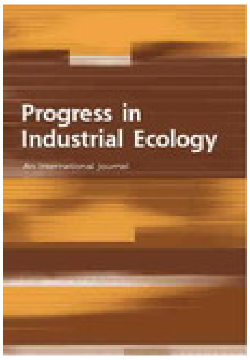

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A new experimental technique for the trailer and truck routing problem

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Abstract: The combinatorial optimisation problem named the trailer and truck routing problem (TTRP) is analysed in diverse directions. This is due to its real-world impact that influences to different researchers to continue studying its nature. The TTRP continues to develop new evolutionary algorithms. A new experimental technique is proposed where definitions from the chemistry field and evolutionary computing are coupled. Continuous values are used in the solution representation, and every value indicates, in a hydrogen atom, the picometers from the negative particle to the positive particle. The main idea is to take advantage of definitions from the chemistry field to build new members of the population, and to enhance the performance of the algorithm. Different trials are shown to depict and confirm this contribution using diverse instances. Based on the performance of the proposed scheme, we conclude that incorporating radial probability distributions helps to improve the estimation of distribution algorithms.

Keywords: radial probability distribution; vehicle routing problem; VRP; trailer and truck routing problem; TTRP; evolutionary computing; estimation of distribution algorithm.

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1 Introduction

Let consider the trailer and truck routing problem (TTRP) as a member of the routing problems family. It is found in wide and diverse applications in industry (Dantzig and Ramser, 1959; Gillett and Miller, 1974; Bodin et al., 1983; Laporte and Nobert, 1987; Golden and Assad, 1988; Laporte, 1992; Van Breedam, 1995; Laporte et al., 2000; Toth and Vigo, 2002). Studies of TTRP in real-world cases can be found in Semet and Taillard (1993), Gerdessen (1996), and Hoff (2006).

Unlike a classical vehicle routing, trailers are used to delivery parts in the TTRP environment. There exists the possibility to deliver parts using only trucks or trucks with trailers. However, as any real situation, constraints prevent the use of a trailer in certain places. This may be due to road conditions, narrow roads, small bridges, heavy traffic, limited parking spaces, scarce space in the customer location, government regulations, among others. Therefore, during a trip, the trailer parks at a feasible location and the truck continues delivering parts in the route, and finally returns to hitch the trailer and continue the trip.

As any NP-hard problem, the vehicle routing problem (VRP) is commonly solved using a heuristic approach. The exact approach can solve small VRP instances; meanwhile the heuristic approach yields best performance in real-world cases. As with other combinatorial optimisation problems, the VRP family of problems has been tackled efficiently by the heuristics and meta-heuristics (Caric and Gold, 2008). From the study of Lenstra and Rinnooy Kan (1981), it is possible to conclude that any routing problem is NP-hard, because it is not possible to find an optimal solution in polynomial time. Since TTRP is part of the VRP family of problems, it is usually tackled by heuristics and/or metaheuristics as in other routing problems. For large size problems, there is no way to find optimal solutions in a reasonable time (Garey and Johnson, 1979). As with other routing problems, the TTRP is also NP-hard. In addition, routing optimisation problems are solved by heuristics and/or metaheuristics, so it is normal to address the TTRP by the same approach. As an example, Lin et al. (2009) propose simulated annealing (SA) technique to tackle the TTRP.

Other metaheuristics based on evolutionary computing are the estimation of distribution algorithms (EDAs). Their performance is detailed in different papers. In the literature, we can find two kinds of EDAS, pure and hybrid. The first ones need a probability model to produce offspring. A set of pure EDAs is cited in Larrañaga and Lozano (2002).

It is possible to enhance the performance of the method working and coupling a probability model with other methods. These combinations are called hybrid EDAs. The main contribution of the hybrid EDAs is in solving combinatorial problems, such as the Wang et al.'s (2016) research, the Fang et al.'s (2015) algorithm, the Wang et al.'s (2012) method, the Liu et al.'s (2011) study, the Zhang et al.'s (2006) algorithm, and the Peña et al.'s (2004) research. Recently, new EDAs utilise permutation-based representation in the solutions to tackle optimisation problems. This variety is found in distance-based ranking models. Some contributions in this category are the Pérez-Rodríguez and Hernández-Aguirre's (2019) study, the Pérez-Rodríguez and Hernández-Aguirre's (2018) research, the Pérez-Rodríguez et al.'s (2017) paper, and the Ceberio et al.'s (2014) approach.

Based on the previous explanation, there exists a gap to improve EDAs. Improving probability models or creating new models is the goal for the researchers. The objective is to identify more and better probability models, to attend the performance of the algorithm. Therefore, as contribution of this research, *a radial probability model* is used to generate solutions in the EDA core.

The main idea is to combine, and couple the aforementioned concepts to create a new algorithm. We analyse the results of the aforementioned algorithm, called radial hybrid estimation of distribution algorithm for the TTRP (RHEDA-TTRP), against other recent algorithms that efficiently solve the TTRP.

2 Related work

There are other studies similar to TTRP. For example, Semet and Taillard (1993) discuss a VRP using trailers under accessibility restrictions. The authors employ a clustering-based construction methodology to produce solutions, and the authors employ the technique called tabu search heuristic in the proposal. This study does not consider to use a trailer in sub-tours. The complete vehicles are only used to visit customers without accessibility restrictions.

