Journal of Computing Research and Innovation (JCRINN) Vol. 6 No. 4 (2021) (pp10-19)
https://jcrinn.com : eISSN: 2600-8793

Green Inventory Routing Problem using Hybrid Genetic Algorithm

Huda Zuhrah Ab Halim[1*], Nureffa Natasha Mohd Azliana[2], Nuridawati Baharom[3], Nur Fatihah Fauzi[4], Nurizatul Syarfinas Ahmad Bakhtiar[5], Nur Izzati Khairudin[6]

[1,2,3,4,5,6] *Faculty of Computer and Mathematical Sciences,*
Universiti Teknologi MARA Perlis Branch, Arau Campus, 02600 Arau, Perlis, Malaysia

*Corresponding author: *hudazuhrah@uitm.edu.my*
Received Date: 20 August 2021
Accepted Date: 4 September 2021
Published Date: 20 September 2021

HIGHLIGHTS

- Hybrid Genetic Algorithm (HGA) was developed where the hybridization is done at the mutation operator by adopting Inventory Updating Mechanism.
- HGA is tested on two different distribution network, Inventory Routing Problem (IRP) and Green Inventory Routing Problem (GIRP) where GIRP considered the carbon emissions.
- Results showed the total costs of GIRP increased by at most 9.57% compared to IRP.

ABSTRACT

Carbon dioxide (CO_2) is known as one of the largest sources of global warming. One of the ways to curb CO_2 emissions is by considering the environmental aspect in the supply chain management. This paper analyses the influence of carbon emissions on the Inventory Routing Problem (IRP). The IRP network consists of a depot, an assembly plant and multiple suppliers. The deterministic demands vary and are determined by the assembly plant. Fixed transportation cost, fuel consumption cost and inventory holding cost are used to evaluate the system's total cost in which fuel consumption cost is determined by fuel consumption rate, distance, and fuel price. Backordering and split pick-up are not allowed. The main purpose of this study is to analyze the distribution network especially the overall costs of the supply chain by considering the CO_2 emissions as well. The problem is known as Green Inventory Routing Problem (GIRP). The mixed-integer linear programming of this problem is adopted from Cheng et al. wherein this study a different Hybrid Genetic Algorithm is proposed at mutation operator. As predicted, GIRP has a higher total cost as it considered fuel consumption cost together with the transportation and inventory costs. The results showed the algorithm led to different sequences of routings considering the carbon dioxide emission in the objective function.

Keywords: *Green Inventory Routing Problem, Inventory Routing Problem, Hybrid Genetic Algorithm, carbon emission*

INTRODUCTION

Global warming is known to be among the worst challenges in this century and carbon dioxide emission is one of the main contributors. A number of policymakers and researchers have started to pay serious attention to the carbon emission issues as a countermeasure to global warming. Specifically, green logistics is focused to efficiently control carbon emissions. Components in the supply chain management such as production, manufacturing, transportation and inventory are all contributed to carbon emissions (Cheng et al., 2016). Transportation, however, is the most apparent supply chain field that emits most of the emissions (Dekker et al., 2012).

The transportation sector contributed 28% of the Greenhouse Gas (GHG) emissions, of which 85% comes from road transportation (Mustapa & Bekhet, 2016). Thus, managing the carbon dioxide emissions from road transportation will contribute greatly to the environment. Although many companies implement fuel-efficient vehicles, environmentally friendly equipment and facilities, there is still not much research and studies on the impact of carbon emissions on operational decisions level (Hua et al., 2011). Considering the environmental effect on operational decision basis level will greatly reduce the carbon emissions as consolidated strategies will ensure to balance both economic and environmental. Hence, in this study, an inventory routing problem is studied under carbon dioxide emissions, namely Green Inventory Routing Problem (GIRP).

The inventory routing problem (IRP) attempts to concurrently analyze an optimal inventory and distribution plan that minimizes the supply chain's total cost (Moin et al., 2011). Previously, without considering its relationship, inventory and transportations costs have been minimized independently by different departments (Cheng et al., 2016). However, the interconnections between the two have inspired the researchers to model them simultaneously. Many studies showed that considering the two main components IRP the overall cost of the supply chain is significantly reduced (Ramkumar et al., 2012, Bertazzi et al. (2012), Moin and Salhi (2007), Andersson et al. (2010))

Therefore, this study is conducted to determine the impact of carbon emission regulations on the optimal policy of GIRP by calculating the fuel consumption cost. Fuel consumption it is the direct cause of CO_2 emission. The contribution of this study is two folds. First, is to developed Hybrid Genetic Algorithm which the hybridization is at the mutation operators. Instead of mutating one bit of the chromosome, an inventory updating mechanism that do backward and forward transfers between periods that aims to reduce the inventory and hence the number of vehicles. Second, is to analyze and get an insight of the impact of carbon dioxide emission of the GIRP.

