore, the capacity of a single train is equivalent to several hundred trucks, which helps to reduce roadway congestion. Besides all these advantages, different technologies are rising with the intention of improving freight transportation around the world. Among the newest trends, it is necessary to highlight the CargoMover, which is a self-propelled and fully automated vehicle with a payload of up to 60 tons that is controlled by a central computer and directed by wireless communication (Dimitrijevic & Spasovic, 2006, p. 6). Other tendencies in research are automated capsule systems for pallets and containers, either under or above ground, that aim to optimize long and short distance freight transportation as well as reduce negative impact on the environment and roadway congestion. The speed of these systems vary from 40 km/h to top speeds of approximately 90 km/h.

Due to the characteristics and specifications of both transportation modes, the combination of an automated train and a number of electrical vehicles will result in an efficient intermodal delivery network that maximizes the capacity of the system, minimizes delivery time and distribution costs, reduces roadway congestion and energy consumption, increases safety, and contributes to improve air quality and environmental conditions. However, it is necessary to figure out the optimal routes that each transportation mode must follow and the optimal location and number of electrical vehicles needed.

For such a problem, which may be called the Eco-Friendly Intermodal Delivery Problem (EIDP), this research utilizes an iterative optimization algorithm that consists of a feedback mechanism between K-means for optimal clustering customers and a genetic algorithm for optimal train and electrical vehicles TSP routes. This algorithm computes the optimal solution by doing the following:

1. It starts by creating a uniform distribution of customers on a given operating area. Also, it initializes the speed and delivery time for the train and the electric vehicles.
2. Then, it uses K-means to find customer clusters based on average distances between them. With this method, it also finds centroids for each cluster of customers, where distribution centers will be built. An electrical vehicle is then assigned to each distribution center for the “last mile” deliveries.
3. Once the customer clusters and the number and location of distribution centers are determined, then the EIDP algorithm uses a genetic algorithm with two purposes:
    a. To compute the train TSP route from a manufacturing plant to each distribution center and back to the manufacturing plant.

   b. To compute each electrical vehicle (EV) TSP route from its assigned distribution center to all the customers around it and back to the distribution center.

4. Finally, the optimal solution is determined by finding the minimum delivery time associated to a parabolic cost function, which calculates the total delivery time of the intermodal network for different clusters.

## Literature Review

The problem of locating distribution centers and finding optimal routes, given delivery requirements, covers the core topics of distribution system design. Even though operations research has focused mostly on unimodal transportation problems, several research papers have been published within the last few years dealing with the optimization of intermodal transportation. These journal papers have proposed differing methods such as mixed integer linear programing (Arnold, Peeters, Thomas, & Marchand, 2001), genetic and hybrid algorithms (Carlsson & Mikael, 2005), agent-based planning and simulation (Gambardella, Rizzoli, & Funk, 2002), hub-location formulations (Arnold, Peeters, Thomas, & Marchand, 2001), and zero-one goal programming (Kengpol, Tuamme, & Tuominen, 2014) to find good or optimal solutions for such problems. In this case, the Eco-Friendly Intermodal Delivery Problem can be classified into a multiple traveling salesman problem (mTSP), which is a special case of the TSP and VRP (Vehicle Routing Problem).

In simple words, the traveling salesman problem (TSP) consists of finding the shortest possible route given a list of points and the distances between each pair of them with the following conditions: (1) Traveling salesman person (transportation mode) must start from a certain initial point $(x_1, y_1)$*;* (2) Traveling salesman person must visit *n*-1 points just once (where *n*= total number of points); (3) Traveling salesman person must finish the route back again at the initial point $(x_1, y_1)$. The total number of all possible routes is given by a permutation of (*n*-1)!, which makes solving a TSP a very challenging and complex task as *n* approaches infinity.

The TSP was first mathematically formulated in the 1930s by Merrill Flood, who was looking to solve a school bus routing problem, and is one of the most intensively studied problems in optimization (Lawler, Lenstra, Rinnooy Kan, & Shmoys, 1990). In logistics, the TSP has many practical applications where the concept *points* might represent customers, distribution centers, or others, and the concept *distance* might represent travelling times or costs. For example, G. B. Dantzing and J. H. Ramser (1959) proposed a linear programming function to find the optimum routing of a fleet of gasoline delivery trucks between a bulk terminal and several service stations. Later, Clarke and Wright (1964) proposed an efficient algorithm for a digital computer that “enables the rapid selection of an optimum or near-optimum route” (p. 568). Guerra, Murino, and Romano (2007) used this algorithm and the Branch and Bound model to optimize a Location-Routing Problem (LRP), which is a combination of a Vehicle Routing Problem and a Travelling Salesman Problem. In recent years, more research towards the use of genetic algorithms, which transfer evolution and biological principles into optimization models, has been made to solve routing problems (Filip & Otakar, 2011). An example is the application of a genetic algorithm to solve a distribution problem that consists of finding the optimal routes and vehicles to deliver products to remote points in such a way that the distance travelled and distribution costs are minimized (Giraldo, 1999).

