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A HEURISTIC APPROACH FOR GREEN VEHICLE ROUTING

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Abstract. This paper addresses a green capacitated vehicle routing problem that accounts for transportation emissions. A Dynamic Programming approach has been used to formulate the problem. Although small-sized problems can be solved by Dynamic Programming, this approach is infeasible for larger problems due to the curse of dimensionality. Therefore, we propose a Dynamic Programming based solution approach that involves the ideas of restriction, simulation and online control of parameters to solve large-sized problems. The added values of the proposed decision support tool have been shown on a small-sized base case and relatively larger problems. Performance comparisons of the proposed heuristic against other existing Dynamic Programming based solution approaches reveal its effectiveness, as in most of the instance-setting pairs, the proposed heuristic outperforms the existing ones. Accordingly, the proposed heuristic can be used as an alternative decision support tool to tackle real routing problems confronted in sustainable logistics management.

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1. Introduction

The capacitated vehicle routing problem (CVRP) is one of the core problems at operational level logistics management. The problem deals with the distribution of goods from a central depot to a set of dispersed customers by means of a fleet of capacitated vehicles. Each vehicle route starts and ends at the depot without exceeding the capacity of the vehicle at any point in time. The known customer demands must be satisfied by visiting each of them exactly once. The traditional objective for the CVRP is to determine a set of vehicle routes that minimizes the total distance travelled or total time spent [10, 12, 30, 31, 39].

With increasing freight volumes due to the growing population and internationalization of markets, one of the main challenges of the logistics sector is to increase the efficiency of freight logistics [1, 3, 6, 16]. Transportation energy use and resulting Greenhouse Gas (GHG) emissions are the foremost important issues that are considered while evaluating the efficiency of delivery operations [6, 22, 43, 45, 48].

Increasing concerns about oil scarcity and climate change[1] requires advanced methods or approaches to increase fuel usage efficiency in logistics operations. In response, the recent green Vehicle Routing Problem

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[1]European Commission Document (2009). Communication from the Commission – A sustainable future for transport: Towards an integrated, technology-led and user friendly system. http://eur-lex.europa.eu/legal-content/EN/ALL/?uri=CELEX:52009DC0279. Online accessed: July 2018.

(VRP) literature [5,9,17,32,34,35,47] has focused on having optimized sustainable logistics routes by means of using detailed fuel consumption and emission estimations.

The basic VRP is an NP-hard combinatorial optimization problem. Incorporating additional concerns such as explicit fuel consumption estimations further increases the problem complexity. The increase in complexity along with growing competition among logistics chains in practice causes a continuous need to search for better solution approaches for routing problems. Accordingly, the main motivation behind this research is to contribute to the field of logistics management by providing a promising decision support tool. The provided tool can be used for efficient operational decision making.

This paper presents a Dynamic Programming (DP) based heuristic for the green capacitated routing problem with heterogeneous arcs in terms of vehicle speed. The solution approach is able to manage several logistical key performance indicators (KPIs), such as total travelled distance, total energy use (which can be translated into emissions), total driving time, and total routing cost comprising fuel and wage costs. An emission model has been incorporated into the heuristic to estimate transportation costs and emissions more accurately and explicitly. The presented solution approach can be used to obtain close-to-optimal delivery plans for the large-sized routing instances, since exponential memory and computation time requirements of a classical DP model restricts its usage in larger problems.

The rest of the paper is structured as follows. Section 2 presents a review of the relevant literature on the topic to show the contribution of the research. Section 3 presents the formal description of the problem. Section 4 presents a mathematical formulation of the problem and the proposed solution approach. Section 5 presents computational results for the analysed problems. The last section presents conclusions and future research directions.

2. Related literature review

Scholars addressing the green VRP literature regard transportation energy use and GHG emissions as prominent logistical environmental issues (see, for instance, [13, 36–38, 46, 48]). The common goal of all of these attempts on routing problems is to improve the sustainability performance of logistics systems by means of the developed decision support models that can address the concerns for energy use and consequently emissions, while also adhering to economic concerns [21].

The featured green VRP models (see [4,18,19,27,33]) estimate transportation energy use and emissions explicitly through using several comprehensive fuel estimation approaches that take multiple aspects into account such as travelled distance, vehicle load and speed, vehicle characteristics, etc. These studies report the benefits of enhancing green VRP models through accounting for explicit transportation energy use. As discussed in Soysal [41], enhancement of the green VRP models through explicit energy estimation can enable several opportunities such as; (i) reducing relevant operational costs due to more accurate fuel consumption estimation, (ii) planning logistics operations according to the environmental and social objectives and (iii) revealing the trade-off relationships among logistics cost, transportation energy use and emissions. An interested reader on the topic can be referred to the review of recent research on green road freight transportation conducted by Demir *et al.* [15].

Various solution approaches and techniques (*e.g.*, approximate dynamic programming, genetic algorithms, dynamic programming based heuristics, etc.) have been developed for Vehicle Routing Problems (VRPs) to solve large-sized problems. This research focuses on the recent DP based heuristics existing in the literature. These DP based solution approaches are highly flexible frameworks in terms of incorporating various real-life restrictions that have been generally ignored in classical vehicle routing models, such as time-dependent travel times, driving hour regulations, explicit energy use estimation [25, 42]. We do believe that there is a need for research on development of DP based heuristics as routing problems are getting more complex in terms of considering new practical concerns and, in return, these approaches have the potential to handle this complexity. This study contributes to the green VRP literature by proposing a DP based heuristic for the addressed problem.

The classical Restricted Dynamic Programming (RDP) heuristic, which is one of the earlier attempts of developing DP based heuristics, implements the idea of retaining only the limited amount of promising (H most promising) partial tours at each stage of the DP algorithm. This means that every partial path that may lead to an optimal solution is not retained at each stage. The main benefit from the use of this approach is the fact that the exponential explosion of time and memory requirements of the DP algorithm is avoided. However, this heuristic does not guarantee optimality, as the states leading to the optimal solution might be pruned earlier. Gromicho *et al.* [24, 25]; Kok *et al.* [28, 29] present the applicability of the classical RDP heuristic to different variants of VRPs by restricting the state space in this way.

The study of Soysal and Çimen [42] and Soysal *et al.* [44] present another attempt on developing a DP based solution approach, Simulation-Based Restricted Dynamic Programming (SRDP), which is based on weighted random sampling, the classical RDP heuristic and simulation. They propose a different way from the previous attempts for restricting the state space in the DP algorithm. Their expansion approach suggests to select S partial tours using weighted random sampling in addition to the most H promising partial tours at each stage. Afterwards, the best feasible solution for the problem is found through an implemented simulation. The numerical results show that their solution approach can provide promising results within relatively short computation times compared to the classical RDP heuristic.

In this study, we propose a new approach which employs the idea of controlling and updating several key parameters of the algorithm online. This *online control* enables a better exploration of state space in addition to benefiting from the simulation approach to test different partial tours that may result in improved solutions for routing instances. Alternative promising feasible delivery plans provided by means of the proposed solution approach, namely *Restricted Dynamic Programming with Simulation and Online Control* (RDP-SOC) can be used by decision makers who are responsible for logistics operations management. We present in what follows the formal description of the problem.

3. Problem description

The problem at hand is defined on a complete directed graph $G = \{V, A\}$, where $V = \{0, 1, \dots, n\}$ is the node set and A is the arc set. Nodes $i \in V \backslash \{0\}$ correspond to customers, whereas node 0 corresponds to a central depot/warehouse. A set of m homogeneous vehicles, each of which has the capacity of Q, is available at the warehouse to make the deliveries to the customers. Each customer has a known nonnegative demand, q_i, to be satisfied and a service time, h_i. After the service is completed, vehicles leave the nodes without additional waiting. Arcs $(i, j) \in A$ might be heterogeneous in terms of vehicle speed, *i.e.*, average vehicle speeds may vary among arcs. The reason is that some arcs might have multiple road segments in different lengths (distances) and the speed of the vehicle can change according to the road section's traffic congestion and traffic regulations (see, [2]).

The defined problem aims to determine the routes for all vehicles, starting and ending at the warehouse, by respecting the aforementioned assumptions so as to minimize the total cost of delivery operations that includes fuel consumption cost and driver cost. The travel cost between two nodes $i \neq j \in V$ is denoted by $c_{i,j}$. The driver of each vehicle is paid from the beginning of the time horizon until returning back to the depot. Fuel consumption is dependent on travelled distance, vehicle speed and vehicle characteristics.