Another example is found in Semet (1995). The author attends a partial accessibility constrained VRP and provides an integer programming formulation to model the situation. The problem statement mainly differs from the TTRP in that two trips must be executed with different park location, furthermore it is a requirement that all the vehicles must be used, the number of vehicles for any solution must be indicated in advance, and visit the depot is prohibited during any trip.

Gerdessen's (1996) study is another case of VRP with trailers. The problem is solved through four heuristics. The key features of the Gerdessen study, is that all the customers will have only unit demand, and the trailers can park at any customer site.

Drexl (2011) considers diverse capacities between the vehicles, and as another restriction, trucks only can hitch its corresponding trailer. This means that there exists a heterogeneous fleet of trucks and trailers. These aspects differ from the TTRP.

Chao (2002) uses tabu-search method to tackle the TTRP. With tabu search, the author allocates customers to routes at the beginning, followed by an insertion heuristic.

Scheuerer (2006) employs two heuristics to develop initial solutions, and later the solutions are improved through tabu search.

Caramia and Guerriero (2010) address the TTRP through sequential heuristics. First, assigns customers to valid routes, and then produces a trip.

Yu et al. (2011) tackle the TTRP by an ant colony system to build feasible solutions, and then these solutions are improved by a process improvement for each solution.

Lin et al. (2009) detail a heuristic based on SA technique for the TTRP, and Lin et al. (2011) extend the idea to address the time window constraints.

Villegas et al. (2011a) detail a hybrid greedy randomised adaptive search procedure (GRASP) with variable neighbourhood search (VNS) heuristic for the TTRP, and Villegas et al. (2011b) coupled this heuristic with a set-partitioning formulation to tackle the same problem.

If time windows for delivery exist, and the option of load transfer between trailer and truck is required, the paper of Derigs et al. (2013) is suitable when we need to analyse the rich vehicle routing problem (RVRP). The study details how to combine neighbourhood process and local search as a hybrid approach.

Maghfiroh and Hanaoka (2018) solve a real-world situation that considers last mile distribution in disaster response. The author details a modified SA algorithm with VNS for local search. It is a dynamic case of TTRP. The fitness in this research is the total travel time. The dynamicity and stochastic features are tackle by a dynamic simulator that is added to the framework to incorporate new requirements of the customers.

Wang et al. (2018) detail a bat algorithm (BA) to tackle the TTRP. The procedure uses five different neighbourhood structures as part of local search strategy. Moreover, to preserve diversity, a self-adaptive (SA) tuning strategy is used in the proposed algorithm.

Yuan et al. (2020) tackle the TTRP by a backtracking search algorithm (BSA). The algorithm uses four types of route improvement to produce offspring, and a T-sweep heuristic to build the initial population.

Table 1 shows the pros and cons of the recent research.

Table 1 Recent research

Research	*Problem*	*Technique*	*Pros*	*Cons*
Chao (2002)	TTRP	Tabu search	• Easy for understanding and implementing • Detailed instances for comparison	• Little understanding of the search direction • Poor statistical knowledge of the solution space
Scheuerer (2006)	TTRP	Tabu search	• Easy for understanding and implementing	• Little understanding of the search direction • Poor statistical knowledge of the solution space
Lin et al. (2011)	TTRP	Simulated annealing	• Moderately easy for understanding and implementing	• Various parameters to be adjusted • Poor statistical knowledge of the solution space
Derigs et al. (2013)	RVRP	Local search and large neighbourhood	• Moderately easy for understanding and implementing • Hybrid approach	• Various parameters to be adjusted • Poor statistical knowledge of the solution space
Maghfiroh and Hanaoka (2018)	TTRP for last mile distribution	SA algorithm with VNS for local search	• Moderately easy for understanding and implementing • Hybrid approach	• Various parameters to be adjusted • Random demand • Poor statistical knowledge of the solution space
Wang et al. (2018)	TTRP	BA with neighbourhood technique	• Moderately easy for understanding and implementing • Hybrid approach • Bioinspired approach	• Various parameters to be adjusted • Poor statistical knowledge of the solution space
Yuan et al. (2020)	TTRP	Backtracking search algorithm	• Hybrid approach	• Poor statistical knowledge of the solution space

Despite many options and procedures have been implemented to tackle the TTRP, the contribution of this research to the state of the art is integrate the radial probability of the hydrogen, to tackle drawbacks of the EDA and outperform its own performance.

Based on the performance of the proposed scheme, we can conclude that incorporating *radial probability distributions* helps to improve the EDAs.

