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Research Article

Time Window Characteristics in a Heuristic Algorithm for a Full-Truck Vehicle Routing Heuristic Algorithm in An Intermodal Context

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ABSTRACT

Intermodal container terminals handle both the pickup and delivery of containers to and from customers, with these transport activities and terminal handling comprising a significant portion of intermodal transport costs. Efficient operations are therefore essential, particularly when time window constraints limit routing flexibility. This study presents a metaheuristic incorporating time windows to plan container pickups and deliveries. The proposed algorithm operates in three phases: initial solution construction using an insertion heuristic, improvement via local search, and further refinement through a deterministic annealing metaheuristic. The presence of time windows makes the planning more difficult, as the transport company has less flexibility in constructing the transport routes and, as a result, the distance travelled and/or the cost is increased. To assess how time window characteristics affect algorithm performance and cost, the study introduces two temporal descriptors—*concentration* (the clustering of time windows during the day) and *specialization* (the dominance of short or long-time windows in specific periods). The results of the experimental runs of the algorithm are statistically analysed to identify under which conditions of concentration and *specialization* an effect on the cost can be identified. Experimental results reveal that increased *concentration* leads to a rise in both the number of routes (up to 35%) and total cost (around 2%). While *concentration* results in more routes, these routes remain relatively cost-efficient. Furthermore, a lack of *specialization* in concentrated time windows amplifies both the number of routes and the total cost. Finally, the length of time windows influences these effects, with shorter time windows having a reduced impact on *concentration* and *specialization* outcomes compared to longer ones.

Keywords: intermodal transport, time windows, concentration and specialization, deterministic annealing, metaheuristics

INTRODUCTION

Many governments, including the European Union, have implemented transport policies aimed at establishing sustainable transport systems. Among these efforts, the successful promotion of intermodal transport has been identified as a key strategy. Intermodal transport offers several advantages over unimodal transport, including benefits in cost, quality, time, labor efficiency, safety, and security. It is also favored for geographical, environmental, and energy efficiency reasons [1], [2], [3]. From a business perspective, the growing need for speed and agility in the supply chain is prompting firms to rethink traditional logistics services. As a result, interest in intermodal freight transportation has increased significantly across business, research, and policy domains over the past two decades.

Intermodal transport emerges as a distinct mode when the logistics chain is fully integrated, offering a seamless door-to-door service. However, achieving this requires a higher level of coordination to manage the flow efficiently.

Governments and businesses look differently at the costs of intermodal transport or, its alternative road transport. That is because governments also look at external costs. An external cost appears when the economic activity of companies or persons has an impact on other companies or persons and that second group is not fully accounted for. Examples are usage costs related to the usage of transport infrastructure, congestion costs, accident costs, and environmental costs. The business looks at the costs of the door-to-door service to compare intermodal transport with road transport. Understanding these differing perspectives is essential when examining the detailed cost structure of intermodal transport, which includes multiple logistical segments and handling requirements. The cost for a typical intermodal transport route consists of the costs generated by three segments: pre-haulage, main-haulage, and end-haulage—corresponding to the journey from the customer to the terminal, between terminals, and from the terminal to the final customer, respectively. At the (port) terminals, the handling cost is high because of the need for cranes used for the transhipment of containers on barges. The road-based movement of containers between intermodal terminals, depots, and shippers—known as "drayage"—is typically performed by trucks [4], while the main haul is conducted via rail, deep-sea shipping, short-sea shipping, or inland waterways. This cost breakdown highlights the importance of each segment, especially drayage, which—despite covering a relatively short distance—can significantly influence the total cost and efficiency of intermodal transport. Although drayage accounts for only a minor segment of the total distance within an intermodal transport chain, it frequently constitutes a substantial proportion of the overall transportation costs [5]. This disproportion arises from the fact that the main haulage modes in intermodal transport—such as shipping or rail—typically achieve lower unit costs due to their high transport capacities. Consequently, enhancing the efficiency of road-based components, particularly drayage operations, is critical to improving the overall attractiveness and competitiveness of intermodal transport systems.

A literature review on intermodal transport highlights the need for decision-support tools to aid policymakers in developing sustainable freight transportation policies [6]. These tools can facilitate the integration of truck routing and long-haul intermodal service selection, ultimately promoting more efficient and sustainable logistics systems. However, decision-support tools can also assist stakeholders in organizing and optimizing intermodal operations [7]. These tools enable a comparative analysis of transport alternatives across different routes and transport modes [8]. Additionally, shippers often perceive intermodal transport as slow and inflexible, with limited service coverage [9]. Despite these challenges, studies have demonstrated potential benefits. For instance, research on a two-region truck-rail network revealed promising outcomes [10]. El Yaagoubi et al. [11] further advanced the field by integrating optimization, simulation, and managerial perspectives in a short-distance intermodal container service that combines road and rail transport.