We employ a methodology for the estimation of ultimate CO_2 emissions from road transportation operations [8]. According to that approach, the total amount of transportation emissions E (g/km) generated for traversing one km at a constant speed v (km/h) is calculated as follows:

$$E = \frac{k(a + bv + cv^2 + dv^3 + ev^4 + fv^5 + gv^6)}{v} \tag{3.1}$$

where k, a, b, c, d, e, f and g are vehicle specific parameters. The reader is referred to the technical report of Boulter *et al.* [8] for further details on these parameters. After estimating emission levels, we estimate corresponding fuel consumption amounts by using a fuel conversion factor for transport activities.

4. The solution approach

This section first describes the DP algorithm for the addressed problem, then introduces a solution approach.

4.1. Dynamic Programming model

We employ a DP algorithm methodology based on the DP formulation introduced by Bellman [7] and Held and Karp [26] for the Traveling Salesman Problem (TSP). Given a network, the TSP aims to find the shortest possible route that visits each city exactly once and returns to the starting point. The addressed green routing problem is first transformed into the TSP by means of a giant-tour representation, which was introduced by Funke *et al.* [20], then the DP algorithm is used to formulate and solve the problem.

The DP algorithm of the TSP calculates the routes for each vehicle subsequently, which means that there exists only one vehicle called *active vehicle* whose route is being calculated at any point in time. This allows the algorithm to track the information on vehicle load and time (see, [24, 25, 29]). Load tracking enables to respect the vehicle capacities and time tracking enables to calculate driver cost. Algorithm 1 presents the DP algorithm for the addressed problem.

Algorithm 1: The DP algorithm based on Bellman [7] and Held and Karp [26].

Data: $V = \{1, \ldots, n, a_1, \ldots, a_m\}$ where the nodes 1 to n represent customers and $a_1, \ldots, a_m$ represent the dummy depots,
m vehicles are available in dummy depot a_1 (starting point) for delivery,
Q capacity of the homogenous vehicles,
q_i demand of customer i,
utilization average vehicle utilization rate,
$l_{i,j}$ vehicle load between nodes i and j,
$w_{i,j}$ departure time of a vehicle that leaves from node i for node j,
$c_{i,j}$ the travel cost between two nodes $i \neq j \in V$,
Φ the set of visited nodes at any point in time,
$C(\Phi, j)$ referred as a *partial tour*, the cost of starting from dummy depot a_1, visiting all nodes in set Φ exactly once and ending in node j,
C^* the minimum total travel cost of a complete tour, including the return to the starting point node a_1.

Transform the routing problem into its TSP form

Replace the real depot by m dummy depots $(a_1, \ldots, a_m)$ which are all located at the same position.
Assign large numbers for the distances between the dummy depots to prohibit travelling among themselves.

Incorporate additional side constraints on capacity and time to the TSP form

Track the vehicle loads $(l_{i,j})$ between related nodes using an extra state dimension on capacity.
Add node i to a partial tour if the following two conditions are satisfied[2]

1. remaining load in the active truck $\geq q_i$,
2. remaining load in the active truck + Q * number of remaining unused trucks * *utilization* $\geq$ total demand of unvisited customers.

Track the departure time $(w_{i,j})$ from the most previously visited node using an extra state dimension on time.

Use the DP formulation for the TSP

Calculate $C(\Phi, j)$ in the first (4.1) and in each successive stages (4.2) as follows:

$$C(\{j\}, j) = c_{a_1, j}, \quad \forall j \in V \backslash a_1, \tag{4.1}$$

$$C(\Phi, j) = \min_{i \in \Phi \backslash j} \{C(\Phi \backslash j, i) + c_{i,j}\}, \quad \forall j \in \Phi. \tag{4.2}$$

Calculate the minimum total travel cost of a complete tour (C^*), including the return to the node a_1 as follows:

$$C^* = \min_{j \in V \backslash a_1} \left\{C(V \backslash a_1, j) + c_{j, a_1}\right\}. \tag{4.3}$$

Where the travel cost $c_{i,j}$ is calculated as follows:
Calculate emissions and fuel consumption between nodes i and j, FC, using formula (3.1).
Calculate travel time between nodes i and j, TT.
$c_{i,j}$ = TT * Driver wage + FC * Fuel price.

[2]The first condition ensures that the vehicle visits a node, if it has sufficient load to satisfy the demand. The second condition restricts vehicles to visit dummy depots with low utilization rates by taking idle capacity of vehicles into account [42].

4.2. Restricted dynamic programming with simulation and online control

The described DP algorithm is infeasible for the larger routing problems due to enormous computational burden and time requirements. In response, we propose a DP based heuristic algorithm in order to obtain promising results for larger problems within short computation times. The introduced approach involves the ideas of restriction, simulation and online control of parameters.

In what follows, we summarize the RDP-SOC heuristic and provide the necessary steps at each stage of the algorithm:

- List all potential partial tours. Eliminate any unpromising ones online, based on whether their current cost-to-go values allude to a higher cost of a complete tour than that of the best solution found so far.
- Sort a predefined number of the remaining partial tours, and normalize their cost-to-go values.
- Select M most promising partial tours. M is restricted by two parameters updated online at the beginning of each simulation iteration. First, normalized cost-to-go values of any selected partial tours cannot exceed a random rate. Second, M cannot exceed the randomly defined quota of partial tours expanded in each stage ($\hat{H}$).
- If the quota ($\hat{H}$) is not filled, select the remaining $\hat{H} - M$ partial tours according to assigned probabilities with respect to their cost-to-go values, using weighted random sampling.
- Keep track of the selected $\hat{H}$ partial tours in the next stage, until all nodes are visited.

Our heuristic suggests to (i) restrict the number of tracked partial tours in each stage (see, [24,25,28,29]), (ii) use a simulation to try different partial tours that may result in an improved solution (see, [42]), and (iii) control and update key parameters online that enables a better exploration of state space.

To implement the RDP-SOC heuristic, the necessary steps at each stage of the DP algorithm are presented in detail in Algorithm 2. Since RDP-SOC involves random number generation and simulation processes, each run of the algorithm will yield different solutions even for the same problem. A fair performance assessment can be performed by means of a Monte Carlo simulation (*e.g.*, see Algorithm 3).

The recursion requires a proper state space exploration to find close-to-optimal feasible solutions. As distinct from the existing DP based solution approaches, the proposed heuristic introduced above benefits from online control of key parameters that enables to find out promising state space expansion. The potential benefits that could be obtained from the use of the introduced solution approach are investigated in the following section.

5. Numerical experimentation

This section first aims to show the applicability of RDP-SOC on a base case. Then, the performance of the proposed heuristic has been assessed against the classical RDP and SRDP heuristics using the base case, two additional small-sized problems and nine problems that are relatively larger in size.

DP based solution algorithms here for the conducted experiments have been developed using C++ programming language. We have used a computer of Pentium(R) i7-7700 K 4.2 GHz CPU with 8 GB memory.

5.1. Base case analyses

We first describe the addressed problem referred to as the base case and present the corresponding data used. The following seven logistical KPIs have been used for the evaluation of the resultant policies: (i) number of vehicles used, (ii) total travelled distance, (iii) total emissions, (iv) total driving time, (v) total fuel cost, (vi) total wage cost and (vii) total routing cost [11].

Algorithm 2: Algorithm for the RDP-SOC heuristic.