LITERATURE REVIEW

Genetic Algorithm (GA) is a good alternative for IRP due to its simplicity and this is shown by the number of research published.

Among them is Moin et al. (2011) tackle an IRP with a many to one network distribution which consists of a single depot, one assembly plant and multiple suppliers. Each supplier supplies distinct products where the demands set by the assembly plant are deterministic and varies over the planning horizon. Trips are made by capacitated vehicles. Each trip starts at the depot, collects parts from the supplier, then is delivered to the assembly plant, and then vehicles are to be returned to the depot. In this problem, back-ordering is not allowed as any shortage of the automotive parts contributed to a high-priced.

The authors consider a GA for solving the problem and two different representations, binary and real representations were used. The authors have used a uniform crossover that suited the matrix representation where a binary mask of size N × T is randomly generated for each pair of parents. Besides, the authors have used the mutation procedure, which is a genetic operator to sustain genetic diversity from one generation of a population of chromosomes to the next. The authors adapted 14 data sets based on the original 4 data sets given in Lee et al. (2003).

Cheng et al. (2016) consider the impact of carbon emission regulations on the IRP. They consider the same network distribution as in Moin et al (2011). The transportation part considers carbon emission regulations, specifically fuel cost (determined by fuel consumption rate, distance, and fuel price), and inventory holding costs are fixed to evaluate the system's total cost. A nonlinear mixed-integer programming model is proposed for the GIRP.

Salim et al. (2018) propose a hybrid GA with VNS for the IRP at the mutation operator. They consider an outbound network distribution consisting of customers and depot. They have tested their algorithm using Archetti et al. (2012)'s benchmark dataset. Results have showed improvement up to 1.93% as compared to Hybrid Approach to Inventory Routing (HAIR) with 13 best results out of 16. The proposed hybrid GA does not consider the carbon emissions from transportations. They consider only one vehicle to be sent to the supplier that guarantees no stock-out event will be incurred. The authors have considered a different inventory policy which is an order up-to-level policy (OU). The contribution of this study is the development of a new optimization approach that is more efficient and effective for solving small and large instances.

Park et al. (2016) have proposed the strategy of vendor-managed inventory (VMI) routing problem using GA. VMI are strategies adopted by the vendors and their customers to enhance profitability. All decisions regarding customer inventory management are under the vendors' responsibility. The authors determine the best parameter setting by performing sensitivity analysis. The objective function considers production, inventory cost (supplier and customer), transportation cost (fixed and variable) and lost sales. Their algorithm is attempted to find the balance between the lost sales and customer satisfaction. To do so, the solutions are further improved by revising the vehicle routes to reduce the lost sales and transportation costs. The proposed GA has used real representation and built the routes by using saving algorithms (Cordeau et al., 2002). In addition, instead of minimizing the costs, the GA has developed aims to maximize the total profits.

Similarly, Wu et al. (2021) has proposed GA but incorporated the fuel consumption into the variable transportation cost. The authors proposed a two-stage hybrid metaheuristics algorithm to address the problem. A customized genetic algorithm is proposed in the first phase, while a gradient descent algorithm is used in the second phase. From the research published, it can be seen that hybridizing the mutation phase in GA is not given much attention to solve IRP. Therefore, the method will be further developed in this study.

PROBLEM DESCRIPTION

In this study, an automotive part supply network distribution is considered. The network consists of a depot, 0, one assembly plant, P and multiple suppliers $S = \{1,2, \ldots, N\}$. Each supplier supplies distinct products (different automotive parts) to fulfill the demands set by the assembly plant. The deterministic demand, d_{it} varies over the finite planning horizon $H = \{1,2, \ldots, T\}$. The number of homogeneous vehicles with capacity, C available to perform deliveries are assumed to be unlimited. Each vehicle starts at the depot to collect parts from the suppliers and delivers them to the assembly plant. After performing the deliveries, vehicles are to be returned to the depot. The distribution network studied is similar to the one proposed by Cheng et al. (2016). Figure 1 illustrates a network distribution of a depot, an assembly plant and 5 suppliers that supply distinct products.