This research focuses on drayage operations, which typically occur at the beginning and end of the intermodal transport chain. These operations involve the collection and delivery of empty or loaded containers between depots, terminals, and customers' facilities, usually by road within the vicinity of an intermodal terminal. Reinhardt et al. [12] noted that pre- and end-haulage often represent major bottlenecks in efficient liner shipping, primarily due to poor coordination among customers. Similarly, Chen [13] emphasized that while long-haul intermodal transport leverages multiple transport modes, the most critical component for enabling true door-to-door service is the container port drayage operation. Therefore, this research contributes to more efficient drayage operations by investigating how optimization techniques can help to reach this goal.

In drayage operations, decisions relate to which truck has to pick-up a container at the terminal and deliver it to its destination inland, or to pick-up a container at an inland depot or site and deliver it to the terminal, or first pick-up a container at the terminal, deliver it to its destination, and then drive empty to the next pick-up point and deliver

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that container to the terminal. When the set of containers to be picked up or delivered is given, including their locations, the transport company aims to fulfil the services either with the lowest distances travelled or in the shortest time. Finding the best solution is finding the solution to a problem called the 'Vehicle Routing Problem' (VRP), which is used a lot in distribution where a truck with finite capacity has a number of pallets or boxes on board to deliver it to a set of different customers. A similar problem appears when an empty truck visits some customer locations to pick-up boxes or pallets, taking into consideration the finite capacity of the truck. Sometimes, the same truck can pick-up and deliver goods in one route. That is a more complex problem because the truck capacity has to be respected at each customer location. In such a case, the problem is called a 'Pick-up and Delivery Problem'. In our case, there is only one box on board, i.e. the container. Therefore, this specific case is called the 'Full-Truckload Pick-up and Delivery Problem' (FTPDP). In practice, trucks cannot just arrive at the terminal or the customer location without planning. This means that containers have to be picked-up or delivered in a specific time period of the day, called a 'time window'. The addition of the time window may appear due to different reasons: arrival or departure of the ship or train at a terminal, opening hours of the customer location, or a more specific planning system at the customer location to avoid trucks queueing up to pick-up or deliver a container. By including this feature in our decision problem, the problem can be called a 'Full-Truck Pick-up and Delivery Problem with Time Windows' (FTPDPTW). Also note that trucks do multiple trips per day, which complicates the planning given the time windows and travel distances.

Caris and Janssens [14] modeled container drayage within an intermodal terminal's service area as a Full Truckload Pickup and Delivery Problem with Time Windows (FTPDPTW). The Pickup and Delivery Problem (PDP) extends the classical Vehicle Routing Problem (VRP) by allowing customers to both send and receive goods. In the FTPDP variant, each vehicle transports a single load—in this case, a single container. Gronalt et al. [15] studied full truckload transportation between distribution centers. While their Pickup and Delivery Problem with Time Windows (PDPTW) involved goods moved directly between customers, the problem addressed here assumes all container movements either originate from or return to the terminal.

The VRP is a highly studied problem in the field of Operations Research and Logistics, because it has so many different applications and, by this, the VRP offers many variants in the literature. This also means that several reviews on the VRP literature have been published to help scientists and practitioners find their way in the many variants. An extended taxonomy of the problems has been published by Eksioglu et al. [16], and extended by the highly-cited literature review by Braekers et al. [17]. The published material is so large that specialised reviews have appeared, for example, in the field of the full-truckload VRP [18], reverse logistics [19], two-echelon VRP [20], and VRP with multiple commodities [21].

In the Operations Research community, the Vehicle Routing Problem (VRP) is considered an NP-hard problem, which means that no polynomial algorithm exists to solve the problem. Finding optimal solutions for such problems are large would take very long computation times or even not able to find the solution. As the VRP belongs to this class, all extra additions to the problem, like the introduction of time windows, make it even worse. Because the VRPs are operational problems, that need a solution at least one time per day (or sometimes at a higher frequency), exact algorithms are no option. Operations Researchers make use of, what they call, metaheuristics. A metaheuristic is a higher-level procedure to select and tune a heuristic that provides a sufficiently good solution to an optimization problem. That solution may be the optimal one, but not sure. The single solution approach modifies and improves a single candidate solution. Well-known metaheuristics of this type include tabu search, simulated or deterministic annealing, and iterated local search. The population approach maintains and improves multiple candidate solutions. Well-known metaheuristics of this type include evolutionary algorithms, like genetic algorithms, and particle swarm optimization. A history of metaheuristics has appeared in [22].

Also, this study makes use of a metaheuristic algorithm. The choice for such an algorithm is at the same time easy and difficult. There exists no best metaheuristic for a specific problem. Therefore, the choice is open and researcher have to experiment to choose an algorithm that suits their problem. Many researchers make their choice in the early developed algorithms, even if today new metaheuristics are being developed, be it mostly with less added value. This study adopts the Deterministic Annealing (DA) algorithm due to its proven effectiveness in previous research involving Vehicle Routing Problems with Time Windows (VRPTW). Several studies have demonstrated successful applications of DA in solving various types of VRPs [23], [24], [25]. Additionally, the DA heuristic has shown strong performance in addressing another VRP variant—the dial-a-ride problem [26], [27].