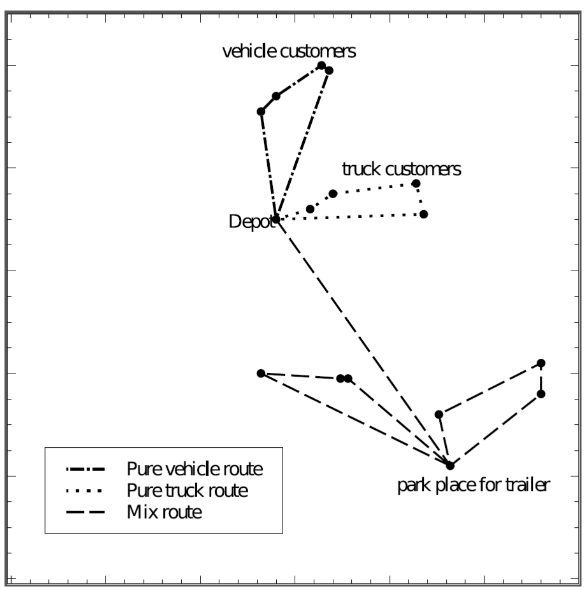
3 Problem statement

From a main depot, vehicles attend diverse customers. These clients can only accept trucks due to manoeuvring space or other physical constraints. The other customers can receive their demand either by truck or by a complete vehicle, i.e., a truck pulling a trailer. To identify customers that only can accept trucks, we name them 'truck customers'. To identify customers that can accept complete vehicles, we name them 'vehicle customers'. In the TTRP, it is possible to produce three type of routes, i.e., routes that only consider truck customers (we name them 'pure truck route'), routes that only consider vehicle customers (we name them 'pure vehicle route'), and routes that consider both trucks customers, and vehicle customers (we name 'mix routes'). A mix route considers to execute a trip with a complete vehicle, and to serve truck customers through the tour. Then the trailer should be parked in a vehicle-customer location, before serving the truck customers. Figure 1 details an example with these three types of routes.

Although the trucks and complete vehicles have a finite capacity, items are normally interchanged between the vehicles used in the corresponding route.

The main purpose is to identify trips with the minimum total distance.

Figure 1 A trailer and truck routing example

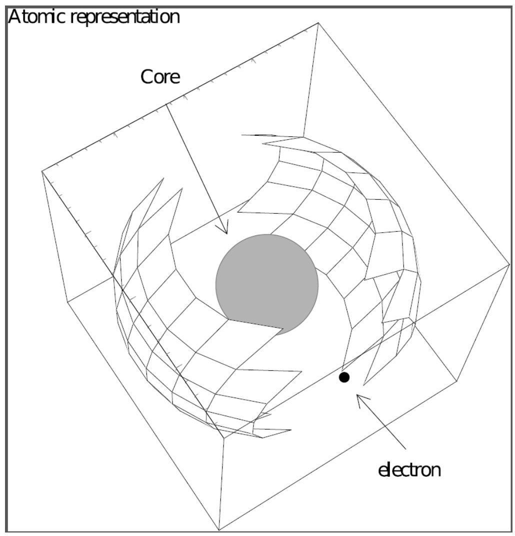


In this research, three decision-making processes should be executed to obtain feasible solutions. The first decision-making is to establish a sequence to visit all the customers. The second decision-making is to define what type of route is elected for each customer. The third decision-making is to identify what parking place is selected for each customer that belongs to a mix route.

4 RHEDA-TTRP framework

The solutions are created by an orbital function that describes the movement of an electron in the atom. The aforementioned movement is expressed by a wave function ψ, and the function ψ^2 represents the probability of finding the electron in a particular point in the atom. Figure 2 depicts a classical draw of the surface of the atom of the hydrogen (H).

Figure 2 A classical draw of the surface of the atom of the hydrogen (H)



4.1 Solution configuration

Three different vectors are considered to represent any solution for the TTRP. First, a trip, i.e., a sequence visiting all the customers is generated. In every position in the trip, contains a continuous value. Then, the solution is a trip of continuous values, called tour vector. Each position in the trip details the distance from the core of the atom to the electron. Table 2 depicts a tour vector.

Table 2 Representation of a tour vector

Tour vector									
4,827.1	1,869.6	41.563	4,833.9	288.919	2,995.36	4,966.2	292.378	3,902	4,639.9

The aforementioned representation is very suitable to consider the radial probability distribution working as a probability model. The solutions are decoded to show valid trips.

The steps are indicated as follows:

First, each customer is initialised with an integer number. In each trip, we need to identify the lowest continuous value and assign it to the first customer, i.e., the first integer number, and so on. Table 3 shows the previous trip, detailed in Table 2, and the result after the decodification.

Table 3 Representation of a tour vector to a valid routing

Customer	1	2	3	4	5	6	7	8	9	10
					Tour vector					
	4,827.1	1,869.6	41.563	4,833.9	288.919	2,995.36	4,966.2	292.378	3,902	4,639.9
Sorting	8	4	1	9	2	5	10	3	6	7

Second, a type-route vector is built. There exist at least two different options for each customer. If the customer only can accept trucks, the customer will be served by a mix route (value 1 in the type-route vector) or by a pure truck route (value 2 in the type-route vector). If the customer can accept complete vehicles, the customer will be served by a pure vehicle route (value 0 in the type-route vector) or by a mix route (valour 1 in the type-route vector). In Table 4, the representation of a type-route vector is detailed.

Table 4 Representation of a type-route vector

Type-route vector									
1	2	0	0	2	2	1	2	2	2

Third, a park-location vector is defined. If the customer will be served by a mix route, a park location should be identified and elected, out of all the feasible parks. However, if the customer will be served by a pure truck route or pure vehicle route, a park location is not required. In Table 5, the representation of a park-location vector is depicted, and based on the information indicated in Table 4.