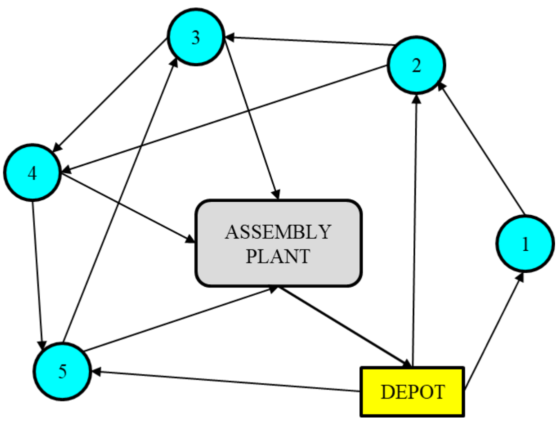

Figure 1: Directed network distribution of 5 suppliers

A few assumptions are made in this problem. Backordering is not allowed as any shortages are high-priced. Inventory holding costs are considered at the assembly plant whereas the initial inventory levels of all products are assumed to be zero. Split pick up is not allowed, that is a supplier can only be visited by at most one vehicle in each period.

In this study, a greener distribution is considered focusing on the carbon dioxide (CO_2) emission from the transportation part of the IRP. Specifically, the emission is calculated from the fuel consumption as it is the direct cause of CO_2 emission (Cachon, 2013; Zhang et al., 2014). Three factors contributing to the consumption are travel distance, weight and travel speed, given that full load trucks travel at high speed and longer distance emits more CO_2.

The objective of the GIRP is to minimize the overall total costs which include transportation cost, inventory cost at the supplier site and carbon dioxide emission. The mixed-integer linear programming of this problem is adopted from Cheng et al. (2016) wherein this study, a different Hybrid Genetic Algorithm is proposed.

METHODOLOGY

Datasets

The data sets are taken from Moin et al. (2011) and Cheng et al. (2016). The 14 data sets are varied in the number of planning horizons to represent small and medium-size problems. The data sets are S3T3, S4T5, S5T7, S7TH, and S9T9 and S12T14. For example, the data set S9T9 indicates 9 suppliers and 9 periods while S5T7 indicates 5 suppliers and 7 periods. However, in this study, only 6 datasets ranging from small to medium were used; S3T3, S4T5, S5T7, S7T5, S9T9 and S12T14.

Hybrid Genetic Algorithm

Genetic Algorithm is one of the well-known metaheuristics methods. In the 1960s, John Holland invented the GA with his students and colleagues at the University of Michigan. By combining the concept of "natural selection" together with the genetics-inspired operators named crossover, mutation, and inversion, the GA search method is a concept of moving from one population of "chromosomes" (strings of ones and zeros, or "bits") to a new population. Every chromosome consists of "genes" (bits), where each gene is a particular "allele" (0 or 1) (Mitchell, 1998).

Genetic Algorithm consists of three main operators, selection, crossover and mutation operators.

Representation

The representation represents a chromosome as a binary matrix of size $(N \times T)$ where N is the number of suppliers while T defines the number of periods. Let Figures 2 (a), (b), (c), and (d) represent the demand, binary, collection and inventory matrices respectively. It illustrates an example of the chromosome representation for a problem with 3 suppliers and 3 periods. For instance, in Figure 2(b), only supplier 2 is visited in period 2. Note that all suppliers must be visited in Period 1 to avoid the lost sales or back-ordering. This is because of the high penalty implemented by the assembly plant.

Figure 2 (c) shows the collection matrix produced from the demand and the binary matrix. From the collection matrix, we can determine the inventory (shown in Figure 2 (d)) that will be multiplied by the holding cost that varies daily. For instance, in Figure 2 (b), Supplier 1 will be visited only in Period 1 and Period 3. Since back-ordering is not allowed, the demand of Supplier 1 in Period 2 needs to be collected in Period 1. Therefore, the collection quantity for Supplier 1 in Period 1 will be for both Period 1 and Period 2. This results in 2 units inventory in Period 1 and the collection for Supplier 2 in Period 2 will be 2+2, which is also to fulfill the 2 units' demand in period 3 as Supplier 2 is not visited in Period 3.