The algorithm is used in this study to run experiments to investigate the influence of time windows on the solution. Time windows make logistics routing decisions more difficult. Especially, this is the case, in which customers can select a time window in which they want their container to be delivered. When more customers select a time window, the dispatching company has less flexibility to construct its delivery routes [28]. When using metaheuristic algorithms to solve scheduling problems with time windows, the optimization algorithms are confronted with less feasible solutions, which leads to additional checks for feasibility during the algorithm runs. While several studies have analysed the drayage operations in intermodal transport, little attention has been given to how the characteristics of time windows influence the performance of the metaheuristic algorithm. For example, how should the algorithm behave when time windows are more concentrated in the morning than in the afternoon? Also, how should the algorithm respond when longer time windows are predominantly scheduled in the morning and shorter ones in the afternoon? Investigating such scenarios requires specific characteristics to describe the set of time windows across all pick-up and delivery operations. Since no prior studies have addressed this type of analysis, these characteristics are not available in the existing literature and therefore must be defined as part of this research. For the first time, time window characteristics are identified based on concepts borrowed from another discipline, i.e. economic geography: concentration and specialization, which will be explained in the Methods section. The research hypothesis states that the presence or absence of concentration and specialization of time windows might influence the behaviour of the metaheuristic, and therefore also the cost of the final solution.

METHODS

The method used in the research is an experiment with the use of a metaheuristic optimization algorithm – the deterministic annealing algorithm –, which has proven to be effective in this type of problem. The experiment relates to the characteristics of the time windows which are the main driver in the research. Therefore, this methodological part includes the description of: (1) the algorithm to solve the FTVRPTW problem; (2) the experimental setting, which includes the concept of the experimental idea and the choice of the parameters for the experiments.

Description of the Algorithm

The algorithm comprises three main phases: (1) construction of an initial solution with an insertion heuristic, (2) improvement of the initial solution using a local search heuristic, and (3) further improvement of the result from step 2 with a deterministic annealing metaheuristic. The algorithm is identical to the one used in [29]. A detailed explanation is omitted in this section. A more detailed explanation is added in Appendix, including the values of the parameters of the algorithm.

Insertion Heuristic

A heuristic approach based on merging pickup and delivery customers is used to generate initial solutions. This process follows a two-stage insertion heuristic. In the first stage, pickup and delivery customers are paired while

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considering hard time windows and limited waiting times between each delivery and its corresponding pickup. These pairs are evaluated and ranked using four weighted criteria: the time window overlap between customers, travel time savings from pairing them, the opportunity cost of not selecting the optimal pair, and differences in time window slack. In the second stage, routes are constructed sequentially. Vehicles are assigned in order of increasing fixed costs, and customer pairs are inserted into routes based on the ascending order of their latest start times. Further details on the insertion heuristic can be found in the Appendix.

Local Search Improvement Heuristic

To enhance the feasible solution generated by the insertion heuristic, a local search method is applied. Three neighborhood structures are defined to explore solution improvements. The CROSS operator exchanges customer pairs between different routes, refining the pairing from the initial insertion phase. The COMBINE operator merges two separate routes into a single one, potentially reducing the number of vehicles used. The INSERT operator relocates customers from one route to another to improve overall efficiency. These neighborhood operations are specific instances of the general λ-exchange mechanism described in [30]. Further details on the local search improvement heuristic can be found in the Appendix.

Deterministic annealing metaheuristic

In a subsequent optimization step, the Deterministic Annealing (DA) algorithm is employed to refine the solutions obtained from the local search improvement heuristic. Also known as "threshold accepting", DA was pioneered as a deterministic alternative to simulated annealing (SA) [23]. In DA, a neighbouring solution with a worse objective value is accepted if the difference in cost between the new solution $C(S')$ and the current solution $C(S)$, $\Delta = C(S') - C(S)$ is smaller than a deterministic threshold value T. This study adopts the implementation strategy outlined in [25]. The ultimate solution obtained from the multilevel local search heuristic serves as the starting point for the DA algorithm.

The three local search operators—CROSS, COMBINE, and INSERT—are integrated into the DA (Deterministic Annealing) framework. Routes are explored in a fixed sequence, with each iteration starting from a randomly selected route. For each pair of routes, at most one move per operator is accepted per iteration. The DA algorithm follows a first-accept strategy, while the local search heuristic selects the best move. The threshold value T is initially set to a maximum value of T_{max}. In each iteration, the threshold value T is decreased by ΔT units if no improvement in the objective function value is achieved. Once T reaches zero, it is reset to $r \times T_{max}$, where r is a random number between 0 and 1. If no improvement is observed after a predefined number of iterations and T reaches zero again, the algorithm restarts with the currently best solution, S_{best}. The process is repeated for a predefined number of iterations. Further details on the Deterministic annealing metaheuristic can be found in the Appendix.