Data: $V = \{1, \ldots, n, a_1, \ldots, a_m\}$ where the nodes 1 to n represent customers and $a_1, \ldots, a_m$ represent the dummy depots.
m vehicles are available in dummy depot a_1 (starting point) for delivery.
Q capacity of the homogenous vehicles.
q_i demand of customer i.
utilization average vehicle utilization rate.
$l_{i,j}$ vehicle load between nodes i and j.
$w_{i,j}$ departure time of a vehicle that leaves from node i for node j.
$c_{i,j}$ the travel cost between two nodes $i \neq j \in V$.
Φ the set of visited nodes at any point in time.
$C(\Phi, j)$ referred as a *partial tour*, the cost of starting from dummy depot a_1, visiting all nodes in set Φ exactly once and ending in node j.
C^* the minimum total travel cost of a complete tour, including the return to the starting point node a_1.
simtime the length of RDP-SOC run in terms of time.
top the number of most promising states selected in order to reduce computational burden and eliminate any potential effects of outlier states while calculating normalized costs.
k the fixed stage intervals where we decide whether to keep a potential partial tour (state), based on if it is promising or not.
min, *runtime*, *obtainedcost*, *dynamicvalue*, *userdecide*, *passedtime* required additional parameters for the algorithm.
min = a sufficiently large number (*i.e.*, a number larger than any potential objective value of a feasible solution);
runtime = 0;
while *runtime* $\leq$ *simtime*[3] **do**
  $\hat{H}$ = select a random integer number from a predefined interval, *e.g.*, a single uniformly distributed random integer number in the interval (50, 100).
  dynamicvalue = select a random real number from a predefined interval, *e.g.*, a single uniformly distributed random real number in the interval (0, 0.2).
  userdecide = select a random real number from a predefined interval, *e.g.*, a single uniformly distributed random real number in the interval (0, 0.2).
  At each stage of the DP algorithm do the following steps in order:
    Step 1: Determine the partial tours selected in the previous stage and possible nodes to visit in this stage. For the initial stage, determine only possible nodes to visit.
    Step 2: Define potential partial tours for this stage using the information obtained in the Step 1.
    Step 3: Calculate the state costs, $C(\Phi, j)$, of each potential partial tour (Φ, j), using the equation (4.2). For the initial stage, use the equation (4.1).
    Step 4: If the *number of stage* mod k is equal to 0, check whether the calculated state costs are higher than the ratio of $(\min/(n+m)) *$ *number of stage* or not. If a state cost is higher than the calculated ratio, ignore and do not expand this state.
    Step 5: Rank the remaining potential partial tours by the cost, $C(\Phi, j)$, from lowest to highest.
    Step 6: Take partial tours (states) from a predefined top interval (the *top* most promising).
    Step 7: Normalize the cost-to-go values of the selected *top* states, $C(\Phi, j)$, between 0 and 1.
    Step 8: Select M most promising partial tours which have the normalized value of smaller than the *dynamicvalue* to expand in the next stage. Note that M is also restricted by $\hat{H}$.
    Step 9: If M is smaller than $\hat{H}$, assign weights to each of the not selected remaining potential partial tours and calculate corresponding cumulative probabilities. Then, select $\hat{H} - M$ partial tours using the weighted random sampling according to the calculated cumulative probabilities and the arbitrary selection threshold within the interval (0, *userdecide*], to expand in the next stage.
    Step 10: Expand only the $\hat{H}$ partial tours in the next stage.
    Step 11: If all nodes $V \backslash a_1$ are visited, calculate the minimum total travel cost of the complete tour, (*obtainedcost*), using the equation (4.3) and go to Step 12. If not, go to Step 1.
    Step 12: Calculate the passed time so far, *passedtime*, while performing the Steps 1–11.
  Check the quality of the feasible route found in terms of total cost:
    if *obtainedcost* $<$ min **then**
      min = *obtainedcost*
      Save the feasible route.
  Track the total runtime: *runtime* += *passedtime*.

5.1.1. Description and Data

The data for the problem has been taken from the Pollution-Routing Problem Instance Library[4]. The data, which is referred to as UK15_01 in the web-site, is based on real distances collected from the chosen United Kingdom cities. The studied transportation network in our base case includes one depot located in Galashiels and 15 customers located in nearby cities, as shown in Figure 1. The name of customer locations together with customer demands and related service times can be seen from the Table 1.

[3]Note that since the *runtime* is checked only once at the beginning of this loop, the *simtime* can be expired before the end of the loop, which means that the final *runtime* may exceed *simtime*. The gap will always be smaller than the length of a single run of the 12 steps. At a cost of slower computation, the runtime may be checked more frequently within the loop.

[4]www.apollo.management.soton.ac.uk/prplib.htm, Online accessed: January 2017.

Algorithm 3: Simulation algorithm for evaluating RDP-SOC.

Data: *simnumber* the length of simulation.
simtime the length of RDP-SOC run in terms of time.
avgcost, *result* required additional parameters for the simulation.
Start simulation:
avgcost = 0.
for *s = 0; s < simnumber; s++* **do**
    result = result of RDP-SOC within *simtime* (see Algorithm 2)
    Update the average cost: *avgcost* += *result*.
Find the average cost of all simulation runs: *avgcost* /= *simnumber*.

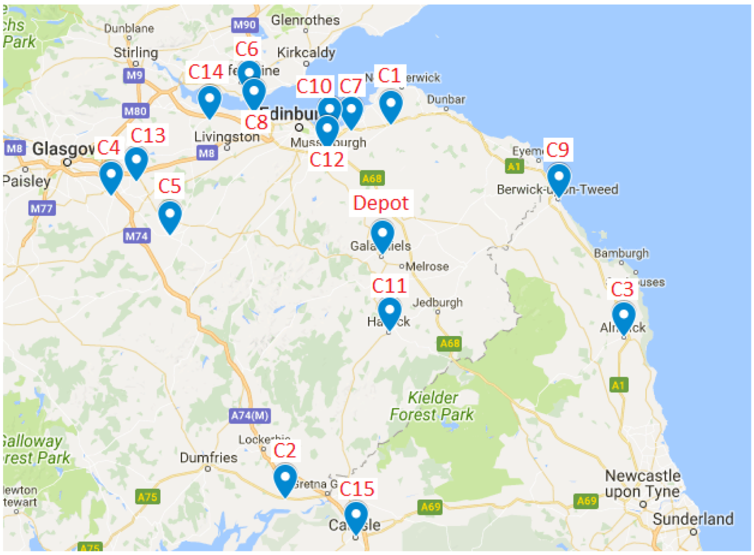

FIGURE 1. Representation of the logistics network.

Two homogeneous rigid heavy goods vehicles with a capacity of 4000 kg are used for the deliveries from the depot to the customers. It is assumed that vehicles consume diesel with an emission standard of Euro V. To calculate ultimate CO_2 emissions, the data presented in the technical report of Boulter *et al.* [8] for the diesel Euro V rigid heavy goods vehicles are used. This technical report presents estimated exhaust emission factors for road vehicles in the UK. To be used in equation (3.1), required parameters are set as follows: $a = 12\,690$, $b = 16.564$, $c = 86.867$, $d = -3.5532$, $e = 0.061462$, $f = -0.0004773$, $g = 0.0000013853$ and $k = 1$ (see page 173 of the report [8]). The fuel conversion factor of 2.63 kg/l has been used to estimate corresponding fuel consumption amounts [14]. Table 2 presents the distance matrix.

The average vehicle speed between the nodes under regular traffic conditions are provided from the Google Maps[5]. As can be seen from the matrix presented in Table 3, average speeds between the nodes vary between nearly 9 m/s and 25 m/s.

Fuel price and wage parameters required to calculate fuel consumption and driver costs are taken as 1.6 €/l and 0.004 €/s, respectively. The objective of the problem is to determine the vehicle routes that start and end at the depot and visit each customer exactly once such that the total routing cost is minimized.

[5]http://maps.google.com.tr/, Online accessed: January 2017.

Table 1. Demand of customers and corresponding service times.

	Demand (in kg)	Service time (in s)
Depot – Galashiels	0	0
C1 – Haddington	178	356
C2 – Annan	397	794
C3 – Alnwick	693	1386
C4 – Hamilton	346	692
C5 – Lanark	785	1570
C6 – Rosyth	803	1606
C7 – Tranent	609	1218
C8 – Queensferry	216	432
C9 – Berwick-Upon-Tweed	345	690
C10 – Musselburgh	748	1496
C11 – Hawick	473	946
C12 – Dalkeith	103	206
C13 – Newarthill	486	972
C14 – Linlithgow	410	820
C15 – Carlisle	627	1254

Table 2. Distances between nodes, in meters.