		Period		
		1	2	3
Supplier	1	4	2	4
	2	2	2	2
	3	2	1	2

Figure 2(a): Demand matrix

		Period		
		1	2	3
Supplier	1	1	0	1
	2	1	1	0
	3	1	0	1

Figure 2(b): Binary representation matrix

		Period		
		1	2	3
Supplier	1	6	0	4
	2	2	4	0
	3	3	0	2

Figure 2(c): Collection matrix

		Period		
		1	2	3
Supplier	1	2	0	0
	2	0	2	0
	3	1	0	0

Figure 2(d): Inventory matrix

Selection Operator

In this study, the unbiased selection, Stcohastic Universal Sampling (SUS) is chosen as compared to the Roulette Wheel Selection (RWS) selection in Cheng et al. (2016).

Crossover

A two-dimensional uniform crossover to suit the matrix representation is employed. A binary matrix of similar size as the representation, ($N \times T$) is used as a mask for parents to determine the children. The binary crossover mask is generated randomly where the position of ones determines values inherited by the first child from the first parent and the zeros from the second parent. The second child is also determined from the same binary mask with zeros position obtained from the first parent. Figure 3 illustrates the uniform crossover operator. The numbers in Green are inherited from Parent 2. Note that in both children, Period 1 is not affected as all suppliers need to be visited.

		Period		
		1	2	3
Supplier	1	**1**	**1**	**0**
	2	**1**	**1**	**0**
	3	**1**	**0**	**0**

Figure 3(a): Parent 1

		Period		
		1	2	3
Supplier	1	**1**	**0**	**0**
	2	**1**	**0**	**1**
	3	**1**	**1**	**1**

Figure 3(b): Parent 2

		Period		
		1	2	3
Supplier	1	1	1	0
	2	0	1	0
	3	1	0	1

Figure 3(c): Crossover mask

		Period		
		1	2	3
Supplier	1	1	1	0
	2	1	1	1
	3	1	1	0

Figure 3(d): Child 1

		Period		
		1	2	3
Supplier	1	1	0	0
	2	1	0	0
	3	1	0	1

Figure 3(e): Child 2

Figure 3: Modified uniform crossover operator

For instance, in Figure 3(c), Supplier 1 shows that the first child will inherit from Parent 1 in Period 1 and Period 2 because the values of crossover mask generated are ones. While the value in Period 3 is inherited from Parent 2 as the mask is zero. Therefore, the first child in Figure 3(d) at the Supplier 1 row, the ones in Period 1 and Period 2 are from the first parent, and the zero is from the second parent. The second child in Figure 3(e) shows the inverse of the first child in Figure 3(d).

Mutation Operator

In this study, the hybrid will be operated on mutation. The strategy to hybridize, is to overcome the weakness of GA that is trapped in local search. By hybridizing, the ability of the search was improve and premature convergence can be avoided. An implementation of Inventory Updating Mechanism is adopted from Moin et al. (2014) where the authors proposed the mechanism in both metaheuristics, Scatter Search (SS) and ABC. The mechanism proposed is the forward and backward transfer, where exchange of deliveries between periods is done with the aim to reduce the vehicle number and the inventory quantities.

RESULTS AND DISCUSSIONS

This section presents the results obtained by the proposed Hybrid Genetic Algorithm (HGA). The HGA is tested on two problems, Inventory Routing Problem (IRP) and Green Inventory Routing Problem (GIRP). The hybrid algorithm is coded in MATLAB 9.7 and run on a 4GB RAM computer with 2.5GHz speed. Six datasets were used to test the performance of the algorithm which varies from small and medium cases. The HGA is tested on six datasets based on the modified dataset by Cheng et al. (2016). The modification is done which considered the carbon dioxide emission and fuel consumption cost. Population size of HGA is fixed at 100 for both small and medium cases and maximum number of generations allowed is 150. The crossover and mutation operators' rate are 0.07 and 0.01 respectively. The parameter is tuned differ from Cheng et al. (2016) due to lower computer specifications.