Experimental Design

Basic Concepts for The Experimental Setting

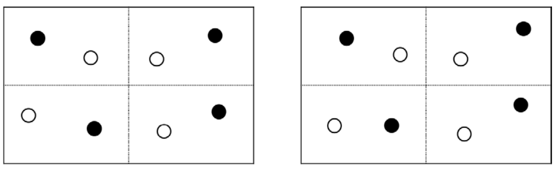
The drayage problem examined in this study encompasses both spatial and temporal dimensions. The spatial aspects pertain to geographical characteristics, such as the size of the area trucks must cover to or from the terminal, the customer density within that area, and the spatial distribution of customers—whether they are uniformly dispersed or clustered in specific regions. The temporal aspects involve the nature of the time windows, including the proportion of customers assigned a time window and the duration of these windows. Each of these factors can potentially affect the performance of the metaheuristic used to solve the problem.

While the influence of spatial factors has been relatively well explored, studies focusing on the temporal dimension—particularly the collective characteristics of the full set of time windows—remain limited. It is generally understood that longer time windows provide greater scheduling flexibility, whereas shorter or tighter time windows increase the complexity of route planning, often resulting in more infeasible combinations and a higher number of trucks required. However, to our knowledge, no research has systematically analyzed the structure of the entire set of time windows.

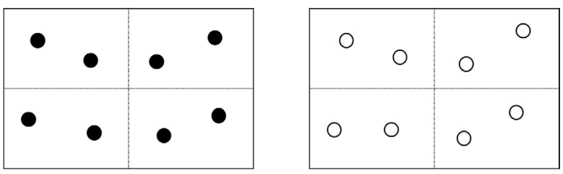
The configuration of time windows may have varying effects on performance. For example, a mix of short and long time windows may produce different outcomes depending on whether short windows are concentrated in the morning and longer ones in the afternoon, or if both are evenly distributed throughout the day. Furthermore, the proportion of short versus long time windows may also influence algorithm performance. These temporal dynamics may interact with spatial characteristics, raising further questions: Do the effects of temporal factors remain consistent when the same number of customers is distributed across a large geographical area as opposed to a smaller one? Understanding these interactions is essential to fully assess the behavior and effectiveness of the metaheuristic in solving the drayage problem.

To understand how these spatial and temporal aspects influence the behavior of the algorithm and its final results, this study sets up some experiments. In the experiments spatial and temporal characteristics take different values, in such a way that differences in performance can be explained by the changes in the characteristics. As there are some random choices during the algorithm process, some replications of the same set of characteristics are required. The results of the replications are statistically analysed to decide whether the effect is real or might have appeared by chance. The performance is measured in two ways: (1) the total cost of the routing plan (at different monitoring points in the algorithm) and (2) the running time of the proposed algorithm. To monitor this process, a few monitoring points are established during the algorithmic process. More specifically, the algorithm is tested using two concepts borrowed from the discipline of Geographical Economics: *specialization* and *concentration*. The concepts, in the context of geographical economics, can be studied in more detail in [31], but are also briefly explained here.

In geographical economics, geographical regions are compared to the spatial distribution of economic activity. *Concentration* refers to the question of how economic activity (e.g. a particular industry or manufacturing sector) is distributed in space. *Specialization* refers to the question of whether or not the share of a region is relatively large compared to the share of other regions. Assume the case, in geographical economics, where they talk about two regions and two types of industries. Both concepts, concentration, and *specialization*, are illustrated using parts of Figure 1: the two boxes represent two regions, and both industries are represented by white and black dots. Figure 1a) shows the case of *no specialization*, *no concentration*. Both regions contain as many white as black dots. Figure



a) The case of no *specialization*, no *concentration*



b) The case of *specialization*

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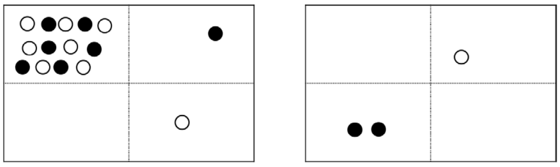

c) b) The case of *concentration*

Figure 1. Illustration of the concepts *specialization* and *concentration*

1b) illustrates the concept of *specialization*: the left region contains all the black dots, and the right region the white dots. Figure 1c) illustrates the concept of *concentration*: the left region contains more dots than the right region.

In our case, the concepts get a different meaning. The 'regions' are translated into two periods of the working day and two types of time windows (long and short):

1. The length of the time windows: two options 'short' and 'long';
2. The concept of *specialization*: shorter are in one period, and longer in the other;
3. The concept of *concentration*: more time windows in one period and less in the other.

Parameter Setting

The experimental setting is generated synthetically, without any link to a real-life situation. The choices for the parameter setting are fully based on the objective of the study: to clearly distinguish which spatial or temporal characteristics have a significant influence on the performance of the algorithm. The choices are motivated in the next paragraphs in the context of this objective.