Table 5 Representation of a park-location vector

Park-location vector									
3	-	-	-	-	-	3	-	-	-

The initial population is randomly generated.

4.2 Fitness

The total travel distance is computed for each member of the population. The total travel distance comes from the travel distance of pure truck routes, adding the travel distance of pure vehicle routes, and adding the travel distance of mix routes. The total travel distance is calculated with the tour of each vehicle and the coordinates of the customers, and the travel distance of the mixed routes includes the distance to the park location.

4.3 Probability model for the park-location decision-making process

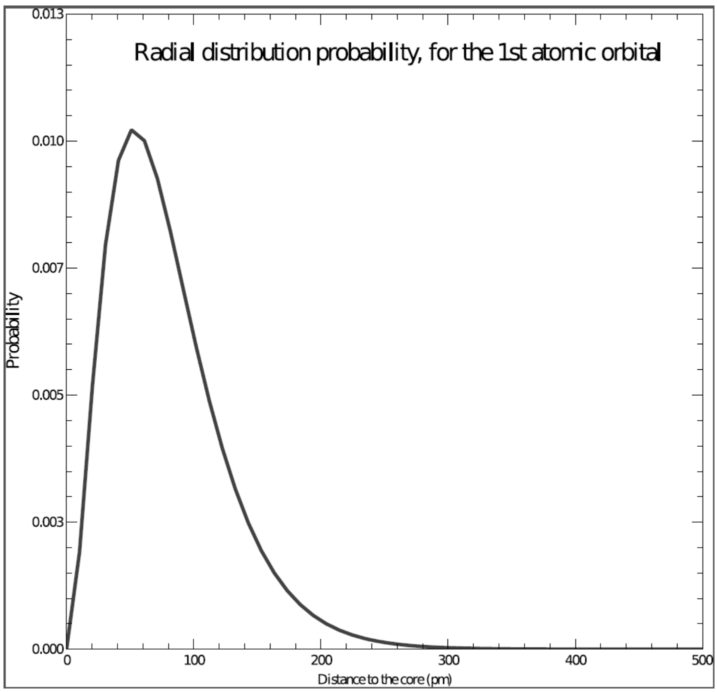
The 1st radial orbital hydrogen distribution $P(r)$ is explained as follows:

$$P_1(r) = 4\left(\frac{Z}{a_0}\right)^3 e^{-\left(\frac{2Zr}{a_0}\right)} r^2 \tag{1}$$

Is the distance from the core to the electron, $Z = 1$ the number of the hydrogen, $a_0 = \dfrac{h^2}{(4\pi^2 me)} = 52.9 \text{ pm}$ (the Bohr radius), m is the mass of the electron, e its charge, and h is the Planck constant.

Figure 3 details the shape of the 1st radial orbital hydrogen distribution.

Figure 3 Shape of the 1st radial orbital hydrogen distribution



The are other radial orbital hydrogen distributions.

$$P_2(r) = \frac{1}{8}\left(\frac{Z}{a_0}\right)^3 \left(2 - \frac{Zr}{a_0}\right) e^{-\left(\frac{Zr}{a_0}\right)} r^2 \tag{2}$$

$$P_3(r) = \frac{1}{243}\left(\frac{Z}{a_0}\right)^3 \left(6 - \frac{12Zr}{3a_0} + \frac{4Z^2r^2}{9a_0^2}\right) e^{-\left(\frac{2Zr}{3a_0}\right)} r^2 \tag{3}$$

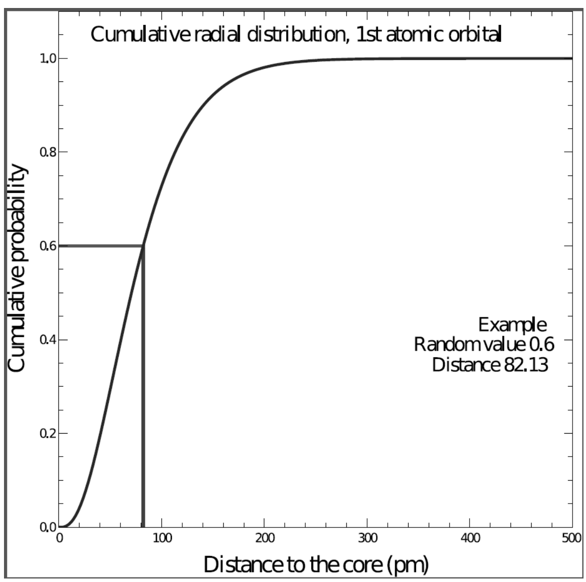
$$P_4(r) = \frac{1}{9,216}\left(\frac{Z}{a_0}\right)^3 \left(24 - \frac{18Zr}{a_0} + \frac{3Z^2r^2}{a_0^2} - \frac{z^3r^3}{8a_0^3}\right) e^{-\left(\frac{Zr}{2a_0}\right)} r^2 \tag{4}$$

A cumulative distribution is built for each radial orbital hydrogen distribution. Therefore, this probability approach is used to generate new park-location vectors, through a cumulative orbital distribution.