Table 1 showed the average of total cost (Total), inventory cost (Inv Cost), number of vehicles (#Veh) and distance (Dist) for both IRP and GIRP; and fuel consumption cost (FC Cost) for GIRP only. The percentage difference (%Δ) between IRP and GIRP is presented in the last column, The average is taken over 5 independent runs. It is expected that, the average total cost of GIRP is higher than the total cost of IRP as it includes fuel consumption costs in addition to the transportation and inventory costs.

Table 1: Average and percentage difference of best solutions of IRP and GIRP

	IRP				GIRP					
DATASET	Total	Inv Cost	# Veh	Dist	Total	Inv Cost	# Veh	Dist	FC Cost	%Δ
S3T3	423.29	3	3	360.29	460.19	6.00	3	360.29	43.97	8.72
S4T5	713.43	12.00	5	601.43	763.83	12.00	5	601.43	50.40	7.06
S5T7	1165.11	24.00	9	961.11	1251.362	27.00	9	960.554	83.81	7.40
S7T5	1308.07	47.40	9	1080.67	1433.286	19.80	9	1140.636	92.85	9.57
S9T9	3004.62	133.20	20.4	2463.42	3151.468	171.60	20.8	2451.36	112.51	4.89
S12T14	6402.99	292.20	45.4	5202.79	6584.188	273.00	45.2	5251.424	155.76	2.83

The results demonstrated that includes CO_2 emissions in the objective function resulted in different sequences of routings. It is observed that IRP and GIRP try to balance between the inventory and distance. This is clearly showed by the inventories and distance in S7T5 and S9T9 for both IRP and GIRP. For S7T5, inventory cost in IRP is slightly higher by 27.6 compared to GIRP, differ from S9T9, GIRP showed a slight high of inventory cost by 38.4 compared to IRP. Fuel consumption costs showed that the bigger the network distribution, the higher the cost. Table 2 presents the average fuel consumption for all datasets.

Table 2: Average Fuel Consumption for all datasets

DATASET	Fuel Consumption ℓ/km
S3T3	74.20
S4T5	125.29
S5T7	208.33
S7T5	230.81
S9T9	279.67
S12T14	387.18

The ability of HGA to avoid trapping in local search is demonstrate by the standard deviation in Table 3. Standard deviation is taken out of 5 independent runs for each dataset. It is inspected that because of the small size of dataset S3T3, S4T5 and S5T7 (IRP only), the HGA is unable to find new solutions.

Table 3: Standard Deviation of the IRP and GIRP

DATASET	IRP	GIRP
S3T3	0.00	0.00
S4T5	0.00	0.00
S5T7	0.00	5.57
S7T5	22.88	0.28
S9T9	51.23	27.44
S12T14	38.19	38.94

Table 4 tabulate the average computational time taken for HGA to obtained optimal solution for each dataset. Both IRP and GIRP problems are NP-hard, so the computational time increase exponentially as the nodes (supplier and period) increased. It is also seen that the computational time of GIRP is significantly longer than IRP.

Table 4: Average CPU time for IRP and GIRP

DATASET	IRP	GIRP
S3T3	1144.29	1334.33
S4T5	1989.87	2779.89
S5T7	3938.90	3490.30
S7T5	3443.18	3808.74
S9T9	7535.27	7276.16
S12T14	18020.86	16416.56

CONCLUSION AND RECOMMENDATIONS

This paper considered two problems, Inventory Routing Problem (IRP) and Green Inventory Routing Problem (GIRP). A hybrid genetic algorithm, HGA is proposed where the hybridization is done in the mutation phase. Instead of one bit changed in a chromosome, a targeted local search, an inventory updating mechanism that aims to reduce the inventory is adopted. The reduction on the inventories is done by transferring inventories backward and forward, and hence reduce the distance and number of vehicles. The GIRP considered carbon dioxide, CO_2 emission by calculating the fuel consumption from the transportation part of the distribution. It is expected that the total cost of GIRP is higher as compared to IRP. Analyses of the inventories, number of vehicles and distance as weight (from inventories) and traveling distance directly contributed to the CO_2 emission. The computing time is proportional to population size and the number of generations, as more possible combinations are considered. Thus, it is recommended to embed a simple and fast local search, such as 1-insertion and swap in an iterated manner. Alternatively, is to implement a powerful local search, like Generalised Insertion (GENI) Method.