The experiments in the study are run on a set of 100 customers, of which there are 50 pickup customers and 50 delivery customers. The data sets differ in terms of geographical spread, i.e. the customers are spread over a smaller or larger area. The smaller area is defined, for both x and y coordinates to be in the interval [0,25]. For the larger area, this interval is [0,50]. The depot is located in the central point of the area. The instances of customer locations are randomly generated. The choice for two areas, of which one is four times bigger than the other, will show the influence of distances between the terminal and the customer, or between one customer and another. It is expected that trucks can handle more customers if distances are smaller, but time windows may disturb this simple reasoning. The working day is considered to be 480 minutes and, for experimental reasons, the day is split into two-time frames: frame 1 from time 0 till 240, and frame 2 from time 240 till 480. The choice for these values is completely artificial, but it might represent an 8-hour working day. The split into two-time frames is necessary for measuring the effect of *concentration* and *specialization*, as will be explained further on.

Two types of time window lengths are chosen: short ones and long ones. As stated earlier, longer time windows allow for better planning and less costs. But in understanding what is long and what is short, this study has made two versions. Two specific sets of time window lengths are chosen: (1) 60 time units for the short ones and 150 time units for the long ones; and (2) 30 time units for the short ones and 75-time units for the long ones. The two sets differ from each other in such a way that the second set has tight windows, which is expected to make efficiency more difficult. However, the ratio between long and short lengths is kept equal to 2.5 for a fair comparison. Time window lengths are fixed; this means that their lengths are not generated at random. Time windows are located at a random point in time in either the first or the second time frame, but in such a way that there appears no overlap of the time window over both frames. For example, a short time window of 60 time units can have its random start in the interval [0, 180] for the first frame (as it ends before 240) and in the interval [240, 420] for the second frame.

From the set of 100 customers, 50 have a short time window and 50 have a long time window. In the case of *no specialization, and no concentration*, time frame 1 hosts 25 short and 25 long time windows; the same is true for time frame 2. In the case of *specialization*, *no concentration,* time frame 1 hosts 40 short and 10 long time windows, while time frame 2 hosts 10 short and 40 long time windows. In the case of *concentration, no specialization*, time frame 1 hosts 40 short and 40 long time windows, while time frame 2 hosts 10 short and 10 long time windows. In the case of *specialization and concentration*, time frame 1 hosts 40 short and 20 long time windows, while time frame 2 hosts 10 short and 30 long time windows.

The experiments are run on a laptop Lenovo model Z50 with Intel® Core™ i7-4510U CPU @ 2.00GHz – 2.60GHz and installed RAM 8GB (shared with on-board Graphic Processing Unit). The program is written in C++ using the MinGW compiler with g++ (GCC) 7.1.0 Copyright© 2017 Free Software Foundation, Inc. The computing times of the algorithm are very small. Depending on the experimental situation, they are situated in the interval [1.0, 3.6] seconds for a set of 100 customers. The algorithm, based on the DA metaheuristic is not exponential, so even if the number of customers is tenfold (which is not realistic in nearly all container terminals), the algorithm can be run on a PC and does not need any high-level computing equipment.

Visualisation of Experimental Instances

Figures 2 and 3 visualise the concepts of *specialization* and *concentration* in this research. Both figures show only the midpoints of the time windows. Figure 2 shows the case of *concentration* and *no specialization*: more time windows, both short and long, appear in the first time frame (0-240). Figure 3 shows the case of *specialization* and *no concentration*: more short time windows in the first time frame (0-240) and more long time windows in the second time frame (240-480). At first sight, it might look like the long time windows are more centred. This is not the case as the midpoints of the time windows are shown. That means that, for the long time windows, the window extends both to the left and the right side of the midpoint with 75 time units, while, for the short time windows, this extension amounts to only 30 time units.

RESULTS AND DISCUSSION

The instances, which are chosen from the input data, refer to what we call 'geographical instances', i.e. a set of *x-y* coordinate pairs for the pickup and delivery customers. The customers are uniformly randomly distributed over the

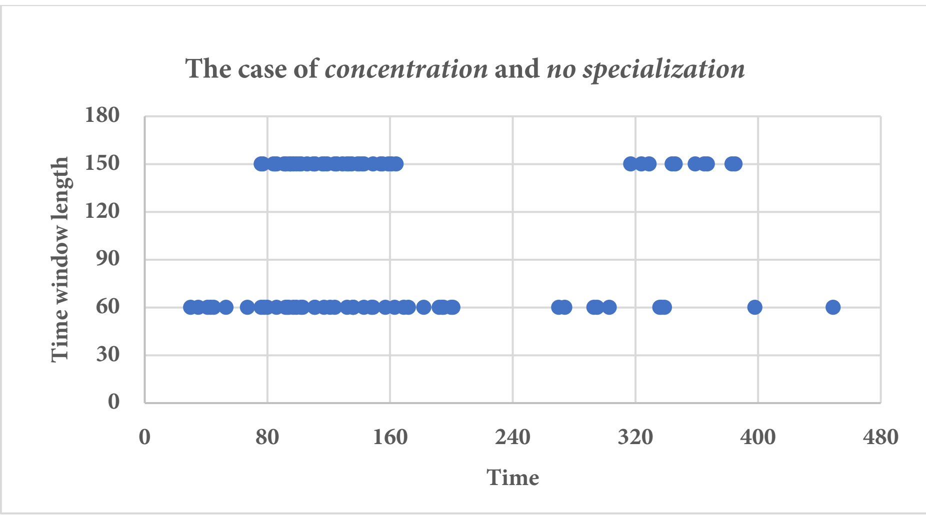

Figure 2. Visualisation of the spread of time windows in the case of *concentration* and *no specialization*