A variation of the TSP is the multiple Traveling Salesman Problem, which consists of determining a set of routes for *m* salesmen who all start from and turn back to their determined initial points $(x_m, y_m)$. As noted by Macharis and Bontekoning (2004), the mTSP with time windows can be applied to model problems in intermodal freight transportation. In this context, Wang and Regan (2002) have developed an iterative method using time-window discretization to solve an mTSP delivery problem with time constraints. Also, Zhang, He, and Pan (2010) have proposed a genetic algorithm method to study multimodal transport networks.

From an operational perspective, the Eco-Friendly Intermodal Delivery Problem herein studies multimodal transport networks as Zhang et al. (2010) did. However, it is mostly focused on the implementation of a train-EVs in tandem delivery system and its optimization by using an evolutionary algorithm that utilizes a feedback mechanism between K-means for optimally clustering customers and a genetic algorithm for optimal mTSP routes.

## Methodology: Optimization Algorithm

### Cost Function

The cost function utilizes an iterative algorithm that uses a feedback mechanism between K-means for customers clustering and a genetic algorithm for optimal train and electrical vehicles TSP routes. This algorithm evaluates the total delivery time of the intermodal network and finds the optimal solution. Once initialized, the function calls the K-means algorithm to find customer clusters based on average distances between them. Also, it finds centroids for each cluster of customers, where distribution centers will be located. An electrical vehicle is then assigned to each distribution center for the “last mile” deliveries. Then, the cost function calls the genetic algorithm with two purposes: (1) to compute the minimum train TSP route from a manufacturing plant to each distribution center and back to the manufacturing plant; and (2) to compute the minimum TSP route that each electrical vehicle (EV) must follow, from its assigned distribution center to all the customers around it, and back to the distribution center. Finally, both train distance and the sum of all the EVs distances are divided by their respective vehicle speeds, and a *for loop* is used to calculate the total time of the system for (k) train stops and (k) electrical vehicles, which is returned as the output of the cost function.

**Intermodal Network: Train-EVs in Tandem Delivery Cost Function**

1) **Initialize**
   a) $T_s$ $\left(\text{Train Speed}\frac{\text{km}}{\text{h}}\right)$; $EV_s$ $\left(\text{Electric Vehicle Speed}\frac{\text{km}}{\text{h}}\right)$;
   b) K (Number of Train Stops and Number of Electric Vehicles);
   c) OperatingArea (Square distance matrix between customers);
   d) $P=\{p_1, p_2, p_3, \ldots, p_n\}$ (Set of customer locations where n is the max.);
2) **For loop:** $K$**=1:1:**$\frac{n}{5}$**;** (for loop for K Train Stops and K Electric Vehicles)
   a) **Call K-means algorithm**
      i) Find K Centroids
      ii) Cluster n customers located at P into K Centroids
   b) **For loop: i = 1:K** (i is the index of each cluster found with K-means algorithm )
      i) Create matrix for each cluster (with index i) with its customers and its centroid
      ii) **Call Genetic Algorithm (Calculate Electric Vehicles Routes)**
         (1) Compute $EV_{Route}$: the min. TSP route that each electric vehicle (EV) must follow, from its assigned distribution center to all the customers around it, and back to the distribution center.
         (2) $EV_{TotalRoutes}= \sum_{i=1}^{n} EV_{Route}$;
   c) **End For loop**
   d) **Call Genetic Algorithm (Calculate Train Routes)**
      i) Compute $Train_{Route}$: the min. train TSP route from a manufacturing plant to each distribution center and back to the manufacturing plant.
   e) **Calculate total distance required to reach all the customers**
      i) $TotalDistance= \sum EV_{TotalRoutes}+Train_{Route}$;
   f) **Calculate total delivery time of the system**
      i) $Train_{DeliveryTime}=\frac{Train_{Route}}{T_s}$;
      ii) $EV_{DeliveryTime}=\frac{Max(EV_{TotalRoutes})}{EV_s}*(CapacityFactor-1)$;
      iii) $TotalDeliveryTime=Train_{DeliveryTime}+EV_{DeliveryTime}$;
   g) Plot Results: TotalDeliveryTime (y-axis) vs. K (x-axis);
3) **End For Loop**
4) **Find Optimal Delivery Time & Display Results**
   a) Min. point in parabolic cost function
   b) Display Results
      i) Optimal K
      ii) Optimal TotalDeliveryTime
5) **End**

*Figure 2: Cost Function*

**K-means algorithm**

K-means clustering is a well-known technique in vector quantization for cluster analysis that was formulated by MacQueen (1967), although the standard algorithm was first proposed by Stuart Lloyd in 1957 as a technique for pulse-code modulation. K-means clustering, also known as Lloyd's algorithm, is an iterative, data-partitioning algorithm that aims to partition the initial data set *S* into *K* clusters in which each point belongs to the cluster with the nearest mean. It is formulated by minimizing a formal objective function, mean-squared-error-distortion:

$$\text{minimize MSE (P)}=\sum_{i=1}^{N}\left|\left|x_i-c_{p(i)}\right|\right|^2$$

Where *N* is the number of data samples; *K* is the number of clusters; $X=\{x_1, x_2, x_3 \ldots, x_N\}$ is an initial set of *N* data samples; $P=\{p(i) \mid i=1, \ldots N\}$ is class label of *X*;
and $C=\{c_j \mid j=1,\ldots K\}$ are *K* cluster centroids (Xu & Franti, 2004).