	Depot	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15
Depot	–	50 941	92 751	91 440	96 450	75 910	76 210	49 310	69 650	64 640	49 720	24 280	44 970	91 230	81 440	94 581
C1	51 061	–	137 773	103 641	92 220	82 280	52 100	15 280	45 540	59 500	21 230	72 601	23 220	83 460	57 960	142 902
C2	92 801	137 743	–	140 991	111 514	94 983	144 893	132 233	137 923	137 732	128 923	69 441	122 493	114 864	133 533	31 220
C3	90 990	103 631	141 351	–	202 421	162 160	149 801	115 361	143 241	50 070	120 501	89 141	117 041	193 391	157 061	118 581
C4	96 200	91 870	111 305	202 802	–	23 070	59 960	79 550	52 810	149 200	72 530	115 100	71 390	9820	42 090	135 015
C5	75 930	82 130	94 894	162 320	23 080	–	56 290	69 810	48 910	135 520	62 790	94 830	59 680	20 620	40 530	118 604
C6	76 390	52 140	144 795	149 631	60 440	56 260	–	39 820	8040	109 170	32 800	100 020	33 360	52 320	20 600	166 484
C7	49 450	15 280	132 263	115 381	79 900	69 960	39 780	–	33 220	71 240	8910	73 080	10 980	71 140	45 640	143 381
C8	69 770	45 520	137 774	143 011	53 160	48 980	8010	33 200	–	102 550	26 180	93 400	26 740	45 040	14 050	159 864
C9	64 610	59 100	137 842	50 100	149 170	135 780	108 720	70 830	102160	–	77 850	69 990	78 550	140 500	114 580	135 311
C10	49 430	21 240	128 745	120 011	72 830	62 890	32 710	8920	26 150	78 270	–	73 060	7220	64 070	38 570	143 361
C11	24 310	72 661	69 411	89 141	115 520	94 980	100 060	73 160	93 500	69 950	73 570	–	68 820	110 300	105 290	712 41
C12	45 090	23 200	122 215	116 961	71 200	59 800	33 450	11 010	26 890	78 940	7130	68 720	–	62 170	39 310	139 021
C13	91 250	83 700	114 645	193 972	10 310	20 630	52 340	71 380	45 190	140 810	64 360	110 150	62 560	–	34 470	138 355
C14	81 960	58 010	133 314	156 841	42 450	40 610	20 380	45 690	14 140	115 040	38 670	105 590	39 230	34330	–	157 024
C15	94 731	143 082	30 970	118 401	135 135	118 604	166 424	143 581	159 864	135 381	143 991	71 371	139 241	138 485	157 154	–

5.1.2. Base case solution

The DP model provides the optimal vehicle routes for the introduced problem within approximately two hours. Summary results which show the performance of the resulting delivery plan in terms of the defined KPIs are presented in Table 4. As can be seen from this table, sustainable logistics decision makers have a chance to track both economic (logistics cost) and environmental (emitted emissions, driving time) performances of the delivery plans provided from the use of the DP model.

Table 5 presents the detailed representation of the resulting delivery plan broken down into each travelled arc. Here, we would like to note that the DP model for the addressed problem regards the imposed average speeds at each arc. Using realistic speed data allows the model to better estimate travel time, fuel consumption (emitted emissions), and therefore resulting logistics cost. Another remark is that both of the available vehicles are employed to satisfy the customer demands. The utilization rates for the first and second vehicles are 97.4% and 83.1%, respectively.

Table 3. Average vehicle speeds between nodes, in m/s.

	Depot	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15
Depot	–	16.33	16.99	16.93	17.66	16.22	18.41	18.26	17.86	16.83	17.63	13.49	17.85	18.77	19.39	16.42
C1	16.37	–	19.79	21.87	22.94	19.31	19.30	25.47	18.51	23.06	20.81	16.35	19.35	24.40	21.00	14.61
C2	17.00	19.62	–	19.58	25.81	22.94	20.82	20.04	20.34	18.36	21.70	18.67	21.27	23.93	22.48	15.77
C3	16.66	21.59	19.47	–	23.27	18.14	20.30	22.10	20.23	21.96	21.37	16.51	20.11	23.88	21.28	19.19
C4	17.06	22.19	25.41	23.31	–	13.26	18.86	21.04	17.96	22.61	19.50	16.12	20.51	9.63	15.25	25.00
C5	16.22	19.28	22.59	18.40	13.74	–	16.75	18.18	15.98	20.17	16.35	16.13	16.86	13.22	14.68	22.72
C6	18.45	19.31	20.98	20.61	19.37	17.05	–	17.46	12.18	21.16	14.39	17.01	16.35	20.76	13.73	21.02
C7	17.54	25.47	20.04	22.36	21.83	17.94	17.00	–	15.82	23.28	13.50	16.68	14.08	23.25	19.50	18.82
C8	17.89	18.50	20.69	20.37	18.85	16.01	12.14	16.27	–	20.84	12.83	16.56	15.37	20.29	11.15	20.82
C9	16.83	21.89	18.23	22.57	22.81	19.85	20.83	22.70	20.51	–	21.99	18.23	21.12	23.65	21.70	17.22
C10	17.91	20.82	19.69	21.51	20.23	16.38	14.35	16.52	12.82	22.49	–	16.91	10.03	21.36	16.92	18.96
C11	13.97	16.59	18.36	17.08	16.18	16.32	17.19	17.17	16.94	18.80	17.03	–	16.87	16.87	18.09	17.46
C12	17.89	19.33	19.40	20.31	21.19	16.61	16.40	13.11	14.94	21.22	9.90	16.36	–	22.53	18.72	18.99
C13	19.01	24.91	23.59	24.49	9.04	13.22	21.81	24.28	21.52	24.19	22.35	16.84	23.70	–	17.95	23.53
C14	19.24	21.02	20.20	21.43	15.72	14.40	14.15	19.53	11.78	22.04	16.53	17.78	18.68	16.35	–	20.61
C15	17.16	18.34	17.80	18.97	26.19	23.82	21.34	19.30	20.98	17.77	19.51	18.30	19.34	24.55	21.29	–

Table 4. Summary results for the base case.

KPIs	Results
# of vehicles used	2
Total travelled distance (km)	667.68
Total emissions (kg)	558.76
Total driving time (h)	14.61
Total fuel cost (€)	339.93
Total wage cost (€)	210.39
Total routing cost (€)	550.32

Table 5. Representation of the resulting delivery plan for the base case.

	Arc	Distance (m)	Speed (m/s)	Travel time (s)	Service time (s)	Emissions (kg)	Fuel consumption (l)
First vehicle	Depot-C5	75 910	16.22	4680	1570	62.20	23.65
	C5-C4	23 080	13.74	1680	692	20.03	7.61
	C4-C13	9820	9.63	1020	972	10.45	3.98
	C13-C14	34 470	17.95	1920	820	27.99	10.64
	C14-C6	20 380	14.15	1440	1606	17.45	6.63
	C6-C8	8040	12.18	660	432	7.44	2.83
	C8-C10	26 180	12.83	2040	1496	23.52	8.94
	C10-C12	7220	10.03	720	206	7.50	2.85
	C12-Depot	45 090	17.89	2520	0	36.61	13.92
Second vehicle	Depot-C7	49 310	18.26	2700	1218	40.06	15.23
	C7-C1	15 280	25.47	600	356	13.26	5.04
	C1-C9	59 500	23.06	2580	690	50.55	19.22
	C9-C3	50 100	22.57	2220	1386	42.34	16.10
	C3-C15	118 581	19.19	6180	1254	96.77	36.80
	C15-C2	30 970	17.80	1740	794	25.15	9.56
	C2-C11	69 441	18.67	3720	946	56.50	21.48
	C11-Depot	24 310	13.97	1740	0	20.93	7.96
	Total	667 682		38 160	14 438	558.76	212.46

TABLE 6. Parameter settings used for the solution approaches.

		Solution approaches			
Problem	Parameter*	DP	RDP	SRDP	RDP-SOC
BC, SIs, LIs**	*simnumber*	–	–	30	30
BC, SIs, LIs	*utilization*	0.9	0.9	0.9	0.9
BC, SIs, LIs	H	–	50, 100, 250, 500, 1000, 2500	–	–
BC, SIs	H and S	–	–	70 and 30	–
LIs	H and S	–	–	7 and 3	–
BC, SIs	$\hat{H}$	–	–	–	Uniform***(50, 100), integer
LIs	$\hat{H}$	–	–	–	Uniform(5, 10), integer
BC, SIs, LIs	*dynamicvalue*	–	–	–	Uniform(0, 0.2), real number
BC, SIs, LIs	*userdecide*	–	–	0.1	Uniform(0, 0.5), real number
BC, SIs, LIs	k	–	–	–	5
BC, SIs	*top*	–	–	–	1000
LIs	*top*	–	–	–	100

Notes. *See Algorithm 2 for the notation meaning. **BC refers base case, SIs refers smaller problems, LIs refers larger problems. ***A single uniformly distributed random number in the given interval.