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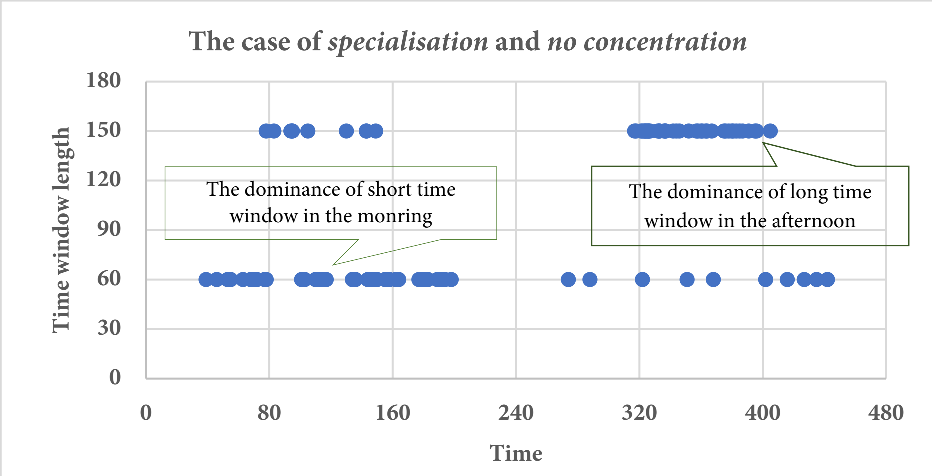

Figure 3. Visualisation of the spread of time windows in the case of *specialization* and *no concentration*

area under study. For the experimental runs, the concept of 'instance' should be understood wider as also time windows are included. The time windows are generated according to the criteria and scenarios, mentioned in the 'Parameter setting' section. Two geographical instances are chosen from the smaller area ([0,25] by [0,25]) and two from the larger area ([0,50] by [0,50]).

For each geographical instance, four scenarios are tested (*no specialization* and no *concentration*; *specialization* and *no concentration*; *concentration* and *no specialization*; *specialization* and *concentration*). Furthermore, two sets of time window lengths are used. While the algorithm (including the DA metaheuristic) has fewer random elements than using the Simulated Annealing metaheuristic, some random choices appear and therefore several replications are required. The variance of the results from the replications will be a crucial factor in the statistical analysis. The number of replications has been set to 5, which is an arbitrary choice. Five replications per (geographical instance/time windows scenario)-combination is required for statistical confidence of the different scenarios. That means that 4 * 5 = 20 experimental runs are required per geographical instance, per time window length set. So, in total 4 * 2 * 20 = 160 run outputs are collected and analysed. The results for the four geographical instances, combined with two time window length sets, are investigated separately in this experimental results section. The customer locations of the four geographical instances are generated independently of each other, so that is why the results are discussed separately.

The performance of the algorithm is compared and analysed through seven indicators or outputs. They are (1) initial number of routes (IniRoutes); (2) cost of the initial solution (IniCost); (3) number of routes after the local search (LSRoutes); (4) cost of the solution after local search (LSCost); (5) final number of routes (FinRoutes); (6) cost of the final solution (FinCost); and (7) Run time (in seconds). Indicators 1 to 4 and 7 are more of an academic nature to investigate how the algorithm behaves in its subsequent steps. Indicators 5 and 6 are useful for the practitioner (and also for academic interest). The factorial design is simple as only two factors are involved each with two levels: *specialization* (with and without) and *concentration* (with and without). But it may be that the influence of the presence or absence of *concentration* is different for the cases with *specialization* or without *specialization*. Therefore, the interaction effect between both factors is also analysed to consider whether the interaction of both factors affects the output.

As the experiments register outcomes of seven dependent variables, a multivariate analysis of variance (MANOVA) is a suitable statistical analysis technique. The mean differences in the outcomes between the two levels of the factors need to be tested for significance. Differences are considered statistically different at a 95% confidence level. The

Table 1. p-value of the factorial design of the output of the experiments located in the small area

Scenarios	Output	TW lengths 1		TW lengths 2	
		1	2	1	2
Specialization	IniRoutes	0.000*	0.000*	0.569	0.355
	IniCost	0.129	0.161	0.489	0.089
	LSRoute	0.008*	0.002*	0.027*	0.229
	LSCost	0.000*	0.035*	0.850	0.241
	FinRoutes	0.012*	0.000*	0.042*	0.176
	FinCost	0.000*	0.001*	0.642	0.436
	Run time	0.018*	0.886	0.000*	0.013*
Concentration	IniRoutes	0.000*	0.000*	0.150	0.553
	IniCost	0.153	0.533	0.618	0.008*
	LSRoute	0.008*	0.005*	0.027*	0.542
	LSCost	0.263	0.448	0.717	0.118
	FinRoutes	0.000*	0.000*	0.003*	0.604
	FinCost	0.094	0.338	0.950	0.226
	Run time	0.263	0.042*	0.111	0.256
*Specialization * Concentration*	IniRoutes	0.000*	0.002*	0.004*	0.196
	IniCost	0.169	0.286	0.238	0.096
	LSRoute	0.008*	0.014*	0.011*	0.400
	LSCost	0.104	0.000*	0.433	0.002*
	FinRoutes	0.000*	0.000*	0.001*	0.176
	FinCost	0.011*	0.000*	0.161	0.085
	Run time	0.459	0.173	0.009*	0.005*