4.4 Sampling

Offspring are obtained through three steps. Step one produces new tour vectors and is executed through the partially matched crossover (PMX) genetic operator. The second step builds new type-route vectors through a swap phase, called reciprocal exchange operator. The feasibility of the exchange is verified according to each type of customer involved in the exchange. If the feasibility is violated, the exchange is discarded. The process is repeated until the feasibility is guaranteed. Finally, step three generates new park-location vectors. This last step is performed through the aforementioned radial distribution. A random value should be generated if the customer will be served by a mix route. Then, the corresponding random value is interpolated in a cumulative probability distribution, previously selected, to identify which distance, between the electron and the core, should be established. Figure 4 shows an example of this process.

Figure 4 Sampling example



Then, the previous distance, obtained from the cumulative distribution, is matched with the nearest distance between the current customer and the others to identify the park-location.

4.5 Generational interchange

A tournament procedure is done to select the best candidates between both populations, i.e., the parents, and the offspring previously evaluated. The algorithm runs within a number of the generations. The RHEDA-TTRP framework is provided below.

Pseudocode RHEDA-TTRP framework

D_0 ← Generate M individuals

Decoding individuals from D_0

FitD$_0$ ← Evaluate individuals (fitness) from decoded D_0
Best ← Store the best individual from D_0
t:= 1
Do
  R_{t-1} ← Radial distribution is computed from any equations (1)–(4)
  Ds$_t$ ← Sampling with PMX operator for tour vectors
  Ds$_t$ ← Sampling with swap operator for type-route vectors
  Ds$_t$ ← Sampling with cumulative R_{t-1} for park-loc vectors
  Decoding individuals from Ds$_t$
  FitDs$_t$ ← Evaluate individuals (fitness) from decoded Ds$_t$
  Best ← if apply, update the best individual from FitDs$_t$
  D$_t$ ←Replacement by binary tournament (D_{t-1} and Ds$_t$)
  t:= t + 1
Until (stopping criterion is met)
Output: Best

5 Results and comparison

We use a standard dataset for the performance comparison between algorithms. These input data are based on Chao (2002) instances. The aforementioned benchmarking instances can be found at http://web.ntust.edu.tw/~vincent/ttrp/.

The characteristics of the instances include the capacity of the complete vehicles, the capacity of the trucks, the coordinates of each customer, the demand of each customer, and what customers can be considered to park trailers in their facilities.

5.1 First comparison

The first comparison is done using the next algorithms:

- The algorithm detailed by Chao (2002).
- The tabu search method presented by Scheuerer (2006).
- The SA heuristics designed by Lin et al. (2011), some metrics are considered in the comparison.

The performance is compared using the first metric, i.e., the relative percentage increase (*RPI*).

$$RPI(c_i) = \frac{c_i - c_*}{c_*} \quad (5)$$

c_* is the best travel distance, and c_i is the travel distance obtained in the i^{th} replication. The mean absolute error (*MAE*).

$$MAE(c_i) = |c_i - c^+| \quad (6)$$

c^+ is the best fitness, and c_i is the fitness obtained in the i^{th} replication. The mean square error (*MSE*).

$$MSE(c_i) = (c_i - c^+)^2 \tag{7}$$

As any stochastic algorithm, the RHEDA-TTRP is executed 30 trials per instance.

Figure 5 details the algorithm performance for the TTRP based on equation (6). As we can see, the RHEDA-TTRP outperforms all the algorithms used in the comparison.

Figure 5 Algorithm performance for the TTRP using the mean absolute error

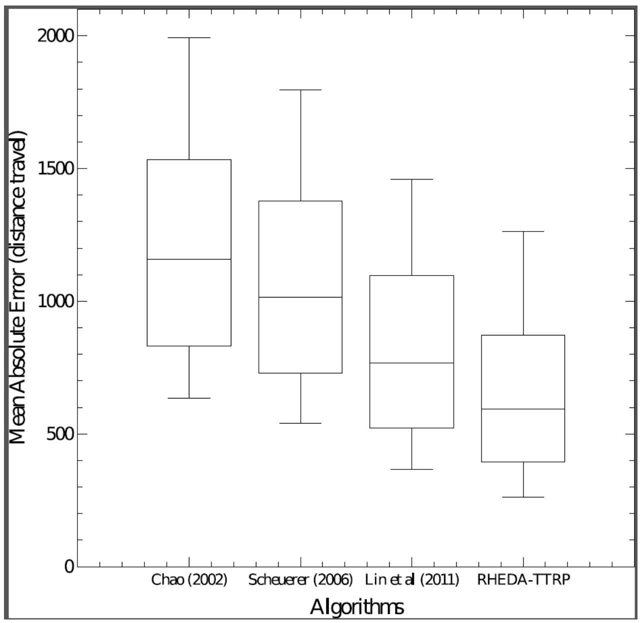


Figure 6 indicates a Dunnett test; there is a statistically significant difference between all the recent algorithms and the RHEDA-TTRP scheme. Based on equation (6), the RHEDA-TTRP scheme outperforms all the recent algorithms for the TTRP.