The proposed algorithm for the Eco-Friendly Intermodal Delivery Problem (EIDP) utilizes the built-in function *k-means* developed by MATLAB for customer clustering, which computes the minimum sum of point-to-cluster-centroid distances of all observations (customers) to each centroid (train stops) in two phases. The first phase, also called *Batch Update,* assigns customers to the nearest cluster centroid all at once and then re-calculates the cluster centroids. This phase typically does not converge to an optimal solution, but it gives a good approximation as a starting point for the second phase, which will converge to a local minimum. This second phase, also called *Online Update*, reassigns points individually only if it reduces the sum of distances. Then, after each reassignment, it recalculates cluster centroids (MathWorks Inc., 2013).

```
Intermodal Network: Customer Clustering with Function KMEANS (K, P)
1) Input
   a) K (Number of Train Stops and Number of Electric Vehicles);
   b) P= {p_1, p_2, p_3, ..., p_n} (Set of customer locations where n is the max. number);
2) Output
   a) C={c_1, c_2,c_3, . . ., c_k};                 (Set of calculated centroids)
   b) L={ l(p)|p=1,2, . . ., n} ;                  (Set of cluster labels for Customer p)
   c) D={ d(p)|p=1,2, . . ., n} ;                  (Set of cluster distances for Customer p)
3) Heuristic
      foreach c_i ∈C do  (for loop)
         c_i :=p_j ∈P ;                            (Initial cluster assignment  according to Phase I)
      end
      foreach p_i ∈P do (for loop)
         l(p_i)  :=ArgMinDistance(p_i, c_j)  where j∈{ 1…k};  (Assigns cust. to closest centroid)
      end
         changed :=false;                           (Flag to stop repeat)
         iter:=0;                                   (Count iteration in repeat)
       repeat   (outer while loop)
         foreach c_i ∈C do  (inner for loop)
            UpdateCluster(c_i) ;                    (Based on Phase II)
         end
         foreach e_i ∈P do (inner for loop)
            minDist  :=ArgMinDistance(p_i, c_j)  where j ∈{ 1…k} ; (Find Minimum distance)
               if minDist ≠l(p_i) then
                  l(p_i):=minDist;                  (Capture Minimum distance)
                  changed :=true;
               end
          end
      until changed==true and iter ≤ MaxIter
```

*Figure 3: K-means Algorithm (Rich, Sturges, Harbison, Weber, & Mourelo, 2016)*

## Genetic Algorithm

The genetic algorithm is a gradient-free, stochastic-based optimization method that utilizes principles from biology and evolution such as natural selection for the optimization of different problems (Holland, 1975 and Goldberg, 1989). In the Eco-Friendly Intermodal Delivery Problem (mTSP), a genetic algorithm adapted from Joseph Kirk (2007) has been developed in Matlab to find the optimal routes that a train and several automated vehicles must follow. This algorithm randomly permutes potential route sequences given a population (train stopping points and customers). Then, it randomly selects a number of routes and it finds the best one from such selection. Once the best one is found, it mutates the route in 5 different ways and it creates a new route for each mutation. The output of this efficient algorithm is an optimal route that minimizes the total distance travelled for large populations (*n*>200) with a limitation in the number of iterations (*i*<500).

```
Intermodal Network: Genetic Algorithm for Optimal Routes
Function CallGenetic(k, C)
1) Input
   C ={c1, c2,c3, . . ., ck} ;        (Set of centroids results from CallKmeans to be TSP routed)
   n = k  where (k>2);
2) Output:
   optimalRoute={r1, r2,r3, . . ., rn};     (TSP route sequences from 1 to n )
   globalMinDist ;                          (Calculated min distance for optimal route )
3) Initialize
   p:=200;                                  (Population size)
   POPpn:=ArgRandPermute(p,n);              (Randomly Permute route sequence matrix)
   DISTij :=ArgEuclideanDistance(ci, cj);   (Square distance matrix between centroids)
   globalMinDist  :=infinity;
   MaxIter :=round(25n^.9);                 ( Max iterations based on route size)
4) Heuristic
foreach 1 to MaxIter do   (outer for loop)
   minDist, index=ArgMinPathDist(POPpn, DISTij);  (Find min distance route in population )
        if minDist < globalMinDist then
             globalMinDist:=minDist;             (Capture Minimum Distance)
             optimalRoute :=POPindex,:;          (Capture Best Route)
        end
   rPOP5,n:=ArgRandSelect(POP);             (Randomly select five routes from population)
   minDist, index=ArgMinPathDist(rPOP5,n, DISTij);   (Find  min distance of the five routes)
   rShuff1:n :=  randShuffle(1:n);                   (Random shuffle 1:n integers)
   rand1, rand2 :=  sort(rShuff1,2 );       (Take two element (A,B) of random shuffle and sort)
   rand2, rand3 := sort(rShuff2,3 );        (Take two elements (B,C) of random shuffle and sort)
    foreach k in 1 to 5 do
      tmpPOP5,n:=getBestRoute(index);
(Get the best of five routes for mutation)
     switch k
        case 2 (Reverse order a random route segment in best sequence A to B)
             tmpPOP(k, rand1:rand2)=tempPOP(k, rand1:-1:rand2);
        case 3 (Reverse order a random route segment in best sequence B to C)
             tmpPOP(k, rand2:rand3)=tempPOP(k, rand2:-1:rand3);
        case 4 (Slide a route (B-C one space left, replace last element with first element)
             tmpPOP(k, rand2:rand3)=tempPOP(k,[ rand2+1:rand3  rand2]);
        case 5 (Swap two centroids in route sequence A to B)
             tmpPOP(k, [rand1 rand2])=tempPOP(k,[ rand2   rand1]);
        otherwise
              do nothing;
      end
      newPop(p-3:p,:) :=tmpPOP;             (Update new population with the mutations of best)
     end
     pop:=newPop;                           (Set population as new population)
end
```