choice for this confidence level is a bit arbitrary but it is common in a lot of research studies. It means that there is a 5% risk of concluding that an influence exists when there is no actual influence. This risk is reflected in *p*-values, produced by the MANOVA. If the *p*-value is less than 5%, we can conclude that the difference between the means is statistically significant. Tables 1 and 2 show the *p*-values for both main effects and the interaction effect on the four geographical instances, obtained from a multivariate analysis of variance (MANOVA). Table 1 exhibits the values for the instances generated in the small area. Table 2 indicates the values for the instances created in the large area.

A first observation, that can be made, is that many more significant influences can be found in the instances from the higher set of time window lengths (long = 150, short = 60) compared to the lower set of time window lengths (long = 75, short = 30). In Tables 1 and 2, the higher set is indicated as TW_lengths_1 and the lower set at TW_lengths_2. By counting the number of statistically significant values in Tables 1 and 2 (indicated by an * next to the value), we learn that the higher set of time window lengths shows 54 significant results, while the lower set shows only 20 significant results. Therefore, we concentrate on the higher set, but focus, from time to time, on the lower set. Regarding the main effects, it can be stated that *specialization* and *concentration* do not affect the cost of the initial solution. On the run time, no significant influence is shown in the large area and only sporadically in the small area. The explanation, further on, concentrates on the other dependent variables.

For the significant cases, indicated in Tables 1 and 2, Tables 3 and 4 show the direction of the effect. For the scenario of *specialization* (resp. *concentration*), the tables show the effect on the variables. If *specialization* (resp. *concentration*) is present, the tables show whether it leads to a higher value (H) or a lower value (L). For the scenario of interaction

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Table 2. p-value of the factorial design of the output of the experiments located in the large area

Scenarios	**Output**	**TW lengths 1**		**TW lengths 2**	
		1	**2**	**1**	**2**
Specialization	IniRoutes	0.004*	0.001*	0.229	0.058
	IniCost	0.756	0.583	0.000*	0.014*
	LSRoute	0.003*	0.036*	0.381	0.139
	LSCost	0.006*	0.001*	0.555	0.195
	FinRoutes	0.115	0.000*	0.479	0.290
	FinCost	0.001*	0.000*	0.540	0.429
	Run time	0.769	0.553	0.062	0.200
Concentration	IniRoutes	0.000*	0.000*	0.325	0.358
	IniCost	0.585	0.876	0.082	0.112
	LSRoute	0.000*	0.036*	0.653	0.285
	LSCost	0.000*	0.009*	0.001*	0.013*
	FinRoutes	0.000*	0.000*	0.658	0.585
	FinCost	0.000*	0.000*	0.042*	0.000*
	Run time	0.286	0.229	0.374	0.206
Specialization * Concentration	IniRoutes	0.004*	0.001*	0.386	0.319
	IniCost	0.390	0.831	0.012*	0.284
	LSRoute	0.001*	0.015*	0.653	0.425
	LSCost	0.000*	0.887	0.367	0.156
	FinRoutes	0.000*	0.000*	0.579	0.403
	FinCost	0.000*	0.483	0.130	0.164
	Run time	0.357	0.290	0.078	0.188

between *specialization* and *concentration*, the tables show which combination, out of four, leads to the highest value of the variables involved.

Tables 3 and 4 show that the effect of *specialization* is not always consistent, but the effect is more consistent in the samples with large areas. Note that in the large area for the shorter time window lengths, only one output variable shows significance (Initial cost). In the small area samples, more significance appears in the shorter time window length set, but the direction is consistent with the longer time window length samples. In contrast, the effect of *concentration* is consistent, showing that in the significant cases, *concentration* leads to a higher number of routes and costs, in the longer time window length set. In the set of examples with shorter time window lengths, the significance is lower, but when it is significant, it is consistent with the set with longer time window lengths (except in the case of the Initial Cost variable). For the examples with longer time window lengths, the effect of the Interaction between the two concepts is consistent, except for the Final Cost variable. It can be seen that for all other significant variables, the highest values for the number of routes and the costs occur with *no specialization*, but with *concentration*. This also applies to the set with shorter time window lengths, while there are fewer significant cases. There is only one exception for the output variable LSCost.