Figure 7 depicts the algorithm performance for the TTRP based on equation (7). Again, the RHEDA-TTRP outperforms all the algorithms used in the comparison.

Figure 8 details another Dunnett test; there is a statistically significant difference between all the recent algorithms and the RHEDA-TTRP scheme. Based on equation (7), the RHEDA-TTRP scheme outperforms all the recent algorithms for the TTRP.

Figure 9 shows the algorithm performance based on equation (5). Again, the RHEDA-TTRP scheme outperforms all the previous results.

Figure 10 indicates the last Dunnett test; there is a statistically significant difference between all the recent algorithms and the RHEDA-TTRP scheme. Based on equation (5), The RHEDA-TTRP scheme outperforms all the recent algorithms for the TTRP.

As we can see, by using three different metrics, the RHEDA-TTRP outperforms the recent algorithms for the TTRP. We can conclude that the radial distribution of the hydrogen is suitable and competitive against hybrid procedures to find the best routings for the TTRP. The RHEDA-TTRP does not need to be hybridised to find the best solutions for the TTRP.

Figure 6 Dunnett test for the TTRP using the mean absolute error

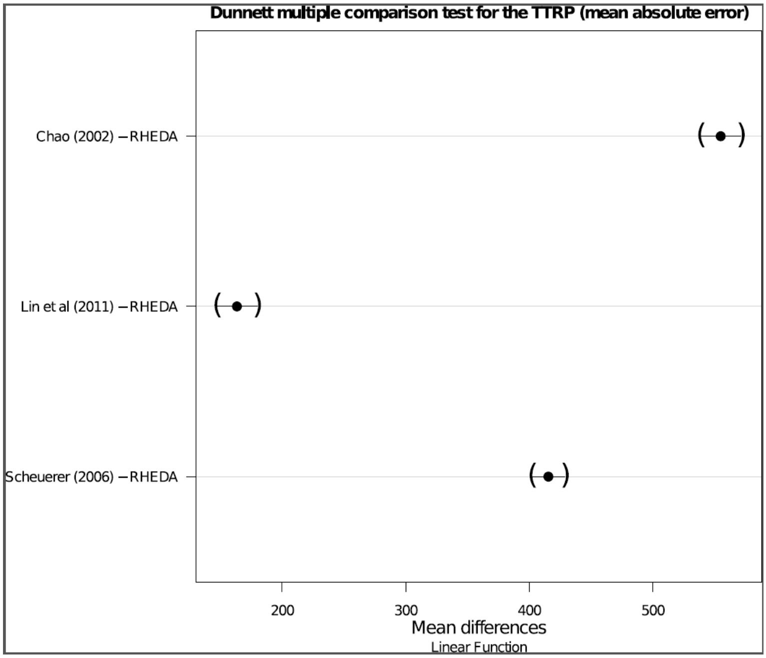


Figure 7 Algorithm performance for the TTRP using the mean square error