5.2. Heuristic performance assessment

This subsection aims to assess the performance of the RDP-SOC heuristic by means of the base case, two small-sized problems and a set of larger problems. In the analyses on the base case and small-sized problems, the performance of the proposed heuristic is compared against the optimal policy provided by the DP algorithm and the feasible policies provided by the classical RDP algorithm (see, [24,25,28,29]) and SRDP heuristic [42]. Due to curse of dimensionality, the DP algorithm is infeasible for the larger problems [11]. Therefore, the optimal policies for these problems cannot be calculated by the DP approach. Accordingly, to assess the performance of the RDP-SOC heuristic on the larger problems, feasible solutions which are obtained from the classical RDP and SRDP solution approaches are used. Table 6 presents the parameter settings used for the solution approaches in our computational analyses.

5.2.1. Heuristic applied to base case

This subsection presents the performances of the classical RDP, SRDP and RDP-SOC heuristics on the base case. While defining the time limits (see the required parameter *simtime* in Algorithm 2) for a single run of the SRDP and RDP-SOC heuristics, the observed computation times of the classical RDP algorithm have been used. Table 7 presents the comparison results.

According to the results, for instances 5 and 6, the classical RDP heuristic is able to find optimal solution for the base case, which is €550.32 as presented in Table 4. Although the solution approaches SRDP and RDP-SOC could not obtain the optimal policy, they achieved to provide near-optimal solutions for the base case. Another remark is that the proposed heuristic has slightly outperformed the SRDP heuristic in terms of the average cost. The following subsection provides additional comparison analyses among the aforementioned heuristics on small-sized problems.

5.2.2. Heuristic applied to small-sized problems

This subsection presents the performances of the classical RDP, SRDP and RDP-SOC heuristics on the two additional small-sized problems. These small-sized problems have been obtained from The Pollution-Routing Problem Instance Library[6]. The first problem (UK10_01) has a single depot and 10 customers, whereas the

[6] www.apollo.management.soton.ac.uk/prplib.htm, Online accessed: March 2020.

TABLE 7. Performance assessment of the classical RDP, SRDP and RDP-SOC heuristics on the base case.

#	Classical RDP Setting	Cost (€)	Comp. Time (s)	SRDP Setting	Avg. Cost (€)	Avg. Comp. Time (s)	RDP-SOC Setting	Avg. Cost (€)	Avg. Comp. Time (s)
1	$H = 50$	553.01	1	$H = 70, S = 30$	553.01	1	$50 \leq \hat{H} \leq 100$	553.01	1
2	$H = 100$	553.01	1	$H = 70, S = 30$	553.01	1	$50 \leq \hat{H} \leq 100$	553.01	1
3	$H = 250$	553.01	2	$H = 70, S = 30$	553.01	3	$50 \leq \hat{H} \leq 100$	553.01	3
4	$H = 500$	550.47	4	$H = 70, S = 30$	553.01	4	$50 \leq \hat{H} \leq 100$	553.01	4
5	$H = 1000$	**550.32**	12	$H = 70, S = 30$	553.01	12	$50 \leq \hat{H} \leq 100$	552.91	12
6	$H = 2500$	**550.32**	64	$H = 70, S = 30$	553.01	64	$50 \leq \hat{H} \leq 100$	552.69	64

Notes. Bold values demonstrate the relatively better results.

TABLE 8. Performance assessment of the classical RDP, SRDP and RDP-SOC heuristics on the small-sized problems.

Instances	#	Classical RDP Setting	Cost (€)	Comp. Time (s)	SRDP Setting	Avg. Cost (€)	Avg. Comp. Time (s	RDP-SOC Setting	Avg. Cost (€)	Avg. Comp. Time (s)
UK_10_01	1	$H = 50$	332.77	1	$H = 70, S = 30$	332.77	1	$50 \leq \hat{H} \leq 100$	325.98	1
	2	$H = 100$	332.77	1	$H = 70, S = 30$	332.77	1	$50 \leq \hat{H} \leq 100$	325.98	1
	3	$H = 250$	**325.41**	2	$H = 70, S = 30$	332.77	2	$50 \leq \hat{H} \leq 100$	325.59	2
	4	$H = 500$	**325.41**	3	$H = 70, S = 30$	332.77	3	$50 \leq \hat{H} \leq 100$	**325.41**	3
	5	$H = 1000$	**325.41**	5	$H = 70, S = 30$	332.77	5	$50 \leq \hat{H} \leq 100$	**325.41**	5
	6	$H = 2500$	**325.41**	13	$H = 70, S = 30$	332.77	13	$50 \leq \hat{H} \leq 100$	**325.41**	13
UK_15_02	1	$H = 50$	435.42	1	$H = 70, S = 30$	435.34	1	$50 \leq \hat{H} \leq 100$	435.28	1
	2	$H = 100$	435.34	1	$H = 70, S = 30$	435.34	1	$50 \leq \hat{H} \leq 100$	435.28	1
	3	$H = 250$	434.73	2	$H = 70, S = 30$	435.34	2	$50 \leq \hat{H} \leq 100$	435.26	2
	4	$H = 500$	434.73	4	$H = 70, S = 30$	435.34	4	$50 \leq \hat{H} \leq 100$	433.35	4
	5	$H = 1000$	434.73	12	$H = 70, S = 30$	435.34	12	$50 \leq \hat{H} \leq 100$	427.94	12
	6	$H = 2500$	432.28	53	$H = 70, S = 30$	435.34	53	$50 \leq \hat{H} \leq 100$	**418.54**	53

Notes. Bold values demonstrate the relatively better results.

second problem (UK15_02) has a single depot and 15 customers. In both problems, two homogeneous vehicles are used for the delivery operations. Vehicle capacities are assumed as 3650 and 4000 kg in the first and second problems, respectively. The vehicles travel at an average speed of 90 km/h in all arcs. Other required data for the problems, *i.e.*, distances matrix, customer demands and customer service times can be obtained from the web site of The Pollution-Routing Problem Instance Library. Table 8 presents the comparison results.

The optimal solutions provided by the classical DP algorithm for the first and second problems are €325.41 and €398.29, respectively. According to the results, RDP-SOC outperforms the SRDP heuristic in all instance-setting pairs. The performances of the proposed heuristic are also equal to or better than that of the classical RDP heuristic in 5 out of 6 instance-setting pairs for both UK_10_01 and UK_15_02 problems. Note that both the classical RDP and RDP-SOC are able to provide the optimal solution for UK_10_01. The following subsection provides more extensive performance comparison analyses among the RDP, SRDP and RDP-SOC heuristics on large-sized problems.

5.2.3. Heuristic applied to large-sized problems

This subsection presents the performances of the classical RDP, SRDP and RDP-SOC heuristics in relatively large problems. These large problems have been obtained from The Pollution-Routing Problem Instance Library[7]

[7] www.apollo.management.soton.ac.uk/prplib.htm, Online accessed: January 2017.

and The Routing Problem Library introduced by Solomon [40]. These libraries have been used in many other studies addressing routing problem variants (see, *e.g.*, [4, 23]).

Nine problems each of which has a single depot and 50 customers have been used for the analyses. For the delivery, (i) seven vehicles are employed in problems 1 (UK50_01), 2 (UK50_02) and 5 (UK50_05), (ii) eight vehicles are employed in problems 3 (UK50_03) and 4 (UK50_04), and (iii) four vehicles are employed in problems 6–9 (C101, C201, R101 and RC101). The vehicle capacity is taken as 3650 kg for problems 1–5 and 270 kg for problems 6–9. Other required data for the problems, *i.e.*, distances matrix, customer demands and customer service times can be obtained from the The Pollution-Routing Problem Instance Library and The Routing Problem Library.

The provided data does not contain any information about potential road segments as it has been prepared for the use of traditional routing models. Therefore, we assumed that all arcs have a fraction of urban and non-urban parts. The following approach has been used while defining the corresponding fractions. The arcs between odd customer numbers (*e.g.*, between nodes-customers 1 and 3, 5 and 7 or 47 and 49) and even numbers (*e.g.*, between nodes 2 and 4, 6 and 8 or 48 and 50) have 15% urban and 85% non-urban section. The remaining arcs (*e.g.*, between nodes 1 and 4, 2 and 5 or 47 and 48) have 5% urban and 95% non-urban section. The vehicles travel at an average speed of 40 km/h in urban sections and 90 km/h in non-urban sections. Table 9 presents the comparison results for the selected nine problems.