*Figure 4: Genetic Algorithm (Rich et al., 2016)*

## Experimental Design

This research is intended to study performance criteria and operational aspects such as total delivery times and distances traveled, energy efficiencies, and environmental consequences by comparing results from two different delivery networks, a unimodal transport network and the proposed Eco-Friendly Intermodal Delivery Network. The unimodal network is a centralized delivery system that makes use of *k* standard freight trucks to deliver goods from a manufacturing plant to different clusters of customers. The Eco-Friendly Intermodal Delivery Network is, as stated previously, an mTSP problem where a freight train transports goods from a manufacturing plant to *k* train stopping points, and *k* electrical vehicles take care of the "last mile" deliveries.

In general, when customers are non-uniformly distributed, intermodal delivery networks are known to be more time efficient than centralized delivery systems, which use trucks as their only transportation mode. In other words, the combination of road transportation with another transportation mode provides better operational outcomes when customers are already clustered in different regions or areas, and such regions are separated by large distances. In contrast, centralized delivery systems with *k* number of trucks give better results for uniform, Gaussian, normal, and exponential distributions as long as demand falls within capacity restrictions associated with a truck.

The hypothesis of this experiment is that intermodal delivery networks are more efficient and environmentally friendly than unimodal networks for high volume and long haul transportation, regardless of the customers' distribution, if demand does not fall within the capacity restriction of road transportation vehicles. Therefore, this hypothesis assumes that the electrical vehicles, used for "last mile" deliveries in the intermodal transport network, and the trucks, used in the centralized delivery system, do not have enough capacity to deliver the volume demanded; in contrast to a freight train, whose capacity may be equivalent to hundreds of trucks. With this assumption, a capacity factor has been added to road transportation to compensate for the lack of capacity. Moreover, the average speed of each vehicle of transportation has been taken from official reports published by the Federal Railroad Transportation and the U.S. Department of Transport. Furthermore, this analysis assumes normal conditions for weather and road congestion.

For both delivery systems, several simulations have been conducted by using the evolutionary algorithm proposed in this paper. Such simulations have been performed in Matlab R2014b and the final data generated is attached in Appendix A. All the parameters used for this experiment are summarized in Table 2.

*Table 2: Experimental Design for Operational Analysis*

| Parameters | Unimodal Network | Intermodal Network |
|---|---|---|
| Avg. Train Speed | - | 50 km/h |
| Avg. EVs Speed | - | 60 km/h |
| Avg. Truck Speed | 80 km/h | - |
| Capacity Factor* | 3 | 3 |
| No. Customers | 200 | 200 |
| Operating Area | Uniform Dist. (200) | Uniform Dist. (200) |
| Model | MATLAB™ | MATLAB™ |

**Capacity Factor*:** this parameter represents the number of delivery trips that road vehicles must do when demand exceeds capacity restrictions.

**Total Delivery Time Analysis**

With the assumptions previously stated, Figure 5 has been created to analyze changes in the total delivery time of both, unimodal and intermodal networks, by adding $k$ road vehicles from 2 to 20 ($k$=2, 3, 4, …,20). On one hand, the resultant delivery time cost curve for the unimodal transport network is depicted as exponential and quasi-continuous. As it can be seen in figure 5, the total delivery time can be reduced by 50%

with the addition of just 4 trucks (from 2 to 6). Once this point is reached, the addition of more trucks does not have a huge impact on the time curve, which approaches 15 hours as *k* increases. On the other hand, the time curve for the intermodal transport network is a parabolic, convex, and quasi-continuous cost function. The total delivery time decreases exponentially until the optimal time is achieved at *k* (number of train stops and EVs) = 13, which is 16.2 hours. After this, the addition of train stops and electrical vehicles has a negative impact on the curve by increasing it.