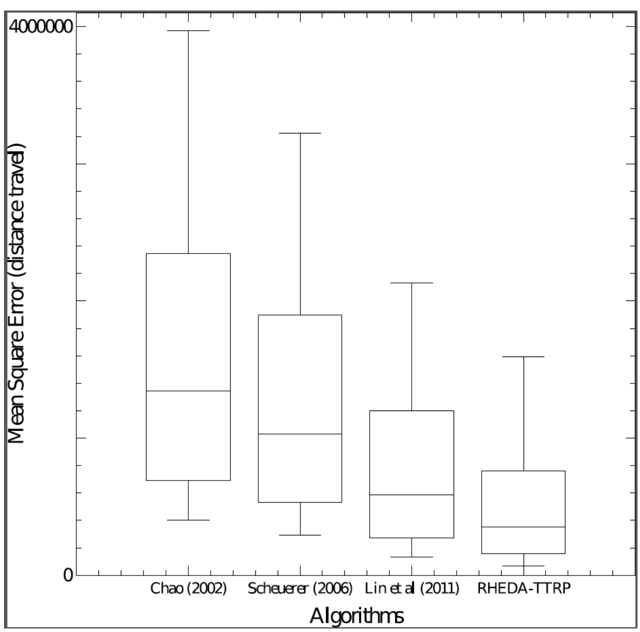


Figure 8 Dunnett test for the TTRP using the mean square error

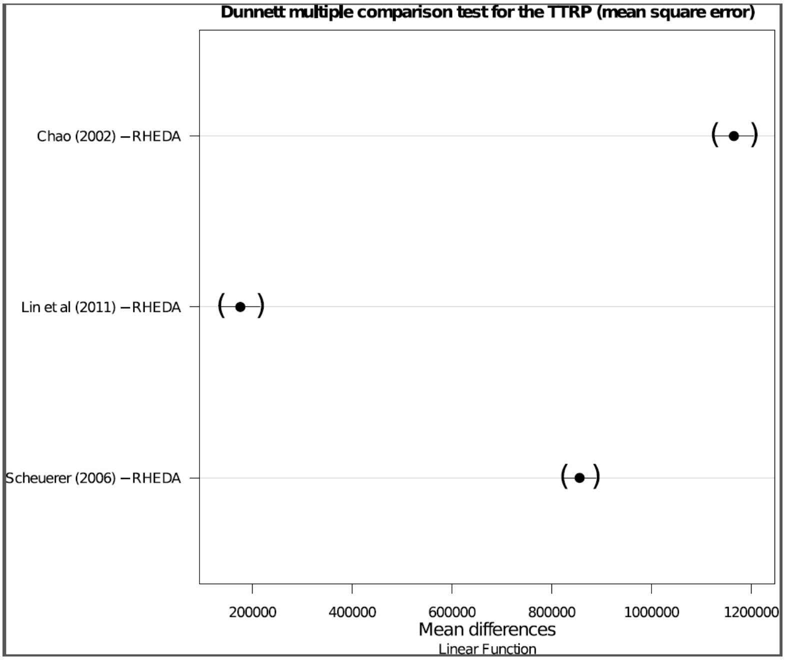


Figure 9 Algorithm performance for the TTRP using the relative percentage increase

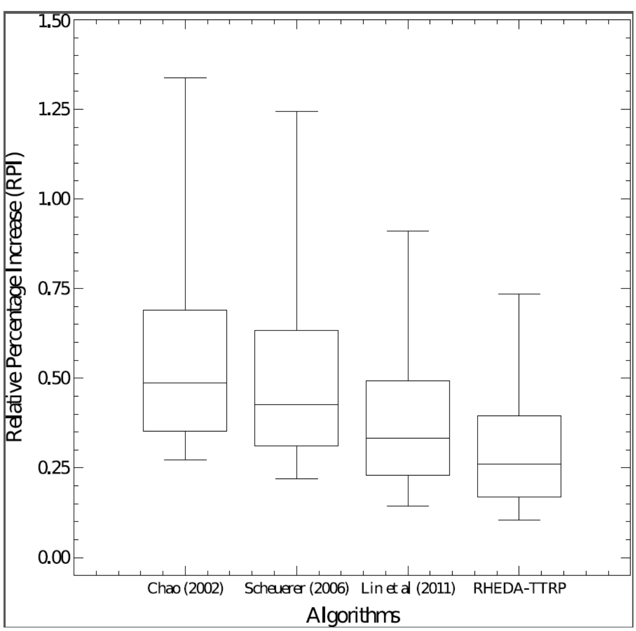
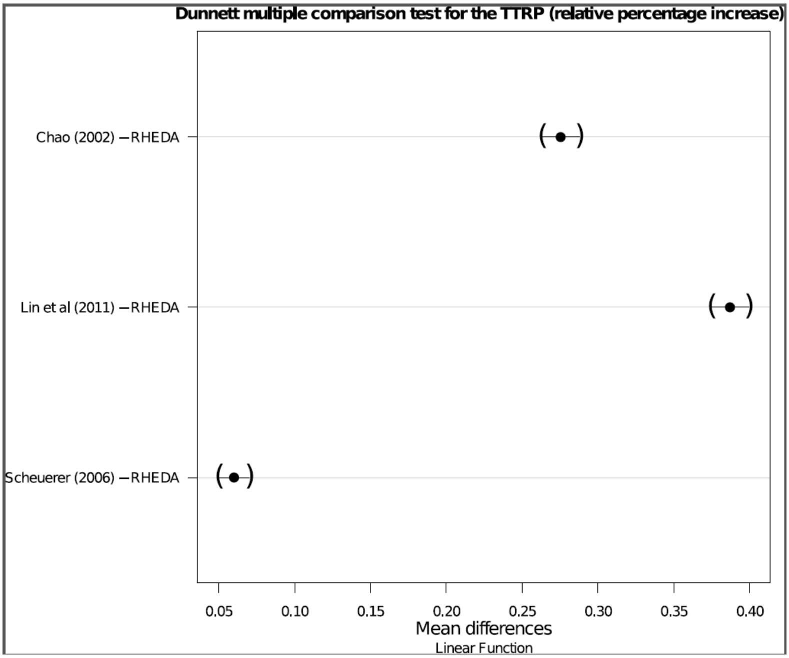


Figure 10 Dunnett test for the TTRP using the relative percentage increase



5.2 *Second comparison*

The second comparison is done using the next algorithms:

- The algorithm detailed by Derigs et al. (2013).
- The SA heuristic designed by Maghfiroh and Hanaoka (2018).
- The BA presented by Wang et al. (2018).

The same metric detailed in Section 5.1., i.e., the *RPI* is used to compare the efficiency of the algorithms.

Figure 11 depicts the algorithm performance based on the equation (5). Again, the RHEDA-TTRP scheme outperforms all the previous results.

The computational time comparison is depicted in Figure 12.

5.3 *Parameters setting*

The key parameters of the RHEDA-TTRP scheme are number of generations, population size, and replacement. It is based on Grefenstette's (1986) research.

- From 20 to 10 generations is defined as stopping criteria.
- From 1,000 to 100 members is considered as population size.
- The replacement varies between 50% and 100% of the population.