As it has been done in the base case, for the first four settings, the time limit for a single run of the SRDP and RDP-SOC heuristics is defined by the observed computation times of the classical RDP algorithm. Large H and S values in instances 5 and 6 require higher computation times. In order to complete 30 runs of the SRDP and RDP-SOC heuristics for the numerical experiments in each problem at a reasonable time, we have used a ratio of 1/2. For example, the observed computation time of the classical RDP algorithm in Instance 1 – Setting 5 is 1122 s. Therefore, the time limit for a single run of the SRDP and RDP-SOC heuristics is set as 1/2 of this number, which is 561 s.

Comparison results show that in all instances, except Instance 1 (UK_01) and Instance 7 (C201), the proposed heuristic provides the least-cost solutions. For the first and seventh instances, the least-cost solutions have been obtained from the classical RDP heuristic, *i.e.*, Instance 1 under Setting 5: €1203.53 and Instance 7 under Settings 4,5,6: €332.02. The obtained least-cost solutions from the proposed heuristic are as follows: Instance 2 – Setting 6: €1218.70, Instance 3 – Setting 6: €1282.70, Instance 4 – Setting 6: €1542.60, Instance 5 – Setting 6: €1300.40, Instance 6 – Setting 6: €268.12, Instance 8 – Setting 6: €401.22, and Instance 9 – Setting 6: €394.10.

An overall comparison between the RDP-SOC and SRDP heuristics reveals that the proposed heuristic outperforms the SRDP in terms of the average total cost in 48 out of the 54 instance-setting pairs. Similarly, the proposed heuristic shows better cost performances in 40 instance-setting pairs compared to the classical RDP heuristic.

Among all instance-setting pairs, the resultant average cost of the proposed heuristic is 1% lower than that of the SRDP heuristic within the same computation time. The obtained average cost-benefit increases to 1.96% when the performance of the RDP-SOC heuristic is compared to that of the classical RDP heuristic. Considering huge budgets devoted to logistics management and small profit margins, these kinds of cost and/or emission savings could yield significant benefits in competitive advantage. Note that the proposed heuristic obtains these results within significantly shorter computation times, *i.e.*, the average computation time of RDP-SOC in all instance-setting pairs (755 s) is almost half of that of the classical RDP (1459 s).

Figure 2 presents the average cost performances of the solution approaches in different settings. For settings 5 and 6, all of the three heuristics are run with the same limit, that is why these setting are referred as 5A and 6A. Note that in the previous analyses a ratio of 1/2 has been used for the run times. In Table A.1, the reader can find the detailed results for performance assessment of the classical RDP, SRDP and RDP-SOC heuristics on the larger instances for settings 5 and 6 with the same time limit.

As can be observed from the figure, compared to the existing solution approaches, the proposed heuristic offers to have promising delivery plans in terms of the average cost in all settings that are run for the same time limit.

TABLE 9. Performance assessment of the classical RDP, SRDP and RDP-SOC on the larger problems.

Instances	#	Classical RDP Setting	Classical RDP Cost (€)	Classical RDP Comp. Time (s)	SRDP Setting	SRDP Avg. Cost (€)	SRDP Avg. Comp. Time (s)	RDP-SOC Setting	RDP-SOC Avg. Cost (€)	RDP-SOC Avg. Comp. Time (s)	% Differences Gap %*	% Differences Gap %**
UK50_01	1	$H = 50$	1305.52	3	$H = 7, S = 3$	1291.96	3	$5 \le \hat{H} \le 10$	1294.14	3	**−0.87%**	0.17%
	2	$H = 100$	1305.52	9	$H = 7, S = 3$	1274.85	9	$5 \le \hat{H} \le 10$	1273.88	9	**−2.42%**	**−0.08%**
	3	$H = 250$	1275.89	58	$H = 7, S = 3$	1251.63	58	$5 \le \hat{H} \le 10$	1253.07	58	**−1.79%**	0.12%
	4	$H = 500$	1224.05	245	$H = 7, S = 3$	1238.63	245	$5 \le \hat{H} \le 10$	1237.19	245	1.07%	**−0.12%**
	5	$H = 1000$	**1203.53**	1122	$H = 7, S = 3$	1227.88	561	$5 \le \hat{H} \le 10$	1233.56	561	2.50%	0.46%
	6	$H = 2500$	1212.01	8450	$H = 7, S = 3$	1220.36	4225	$5 \le \hat{H} \le 10$	1219.60	4225	0.63%	**−0.06%**
UK50_02	1	$H = 50$	1363.75	5	$H = 7, S = 3$	1338.94	5	$5 \le \hat{H} \le 10$	1299.97	5	**−4.68%**	**−2.91%**
	2	$H = 100$	1252.04	18	$H = 7, S = 3$	1314.97	18	$5 \le \hat{H} \le 10$	1277.39	18	2.02%	**−2.86%**
	3	$H = 250$	1321.90	59	$H = 7, S = 3$	1292.55	59	$5 \le \hat{H} \le 10$	1260.06	59	**−4.68%**	**−2.51%**
	4	$H = 500$	1232.79	245	$H = 7, S = 3$	1284.12	245	$5 \le \hat{H} \le 10$	1242.27	245	0.77%	**−3.26%**
	5	$H = 1000$	1255.19	1138	$H = 7, S = 3$	1273.84	569	$5 \le \hat{H} \le 10$	1236.19	569	**−1.51%**	**−2.96%**
	6	$H = 2500$	1230.16	8210	$H = 7, S = 3$	1257.70	4105	$5 \le \hat{H} \le 10$	**1218.70**	4105	**−0.93%**	**−3.10%**
UK50_03	1	$H = 50$	1366.00	5	$H = 7, S = 3$	1313.10	5	$5 \le \hat{H} \le 10$	1310.21	5	**−4.08%**	**−0.22%**
	2	$H = 100$	1328.73	12	$H = 7, S = 3$	1308.81	12	$5 \le \hat{H} \le 10$	1302.76	12	**−1.95%**	**−0.46%**
	3	$H = 250$	1327.68	65	$H = 7, S = 3$	1293.56	65	$5 \le \hat{H} \le 10$	1288.27	65	**−2.97%**	**−0.41%**
	4	$H = 500$	1305.82	275	$H = 7, S = 3$	1286.78	275	$5 \le \hat{H} \le 10$	1285.75	275	**−1.54%**	**−0.08%**
	5	$H = 1000$	1295.40	1250	$H = 7, S = 3$	1285.74	625	$5 \le \hat{H} \le 10$	1285.35	625	**−0.78%**	**−0.03%**
	6	$H = 2500$	1286.57	9100	$H = 7, S = 3$	1285.02	4550	$5 \le \hat{H} \le 10$	**1282.70**	4550	**−0.30%**	**−0.18%**
UK50_04	1	$H = 50$	1643.56	4	$H = 7, S = 3$	1623.19	4	$5 \le \hat{H} \le 10$	1607.18	4	**−2.21%**	**−0.99%**
	2	$H = 100$	1653.75	14	$H = 7, S = 3$	1601.70	14	$5 \le \hat{H} \le 10$	1597.53	14	**−3.40%**	**−0.26%**
	3	$H = 250$	1625.60	67	$H = 7, S = 3$	1585.52	67	$5 \le \hat{H} \le 10$	1574.71	67	**−3.13%**	**−0.68%**
	4	$H = 500$	1612.00	281	$H = 7, S = 3$	1570.42	281	$5 \le \hat{H} \le 10$	1563.98	281	**−2.98%**	**−0.41%**
	5	$H = 1000$	1602.29	1328	$H = 7, S = 3$	1565.76	664	$5 \le \hat{H} \le 10$	1560.20	664	**−2.63%**	**−0.36%**
	6	$H = 2500$	1574.08	9500	$H = 7, S = 3$	1558.27	4750	$5 \le \hat{H} \le 10$	**1542.60**	4750	**−2.00%**	**−1.01%**
UK50_05	1	$H = 50$	1379.10	5	$H = 7, S = 3$	1359.78	5	$5 \le \hat{H} \le 10$	1356.28	5	**−1.65%**	**−0.26%**
	2	$H = 100$	1391.77	18	$H = 7, S = 3$	1341.98	18	$5 \le \hat{H} \le 10$	1346.88	18	**−3.23%**	0.37%
	3	$H = 250$	1312.93	106	$H = 7, S = 3$	1333.32	106	$5 \le \hat{H} \le 10$	1332.18	106	1.47%	**−0.09%**
	4	$H = 500$	1312.93	266	$H = 7, S = 3$	1329.73	266	$5 \le \hat{H} \le 10$	1323.82	266	0.83%	**−0.44%**
	5	$H = 1000$	1311.91	1128	$H = 7, S = 3$	1327.97	564	$5 \le \hat{H} \le 10$	1320.09	564	0.62%	**−0.59%**
	6	$H = 2500$	1314.70	8400	$H = 7, S = 3$	1322.61	4200	$5 \le \hat{H} \le 10$	**1300.40**	4200	**−1.09%**	**−1.68%**
C101	1	$H = 50$	293.37	2	$H = 7, S = 3$	291.54	2	$5 \le \hat{H} \le 10$	293.30	2	**−0.03%**	0.60%
	2	$H = 100$	282.36	7	$H = 7, S = 3$	288.02	7	$5 \le \hat{H} \le 10$	288.90	7	2.32%	0.31%
	3	$H = 250$	282.36	41	$H = 7, S = 3$	284.02	41	$5 \le \hat{H} \le 10$	281.54	41	**−0.29%**	**−0.88%**
	4	$H = 500$	280.85	171	$H = 7, S = 3$	282.78	171	$5 \le \hat{H} \le 10$	277.56	171	**−1.17%**	**−1.85%**
	5	$H = 1000$	280.85	754	$H = 7, S = 3$	282.16	377	$5 \le \hat{H} \le 10$	273.94	377	**−2.46%**	**−2.91%**
	6	$H = 2500$	280.85	5070	$H = 7, S = 3$	278.52	2535	$5 \le \hat{H} \le 10$	**268.12**	2535	**−4.53%**	**−3.73%**
C201	1	$H = 50$	357.13	2	$H = 7, S = 3$	363.43	2	$5 \le \hat{H} \le 10$	358.78	2	0.46%	**-1.28%**
	2	$H = 100$	348.16	7	$H = 7, S = 3$	356.50	7	$5 \le \hat{H} \le 10$	344.36	7	**−1.09%**	**−3.41%**
	3	$H = 250$	332.16	45	$H = 7, S = 3$	342.69	45	$5 \le \hat{H} \le 10$	339.49	45	2.21%	**−0.93%**
	4	$H = 500$	**332.02**	187	$H = 7, S = 3$	341.84	187	$5 \le \hat{H} \le 10$	338.47	187	1.94%	**−0.99%**
	5	$H = 1000$	**332.02**	850	$H = 7, S = 3$	341.57	425	$5 \le \hat{H} \le 10$	337.16	425	1.55%	**−1.29%**
	6	$H = 2500$	**332.02**	5374	$H = 7, S = 3$	338.04	2687	$5 \le \hat{H} \le 10$	334.21	2687	0.66%	**−1.13%**
R101	1	$H = 50$	456.14	2	$H = 7, S = 3$	456.07	2	$5 \le \hat{H} \le 10$	449.45	2	**−1.47%**	**−1.45%**
	2	$H = 100$	456.14	8	$H = 7, S = 3$	434.32	8	$5 \le \hat{H} \le 10$	432.20	8	**−5.25%**	**−0.49%**
	3	$H = 250$	446.50	49	$H = 7, S = 3$	413.77	49	$5 \le \hat{H} \le 10$	413.19	49	**−7.46%**	**−0.14%**
	4	$H = 500$	441.75	209	$H = 7, S = 3$	410.62	209	$5 \le \hat{H} \le 10$	406.87	209	**−7.90%**	**−0.91%**
	5	$H = 1000$	440.56	990	$H = 7, S = 3$	409.93	495	$5 \le \hat{H} \le 10$	406.65	495	**−7.70%**	**−0.80%**
	6	$H = 2500$	408.77	6645	$H = 7, S = 3$	408.22	3323	$5 \le \hat{H} \le 10$	**401.22**	3323	**−1.85%**	**−1.72%**
RC101	1	H = 50	446.90	2	$H = 7, S = 3$	452.99	2	$5 \le \hat{H} \le 10$	439.78	2	**−1.59%**	**−2.92%**
	2	$H = 100$	444.81	8	$H = 7, S = 3$	432.53	8	$5 \le \hat{H} \le 10$	418.02	8	**−6.02%**	**−3.35%**
	3	$H = 250$	437.45	43	$H = 7, S = 3$	419.90	43	$5 \le \hat{H} \le 10$	400.66	43	**−8.41%**	**−4.58%**
	4	$H = 500$	453.51	173	$H = 7, S = 3$	415.33	173	$5 \le \hat{H} \le 10$	399.01	173	**−12.02%**	**−3.93%**
	5	$H = 1000$	453.01	811	$H = 7, S = 3$	410.91	406	$5 \le \hat{H} \le 10$	395.68	406	**−12.66%**	**−3.71%**
	6	$H = 2500$	448.91	5973	$H = 7, S = 3$	397.43	2987	$5 \le \hat{H} \le 10$	**394.10**	2987	**−12.21%**	**−0.84%**
		Average:	**924.00**	**1459**		**915.07**	**755**		**905.92**	**755**	−1.96%	−1.00%