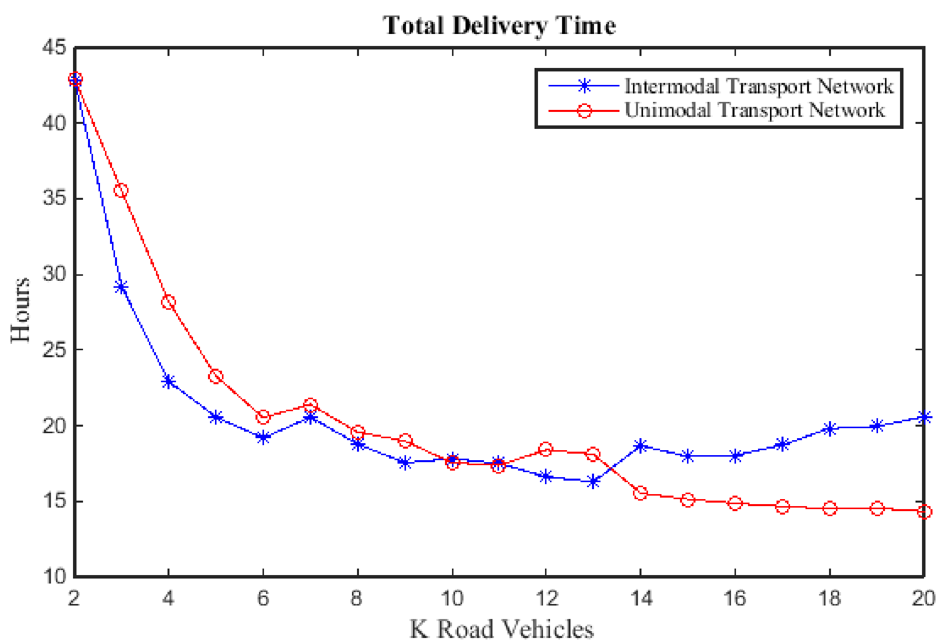


*Figure 5: Time Analysis*

In terms of delivery times, a unimodal transport network achieves better results (with times that are close to 15 hours) at 14 trucks and higher. However, by looking at the decrement in time *($\nabla$Delivery Time)* versus the increment in road vehicles *($\Delta$ K Road Vehicles)*, the intermodal transport network gives the best outcome at *k* =13 with a total delivery time of 16.2 hours, which will become the optimal solution after analyzing other factors.

**Distance Traveled Analysis**

Distance (km) is another operational factor that needs to be analyzed. Figure 6 shows a comparison between the total distances traveled for each transportation network. As shown in the graph, both distance curves are linear and quasi-continuous, which means that both of them increase as the number of trucks and electrical vehicles increase at an almost constant rate. However, the distance traveled by trucks (red line with circles) increases at a much higher rate than the total distances traveled by both train and EVs (blue line with stars). This is due to the capacity factor added to this experiment, which multiplies the total distances traveled by road vehicles by 3 to compensate for their lack of capacity. With these restrictions, an intermodal delivery network that utilizes a freight train for high capacity and long-haul transportation would be more efficient than a centralized delivery system, regardless of the customer's distribution.

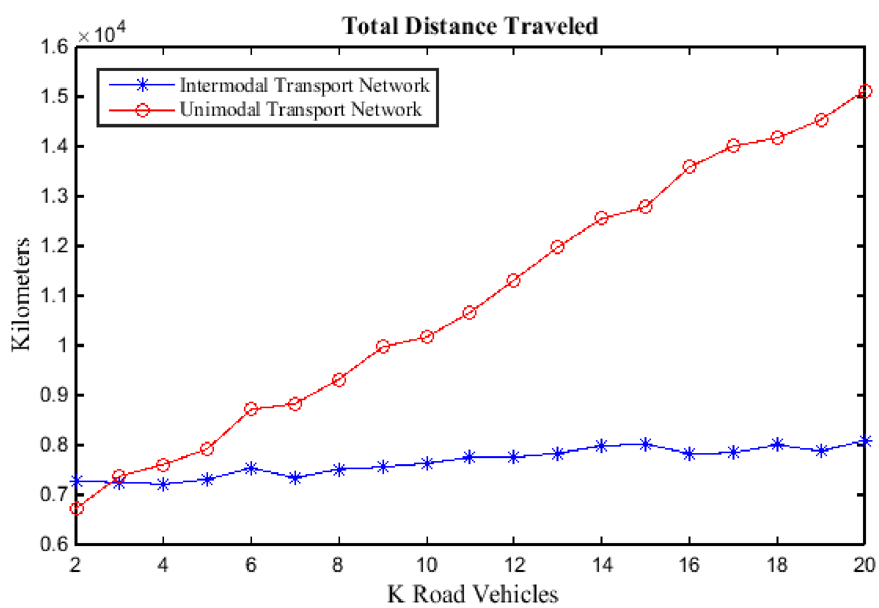


*Figure 6: Distance Analysis*

Besides studying the total distances of each transportation network, it is very important to know the average distances that each transportation mode needs to travel in order to reach all the customers. As it is shown in Figure 7, the average distance traveled by each road vehicle in both delivery networks decreases exponentially as the number of vehicles increases. However, it decreases at a faster rate for electrical vehicles (Intermodal Delivery Network-EV) than for trucks (Unimodal Delivery Network-Truck). This is due to the distance traveled by the freight train in the intermodal delivery network, which increases linearly at an almost constant rate from 200 km at *k* (number of electric vehicles) = 2 to roughly 900 km at *k* = 20.