Figure 11 Algorithm performance for the TTRP using the relative percentage increase

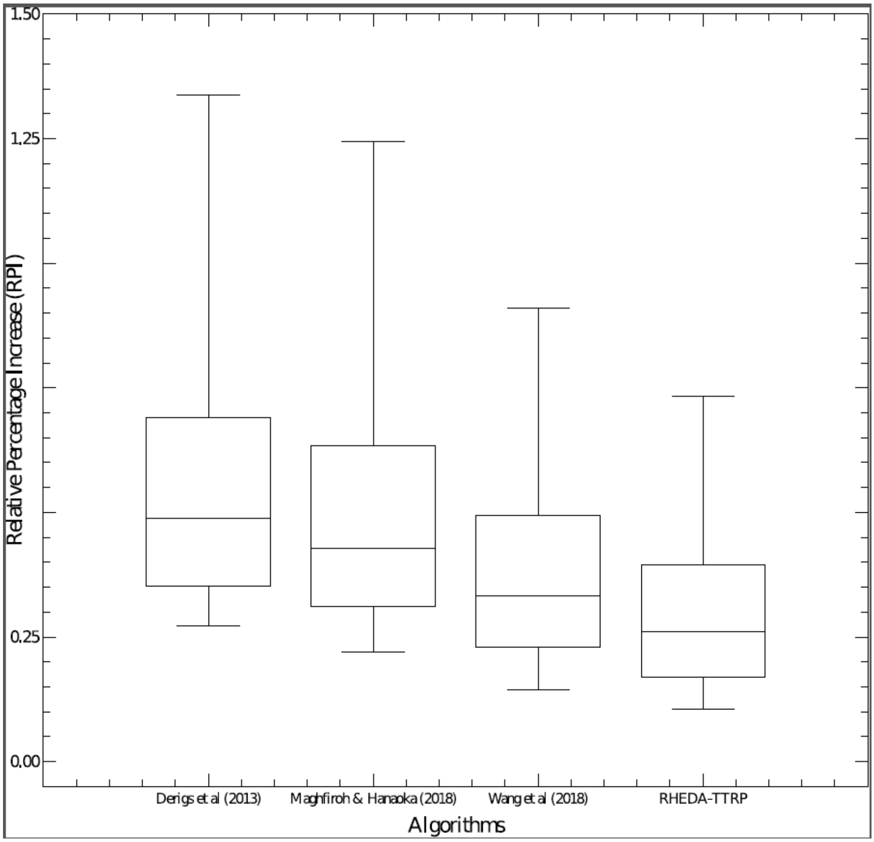
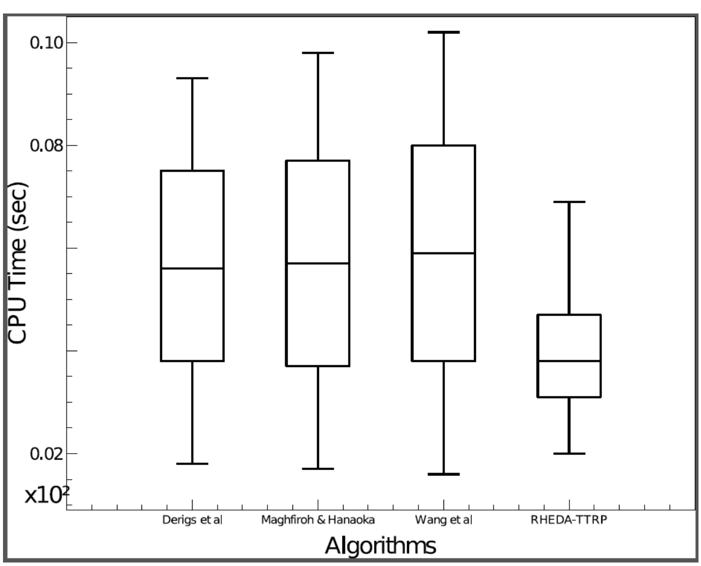


Figure 12 Computational time comparison



Four combinations are run in order to identify the best of them to enhance the efficiency of the algorithm. None is considerably better than the others. Therefore, it is possible to do the comparison with any of the combinations.

6 Conclusions

A discussion of the TTRP considers different routings, for each vehicle, as many logistics environments are detailed in this paper. To obtain an efficiently management and control of the routing systems is substantial to attend this problem. To tackle the problem, the RHEDA-TTRP scheme is proposed. Based on the results previously shown, the RHEDA-TTRP is competitive. In order to avoid delays in delivery orders, this approach could improve the service level by implementing the proposal method.

We recommend implementing the RHEDA-TTRP in real-world environments based on the results previously detailed.

We conclude that a new field of study is possible if we consider radial functions to work with the EDA scheme for solving optimisation issues.

When we use large data sets, the RHEDA-TTRP is stable based on the computational performance.

Based on the performance of the proposed scheme, we can conclude that incorporating radial probability distributions helps to improve the EDAs. We consider all the constraints involved in the problem to generate feasible solutions. However, this approach cannot handle new requirements meanwhile the vehicles are delivering parts in the trips.

We use radial distributions to help the EDA to remain exploitative and exploratory capability.

A list of items as future research needs is detailed below:

- Consider other elements to compute other radial functions.
- Other real-world logistics features should be included to create new algorithms.
- Other dynamic features should be included to test the proposed algorithm.
- A new interface should be programmed to be friendly the use of the algorithm for workers. We conclude that radial probabilities have been scarcely studied to build new EDAs.

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