Notes. *The percentage gap between average costs obtained from the RDP and RDP-SOC heuristics. **The percentage gap between average costs obtained from the SRDP and RDP-SOC heuristics. Bold values demonstrate the relatively better results.

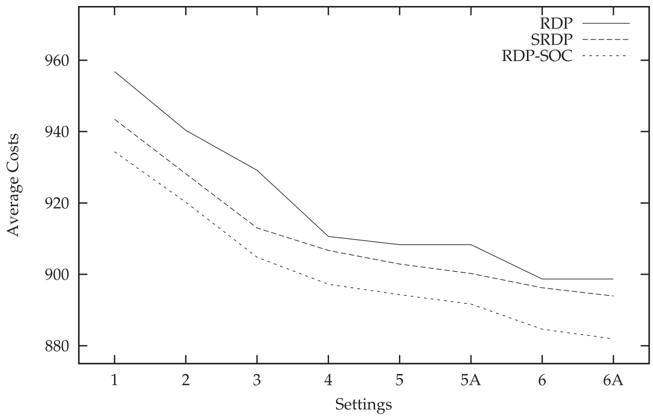

FIGURE 2. Average cost performances of the solution approaches in different settings.

TABLE 10. Representation of the resulting delivery plan for the base case when the same speed is assumed at every arc.

	Arc	Distance (m)	Speed (m/s)	Travel time (s)	Service time (s)	Emissions (kg)	Fuel consumption (l)
First vehicle	Depot-C5	75 910	25	3036	1570	65.65	24.96
	C5-C4	23 080	25	923	692	19.96	7.59
	C4-C13	9820	25	393	972	8.49	3.23
	C13-C14	34 470	25	1379	820	29.81	11.34
	C14-C6	20 380	25	815	1606	17.63	6.70
	C6-C8	8040	25	322	432	6.95	2.64
	C8-C10	26 180	25	1047	1496	22.64	8.61
	C10-C12	7220	25	289	206	6.24	2.37
	C12-Depot	45 090	25	1804	0	39.00	14.83
Second vehicle	Depot-C11	24 280	25	971	946	21.00	7.98
	C11-C2	69 411	25	2776	794	60.03	22.83
	C2-C15	31 220	25	1249	1254	27.00	10.27
	C15-C3	118 401	25	4736	1386	102.40	38.94
	C3-C9	50 070	25	2003	690	43.30	16.47
	C9-C1	59 100	25	2364	356	51.11	19.44
	C1-C7	15 280	25	611	1218	13.22	5.02
	C7-Depot	49 450	25	1978	0	42.77	16.26
	Total	667 402		26 696	14 438	577.23	219.48

Our computation analyses reveal the added values of the proposed RDP-SOC heuristic for the green routing problem. We acknowledge the fact that the proposed heuristic does not always guarantee a better solution than the ones which can be obtained from the classical RDP and SRDP heuristics. However, in most of the instance-setting pairs, the proposed heuristic outperforms the existing DP based solution approaches. The results demonstrate that RDP-SOC can be used as an alternative decision support tool to tackle large-sized VRPs confronted in sustainable logistics management.

5.3. The effects of heterogeneity in arcs

This subsection is devoted to analyse the effects of having heterogeneous arcs in terms of vehicle speed. The analyses here is conducted to show the possibility of a significant change in the results when there exist heterogeneous arcs in the logistics network, such that the routes and KPI values may considerably alter.

Table 11. Results when the proposed route, which assumes the same speed at every arc, is implemented with the realistic vehicle speeds.