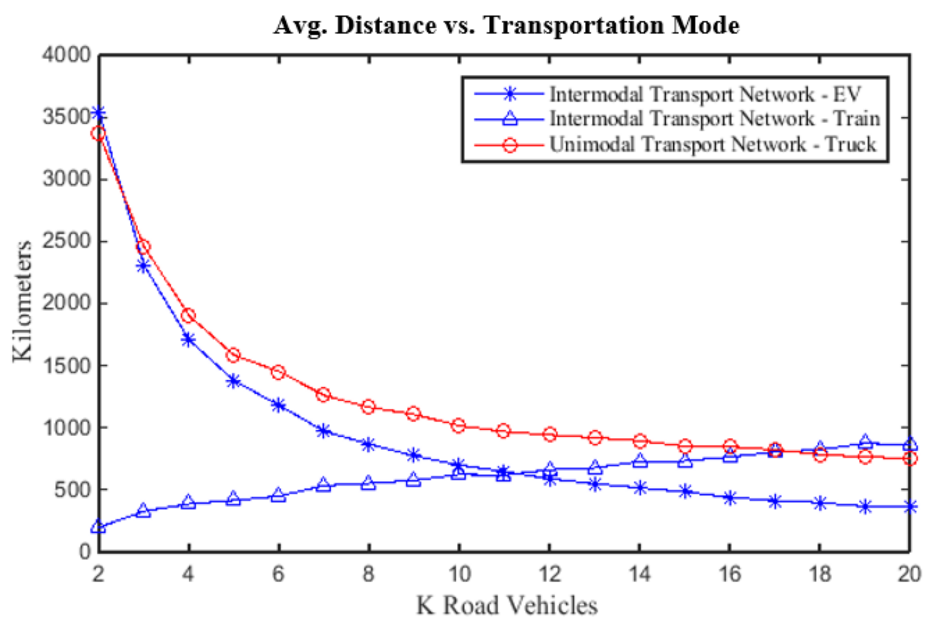


*Figure 7: Distance Analysis vs. Transportation Mode*

In the previous section, this research stated that the optimal delivery time (16.2 hours) for the intermodal delivery network is achieved when *k* = 13. At this point, the total distances traveled are the following:

- Intermodal Delivery Network – Train: 678 km
- Intermodal Delivery Network – EV: 183.33*3 (capacity factor) = 550 km / EV
- Unimodal Delivery Network – Truck: 282.75*3 (capacity factor) = 921 km / truck

In the intermodal delivery network, the distances traveled by the EVs and the train fall within the boundaries established by Rodrige (2013) in the cost-analysis of different types of transportation (Figure 1), where road distribution costs are optimal under 600 km and train distribution costs are minimum between 600 km and 1,500 km approximately. However, the centralized delivery system has higher costs because it exceeds the optimal limit of 600 km. Also, in regards of road transportation, the intermodal delivery network allows the use of electrical vehicles such as the all-electrical 18 ton truck developed by BRUSA, while the unimodal delivery network has to implement conventional trucks as the only transportation mode due to battery life restrictions.

**Energy Consumption and Environmental Analysis**

Energy consumption and $CO_2$ emissions are probably two of the most important aspects in operational analysis due to the costs associated with them and the impact on the sustainability of the environment and the community. According to Garcia-Alvarez, Perez-Martinez, and Gonzalez-Franco (2013), energy consumption by different modes of freight transport, rail and road, is influenced by the following factors: (1) Indirect, which includes construction and maintenance of infrastructure, vehicle maintenance, and network characteristics; (2) Direct, which includes logistical, technical and operational aspects such as weight, aerodynamics, engine, fuel type, and capacity of the vehicle. Both of these factors have a huge impact on the ratios of energy consumption and $CO_2$ emissions, and therefore, it is very easy to find discrepancies among different articles and reports.

In this research, the ratios for energy consumption and $CO_2$ emissions, expressed in kilowatt-hours per ton-kilometer and grams of $CO_2$ per ton-kilometer respectively, have been extracted from a table created by several experts on the field of transportation (Garcia-Alvarez et al., 2013). For this experiment in particular, the ratios used to compare the energy efficiency of the proposed intermodal delivery network versus the unimodal transport network are the following:

*Table 3: Energy & Carbon Dioxide Rates*

| Transportation Mode | Energy (kwh / ton km) | $CO_2$ (g / ton km) |
|---|---|---|
| Diesel Truck - Unimodal | 5.5 | 99.7 |
| Electric Train - Intermodal | 0.9 | 19.4 |
| Electric Truck (EV) – Intermodal* | 3.85 | 59.82 |

**Electric Truck (EV) Intermodal*:** "On average in the U.S., electric urban trucks use about 30% less total energy and 40% less greenhouse gases than diesel trucks" (Lee, Thomas, & Brown, 2013)

Just by looking at the ratios, the intermodal delivery network is expected to be more environmentally-friendly because the electric train is 4 to 5 times more efficient than a standard diesel truck. Also, electric trucks, whose capacities vary from 6 up to 40 tons, can reduce energy consumption and $CO_2$ emissions by more than 30-40 %, as stated by many experts in urban deliveries and road transportation (Lee, Thomas, & Brown, 2013). Figure 8 shows how intermodal delivery networks, having electricity as the main source of energy, improve air quality and environmental conditions as long as road transportation is required to make more delivery trips in order to overcome its capacity restrictions. In this case, both $CO_2$ emissions and energy consumption are dependent on the total distance traveled for each delivery network, which has been analyzed in section "Distance Traveled Analysis." As the number of road vehicles increases, the energy consumption and the total $CO_2$ emissions in the unimodal transport network increases linearly at a very rapid rate, while these stay almost constant in the proposed intermodal delivery network.