REFERENCES

Andersson, H., Hoff, A., Christiansen, M., Hasle, G., & Løkketangen, A. (2010). Industrial aspects and literature survey: Combined inventory management and routing. *Computers & operations research, 37*(9), 1515-1536. doi:10.1016/j.cor.2009.11.009

Archetti, C., Bertazzi, L., Hertz, A., & Speranza, M. G. (2012). A hybrid heuristic for an inventory routing problem. *INFORMS Journal on Computing, 24*(1), 101-116. doi:10.1287/ijoc.1100.0439

Bertazzi, L., & Speranza, M. G. (2012). Inventory routing problems: an introduction. *EURO Journal on Transportation and Logistics, 1*(4), 307-326. doi:10.1007/s13676-012-0016-7

Cachon, G. (2013). Retail Store Density and the Cost of Greenhouse Gas Emissions. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.2275350

Cheng, C., Qi, M., Wang, X., & Zhang, Y. (2016). Multi-period inventory routing problem under carbon emission regulations. *International Journal of Production Economics, 182,* 263–275. https://doi.org/10.1016/j.ijpe.2016.09.001

Cordeau, J.-F., Gendreau, M., Laporte, G., Potvin, J.-Y., & Semet, F. (2002). A guide to vehicle routing heuristics. *Journal of the Operational Research society*, *53*(5), 512-522

Dekker, R., Bloemhof, J., & Mallidis, I. (2012). Operations Research for green logistics - An overview of aspects, issues, contributions and challenges. *European Journal of Operational Research*, *219*(3), 671–679. https://doi.org/10.1016/j.ejor.2011.11.010

Hua, G., Qiao, H., & Li, J. (2011). Optimal order lot sizing and pricing with carbon trade. *ICEIS 2011 - Proceedings of the 13th International Conference on Enterprise Information Systems*, *3 ISAS*, 533–536. https://doi.org/10.2139/ssrn.1796507

Lee, C.-G., Bozer, Y. A., & White III, C. (2003). A heuristic approach and properties of optimal solutions to the dynamic inventory routing problem. In: Working Paper.

Mitchell, M. (1998). An introduction to genetic algorithms.

Moin, N. H., & Salhi, S. (2007). Inventory routing problems: a logistical overview. *Journal of the Operational Research society*, *58*(9), 1185-1194. doi:10.1057/palgrave.jors.2602264

Moin, N. H., Ab Halim, H. Z., & Yuliana, T. (2014). Metaheuristics for multi products inventory routing problem with time varying demand. *AIP Conference Proceedings*, *1605*(February 2015), 3–9. https://doi.org/10.1063/1.4887556

Moin, N. H., Salhi, S., & Aziz, N. A. B. (2011). An efficient hybrid genetic algorithm for the multi-product multi-period inventory routing problem. *International Journal of Production Economics*, *133*(1), 334–343. https://doi.org/10.1016/j.ijpe.2010.06.012

Mustapa, S. I., & Bekhet, H. A. (2016). Analysis of CO_2 emissions reduction in the Malaysian transportation sector: An optimisation approach. *Energy Policy*, *89*(2016), 171–183. https://doi.org/10.1016/j.enpol.2015.11.016

Park, Y.-B., Yoo, J.-S., & Park, H.-S. (2016). A genetic algorithm for the vendor-managed inventory routing problem with lost sales. *Expert systems with applications*, *53*, 149-159.

Ramkumar, N., Subramanian, P., Narendran, T. T., & Ganesh, K. (2012). Mixed integer linear programming model for multi-commodity multi-depot inventory routing problem. *Opsearch*, *49*(4), 413–429. https://doi.org/10.1007/s12597-012-0087-0

Salim, A. S. M., Mounira, T., & Ouajdi, K. (2017, October). A Hybrid Genetic Algorithm for the Inventory Routing Problem. In *2017 IEEE/ACS 14th International Conference on Computer Systems and Applications (AICCSA)* (pp. 987-994). IEEE.

Wu, W., Zhou, W., Lin, Y., Xie, Y., & Jin, W. (2021). A hybrid metaheuristic algorithm for location inventory routing problem with time windows and fuel consumption. *Expert systems with applications*, *166*, 114034.

Zhang, S., Lee, C. K. M., Choy, K. L., Ho, W., & Ip, W. H. (2014). Design and development of a hybrid artificial bee colony algorithm for the environmental vehicle routing problem. *Transportation Research Part D: Transport and Environment*, *31*, 85–99. https://doi.org/10.1016/j.trd.2014.05.015