	Arc	Distance (m)	Speed (m/s)	Travel time (s)	Service time (s)	Emissions (kg)	Fuel consumption (l)
First vehicle	Depot-C5	75 910	16.22	4680	1570	62.20	23.65
	C5-C4	23 080	13.74	1680	692	20.03	7.61
	C4-C13	9820	9.63	1020	972	10.45	3.98
	C13-C14	34 470	17.95	1920	820	27.99	10.64
	C14-C6	20 380	14.15	1440	1606	17.45	6.63
	C6-C8	8040	12.18	660	432	7.44	2.83
	C8-C10	26 180	12.83	2040	1496	23.52	8.94
	C10-C12	7220	10.03	720	206	7.50	2.85
	C12-Depot	45 090	17.89	2520	0	36.61	13.92
Second vehicle	Depot-C11	24 280	13.49	1800	946	21.25	8.08
	C11-C2	69 411	18.36	3780	794	56.41	21.45
	C2-C15	31 220	15.77	1980	1254	25.74	9.79
	C15-C3	118 401	18.97	6240	1386	96.49	36.69
	C3-C9	50 070	21.96	2280	690	42.02	15.98
	C9-C1	59 100	21.89	2700	356	49.56	18.84
	C1-C7	15 280	25.47	600	1218	13.26	5.04
	C7-Depot	49 450	17.54	2820	0	40.17	15.27
	Total	667 402		38 880	14 438	558.11	212.21

Let's assume that vehicles travel at a speed of 25 m/s (90 km/h) at every arc in the base case. This means that vehicles have the chance to retain their speeds at each arc. The detailed representation of the resulting delivery plan obtained when the DP model assumes the same speed at every arc is presented in Table 10.

The estimated total logistics cost of this delivery plan presented in Table 10 is €515.7. Note that the provided delivery plan cannot be directly implemented in practice, as speed limits will not allow vehicles to have the same travel speeds in urban roads as in non-urban ones. We present the implementation of the proposed delivery plan, which assumes the same speed at every arc, with the realistic vehicle speeds in Table 11.

According to the results presented in Table 11, the total logistics cost of the delivery plan under realistic travel times is €552.81. This means that when the delivery plan obtained using the data set that ignores heterogeneity in arcs is implemented in practice, the resulting total logistics cost is more than expected. Note that this resulting total logistics cost is 0.5% higher than the one obtained when the realistic speeds are used (see Tab. 4).

Another key issue is that the DP model proposes a different delivery plan in terms of vehicle routes when the heterogeneity in arcs is ignored. As can be checked from Tables 5 and 10 or 11, although the resulting route for the first vehicle has not been altered, this is not the case for the second one.

6. Conclusions

Maintaining environmentally friendly operations in logistics management is a challenge for companies. This paper accordingly presents a decision support tool that can aid decision-making processes in operational level efficient logistics management. The introduced DP based solution approach can be used to have promising feasible delivery plans within short computational times for the larger problems. As distinct from the traditional approaches, the solution approach estimates fuel consumption based on travelled distance, vehicle speed and vehicle characteristics while constructing vehicle routes.

The added values of the RDP-SOC heuristic have been shown on a small-sized base case and five relatively larger problems. Performance comparisons of the proposed heuristic against other DP based recent solution approaches (the RDP and SRDP heuristics) reveal the effectiveness of the proposed approach in larger problems. According to the numerical analyses on heuristic performance, the proposed heuristic outperforms the SRDP in terms of the average total cost in 48 out of the 54 instance-setting pairs. Similarly, the proposed heuristic shows better cost performances in 22 instance-setting pairs compared to the classical RDP heuristic within significantly shorter computation times.

Additional analysis to reveal the effects of heterogeneity in arcs shows that when heterogeneity is ignored, the resulting delivery plan may change and has a higher logistics cost.

These results on small and large-sized instances confirm that the proposed solution approach can be used as an alternative decision support tool to tackle large-sized VRPs. It is worth mentioning that the introduced DP based solution approach is also highly flexible in terms of incorporating other potential problem-specific constraints such as uncertainty in travel or service times, the existence of customer time windows or having time-dependent travel times in arcs due to traffic congestion. Future studies on routing problems might focus on finding out better ways for state-space exploration in the DP algorithm and incorporate the aforementioned dimensions. We believe that this research has the potential to lead the way for further enhancements.

Appendix A.

Table A.1. Performance assessment of the classical RDP. SRDP and RDP-SOC on the larger instances for settings 5 and 6 with the same time limit.

	#	Classical RDP			SRDP			RDP-SOC			% Differences	
		Setting	Cost (euro)	Comp. Time (s)	Setting Cost (euro)	Avg. Time (s)	Avg. Comp.	Setting	Avg. Cost (euro)	Avg. Comp. Time (s)	Gap %*	Gap %**
UK50_01	5A	H = 1000	**1203.53**	1122	$H=7, S=3$	1225.46	1122	$5 \leq \hat{H} \leq 10$	1230.65	1122	2.25%	0.42%
	6A	$H=2500$	1212.01	8450	$H=7, S=3$	1219.60	8450	$5 \leq \hat{H} \leq 10$	1218.60	8450	0.54%	**–0.08%**
UK50_02	5A	H = 1000	1255.19	1138	$H=7, S=3$	1270.43	1138	$5 \leq \hat{H} \leq 10$	1233.20	1138	**–1.75%**	**–2.93%**
	6A	$H=2500$	1230.16	8210	$H=7, S=3$	1255.62	8210	$5 \leq \hat{H} \leq 10$	**1215.71**	8210	**–1.17%**	**–3.18%**
UK50_03	5A	H = 1000	1295.40	1250	$H=7, S=3$	1284.81	1250	$5 \leq \hat{H} \leq 10$	1284.70	1250	**–0.83%**	**–0.01%**
	6A	$H=2500$	1286.57	9100	$H=7, S=3$	1283.02	9100	$5 \leq \hat{H} \leq 10$	**1279.65**	9100	**–0.54%**	**–0.26%**
UK50_04	5A	H = 1000	1602.29	1328	$H=7, S=3$	1561.66	1328	$5 \leq \hat{H} \leq 10$	1548.25	1328	**–3.37%**	**–0.86%**
	6A	$H=2500$	1574.08	9500	$H=7, S=3$	1553.69	9500	$5 \leq \hat{H} \leq 10$	**1532.41**	9500	**–2.65%**	**–1.37%**
UK50_05	5A	H = 1000	1311.91	1128	$H=7, S=3$	1325.88	1128	$5 \leq \hat{H} \leq 10$	1318.17	1128	0.48%	**–0.58%**
	6A	$H=2500$	1314.70	8400	$H=7, S=3$	1320.23	8400	$5 \leq \hat{H} \leq 10$	**1296.43**	8400	**–1.39%**	**–1.80%**
C101	5A	H = 1000	280.85	754	$H=7, S=3$	280.64	754	$5 \leq \hat{H} \leq 10$	272.99	754	**–2.80%**	**–2.73%**
	6A	$H=2500$	280.85	5070	$H=7, S=3$	274.51	5070	$5 \leq \hat{H} \leq 10$	**267.20**	5070	**–4.86%**	**–2.66%**
C201	5A	H = 1000	**332.02**	850	$H=7, S=3$	341.25	850	$5 \leq \hat{H} \leq 10$	336.28	850	1.28%	**–1.46%**
	6A	$H=2500$	**332.02**	5374	$H=7, S=3$	337.50	5374	$5 \leq \hat{H} \leq 10$	332.56	5374	0.16%	**–1.46%**
R101	5A	H = 1000	440.56	990	$H=7, S=3$	408.56	990	$5 \leq \hat{H} \leq 10$	405.23	990	**–8.02%**	**–0.82%**
	6A	$H=2500$	408.77	6645	$H=7, S=3$	406.87	6645	$5 \leq \hat{H} \leq 10$	**401.12**	6645	**–1.87%**	**–1.41%**
RC101	5A	H = 1000	453.01	811	$H=7, S=3$	403.35	811	$5 \leq \hat{H} \leq 10$	395.50	811	**–12.70%**	**–1.95%**
	6A	$H=2500$	448.91	5973	$H=7, S=3$	394.40	5973	$5 \leq \hat{H} \leq 10$	**393.52**	5973	**–12.34%**	**–0.22%**
		Average:	**903.49**	**4227**		**897.08**	**4227**		**886.79**	**4227**	–1.85%	–1.15%

Notes. *The percentage gap between average costs obtained from the RDP and RDP-SOC heuristics. **The percentage gap between average costs obtained from the SRDP and RDP-SOC heuristics. Bold values demonstrate the relatively better results.

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