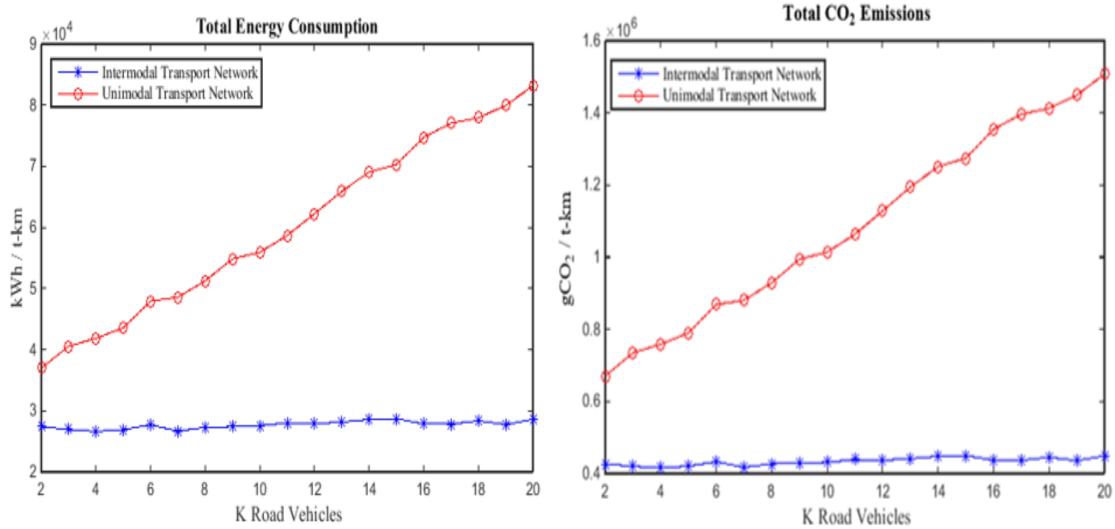


*Figure 8: Total Energy & $CO_2$ Emissions Analysis*

Finally, this research compares specifically all the operational factors, which include delivery times, distances traveled, energy consumption, and $CO_2$ emissions, for *k (number of road vehicles)* = 13, which is the optimal delivery time for this simulation.

*Table 4: Unimodal vs. Intermodal*

| Operational Factors | Unimodal Network | Intermodal Network |
|---|---|---|
| Total Delivery Time | 18.1 h | 16.2 h |
| Total Distance Traveled | 11,979.95 km | 7,835.37 km |
| Total Energy Consumption | 69,028.01 kWh / t | 28,593.58 kWh / t |
| Total $CO_2$ Emissions | 1,251,289.55 $CO_2$g / t | 448,224.97 $CO_2$g / t |
| **Optimal** | | ✓ |

As shown in the table above, the intermodal delivery network, which combines an electric train with thirteen electric trucks, not only achieves the most optimal time with the least number of road vehicles, but it also results in an eco-friendly delivery network that maximizes the capacity of the system, minimizes total distances traveled, reduces roadway congestion and energy consumption, and contributes to improve air quality and environmental conditions by lowering $CO_2$ emissions more than 50%.

## Conclusion

This research has proposed an optimization algorithm that consists of a feedback mechanism between K-means and a genetic algorithm to find the optimal routes between distribution centers and surrounding customers as a multiple traveling salesman problem (mTSP). After conducting several simulations in MATLAB R2014b, this research has showed that intermodal delivery networks, which may combine a train and several electric vehicles, are more efficient and environmentally friendly than unimodal networks for high volume and long haul transportation, regardless of the customers' distribution, if demand does not fall within the capacity restriction of road transportation vehicles. Such combination results in an Eco-Friendly Delivery Network that maximizes the capacity of the system, minimizes total distances traveled, reduces roadway congestion and energy consumption, and contributes to improve air quality and environmental conditions by lowering $CO_2$ emissions more than 50%.

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# Appendix A

Final Data Generated in Matlab R2014B

*Table 5: Simulation Intermodal Transport Network*

| Simulation Intermodal Trasnport Network | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| K | Operating Area | Customers | Capacity Factor | Train Distance | Total EVs Distance | Train Speed | EVs Speed | Total Del. Time | Total Distances | Avg. Km / EV |
| 2 | 200 | 200 | 3 | 199.49 | 7,069.28 | 50 | 60 | 42.86 | 7,268.77 | 3,534.64 |
| 3 | 200 | 200 | 3 | 330.17 | 6,922.65 | 50 | 60 | 29.19 | 7,252.83 | 2,307.55 |
| 4 | 200 | 200 | 3 | 387.97 | 6,826.77 | 50 | 60 | 22.92 | 7,214.74 | 1,706.69 |
| 5 | 200 | 200 | 3 | 416.52 | 6,897.44 | 50 | 60 | 20.57 | 7,313.96 | 1,379.49 |
| 6 | 200 | 200 | 3 | 450.93 | 7,086.61 | 50 | 60 | 19.18 | 7,537.55 | 1,181.10 |
| 7 | 200 | 200 | 3 | 535.62 | 6,808.14 | 50 | 60 | 20.57 | 7,343.76 | 972.59 |
| 8 | 200 | 200 | 3 | 553.51 | 6,958.81 | 50 | 60 | 18.78 | 7,512.32 | 869.85 |
| 9 | 200 | 200 | 3 | 577.35 | 6,982.54 | 50 | 60 | 17.55 | 7,559.89 | 775.84 |
| 10 | 200 | 200 | 3 | 624.30 | 7,008.66 | 50 | 60 | 17.82 | 7,632.96 | 700.87 |
| 11 | 200 | 200 | 3 | 619.93 | 7,133.15 | 50 | 60 | 17.50 | 7,753.08 | 648.47 |
| 12 | 200 | 200 | 3 | 662.42 | 7,092.03 | 50 | 60 | 16.61 | 7,754.45 | 591.00 |
| 13 | 200 | 200 | 3 | 677.83 | 7,157.55 | 50 | 60 | 16.28 | 7,835.38 | 550.58 |
| 14 | 200 | 200 | 3 | 728.85 | 7,256.52 | 50 | 60 | 18.68 | 7,985.38 | 518.32 |
| 15 | 200 | 200 | 3 | 733.34 | 7,286.75 | 50 | 60 | 17.96 | 8,020.10 | 485.78 |
| 16 | 200 | 200 | 3 | 765.75 | 7,060.42 | 50 | 60 | 18.04 | 7,826.17 | 441.28 |
| 17 | 200 | 200 | 3 | 804.89 | 7,039.29 | 50 | 60 | 18.73 | 7,844.17 | 414.08 |
| 18 | 200 | 200 | 3 | 823.93 | 7,178.23 | 50 | 60 | 19.81 | 8,002.16 | 398.79 |
| 19 | 200 | 200 | 3 | 874.98 | 7,003.44 | 50 | 60 | 19.96 | 7,878.42 | 368.60 |
| 20 | 200 | 200 | 3 | 864.95 | 7,231.05 | 50 | 60 | 20.59 | 8,096.00 | 361.55 |

*Table 6: Simulation Unimodal Transport Network*

| Simulation Unimodal Transport Network | | | | | | | |
|---|---|---|---|---|---|---|---|
| K | Operating Area | Customers | Capacity Factor | Truck Distance | Truck Speed | Total Del. Time | Avg. Km / Truck |
| 2 | 200 | 200 | 3 | 6,727.73 | 80 | 42.94 | 3,363.87 |
| 3 | 200 | 200 | 3 | 7,376.22 | 80 | 35.51 | 2,458.74 |
| 4 | 200 | 200 | 3 | 7,609.67 | 80 | 28.16 | 1,902.42 |
| 5 | 200 | 200 | 3 | 7,924.04 | 80 | 23.27 | 1,584.81 |
| 6 | 200 | 200 | 3 | 8,716.64 | 80 | 20.54 | 1,452.77 |
| 7 | 200 | 200 | 3 | 8,832.27 | 80 | 21.40 | 1,261.75 |
| 8 | 200 | 200 | 3 | 9,320.59 | 80 | 19.57 | 1,165.07 |
| 9 | 200 | 200 | 3 | 9,974.70 | 80 | 19.00 | 1,108.30 |
| 10 | 200 | 200 | 3 | 10,171.28 | 80 | 17.55 | 1,017.13 |
| 11 | 200 | 200 | 3 | 10,666.90 | 80 | 17.38 | 969.72 |
| 12 | 200 | 200 | 3 | 11,316.38 | 80 | 18.40 | 943.03 |
| 13 | 200 | 200 | 3 | 11,979.95 | 80 | 18.11 | 921.53 |
| 14 | 200 | 200 | 3 | 12,550.55 | 80 | 15.54 | 896.47 |
| 15 | 200 | 200 | 3 | 12,785.01 | 80 | 15.13 | 852.33 |
| 16 | 200 | 200 | 3 | 13,587.09 | 80 | 14.87 | 849.19 |
| 17 | 200 | 200 | 3 | 14,009.05 | 80 | 14.67 | 824.06 |
| 18 | 200 | 200 | 3 | 14,169.81 | 80 | 14.50 | 787.21 |
| 19 | 200 | 200 | 3 | 14,536.40 | 80 | 14.54 | 765.07 |
| 20 | 200 | 200 | 3 | 15,121.65 | 80 | 14.34 | 756.08 |

## Appendix B

In this thesis, all the content cited from the paper Optimization of a truck-drone in tandem delivery network using k-means and a genetic algorithm, published in the *Journal of Industrial Engineering and Management*, and written by Robert Rich, Robert Sturges, Tim Harbison, Troy Weber, and Sergio Mourelo, meets with all the copyright concerns.



*Figure 9: Copyright Notice JIEM*