Table 3 presents results for the small area scenario, where shorter distances are involved. In the absence of time windows, one might logically expect that more customers could be served within the terminal's opening hours due to reduced travel times. However, the presence of time windows—whether specialised, concentrated, or neither—complicates this straightforward reasoning. From a practitioner's perspective, focusing on the final cost and the

Table 3. The direction of the effect from *specialization*, *concentration*, and their interaction for the small area

Scenarios	**Output**	**TW lengths 1**		**TW lengths 2**	
		1	**2**	**1**	**2**
Specialization	IniRoutes	L	L		
	IniCost				
	LSRoute	L	L	L	
	LSCost	H	L		
	FinRoutes	L	L	L	
	FinCost	H	L		
	Run time	L		L	L
Concentration	IniRoutes	H	H		
	IniCost				L
	LSRoute	H	H	H	
	LSCost				
	FinRoutes	H	H	H	
	FinCost				
	Run time		H		
Specialization * *Concentration*	IniRoutes	NS, C	NS, C	NS, C	
	IniCost				
	LSRoute	NS, C	NS, C	NS, C	
	LSCost		NS, C		S, NC
	FinRoutes	NS, C	NS, C	NS, C	
	FinCost	S, C	NS, C		
	Run time			NS, C	NS, C

number of routes, the table reveals that *specialization* leads to a reduction in the number of routes (denoted as L), while *concentration* leads to an increase (denoted as H). Consequently, it is consistent that the highest number of routes occurs in the combination no *specialization*, *concentration* (NS, C).

When it comes to the final cost, the results are less straightforward: *specialization* yields conflicting or insignificant outcomes, and *concentration* shows no significant cost effects. This suggests that, in concentrated scenarios, the algorithm compensates by creating more routes while maintaining a balanced or lower total cost. This outcome is naturally influenced by the fixed daily cost of vehicle use, which includes driver wages, maintenance, insurance, and depreciation. From an academic standpoint, it is noteworthy that the effects of *specialization* and *concentration* on the number of routes are evident from the very first phase of the algorithm (IniRoutes) and persist through to the final phase (FinRoutes).

In terms of numerical data (which are not shown in Table 3), the presence of *concentration* leads, on average, to between 16% and 23% more routes and, when combined with no *specialization*, even to between 30% and 35%. The final cost in the case is *specialization* is only between 0.4% and 2% higher than without *specialization* and, in the case of *concentration*, the difference is not significant. It can be concluded that, in the case of *concentration*, the algorithm builds more but more efficient routes. Such a trade-off, of course, depends on the fixed daily cost of a vehicle.

Table 4 presents the results for the large area scenario, where longer travel distances naturally lead to expectations of more routes and higher costs. However, the primary focus is on the effects of *specialization* and *concentration*, assuming constant travel distances. In these large-area cases, the influence of *specialization* remains unclear and

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Table 4. The direction of the effect from *specialization*, *concentration*, and their interaction for the large area

Scenarios	Output	TW lengths 1		TW lengths 2	
		1	2	1	2
Specialization	IniRoutes	L	L		
	IniCost			H	H
	LSRoute	L	L		
	LSCost	H	H		
	FinRoutes		L		
	FinCost	H	H		
	Run time				
Concentration	IniRoutes	H	H		
	IniCost				
	LSRoute	H	H		
	LSCost	H	H	H	H
	FinRoutes	H	H		
	FinCost	H	H	H	H
	Run time				
*Specialization * Concentration*	IniRoutes	NS, C	NS, C		
	IniCost			NS, C	
	LSRoute	NS, C	NS, C		
	LSCost	NS, C			
	FinRoutes	NS, C	NS, C		
	FinCost	NS, C			
	Run time				

inconsistent across scenarios. In contrast, the effect of *concentration* is much more pronounced: when significant, it consistently leads to higher values across all dependent variables. Moreover, the combination of *no specialization*, *concentration* tends to further amplify these values, where statistically significant. The most notable finding is that *concentration* consistently results in higher final costs across all scenarios. While the increase may appear modest—only a few percentage points—it is statistically significant. Given the typically low profit margins in the transport sector, even small cost increases are economically meaningful.

In terms of numerical data (which are not shown in Table 4), the presence of *concentration* leads, on average, to between 18% and 19% more routes. *Specialization* leads to 15% fewer routes. The final cost in the case is *specialization* is, on average 3% higher than without *specialization*. In the case of *concentration*, the presence of *concentration* is on average 2% higher compared to the case of no *concentration*.

Confidence in the algorithm's suitability has increased through extensive experimentation. Previous studies demonstrated that the algorithm produces final routing solutions that closely approximate the optimal outcome. However, it is important to note that these validations were conducted on small-sized problem instances, as the problem sizes addressed in this study are too large to yield optimal solutions within a reasonable computation time. Regarding run time—one of the seven dependent variables—the algorithm consistently delivers solutions within a few seconds. Moreover, Tables 3 and 4 show that the two investigated characteristics, *specialization*, and *concentration*, have minimal impact on run time. The only exception is in the small area scenario, where *specialization* slightly reduces run time, indicating a positive effect.

A Note on The Set-Covering Formulation

Already 60 years ago, the VRP was formulated as a set covering problem [32]. The authors claim that, if the capacity of a truck can be expressed by an integer number, all feasible routes can be enumerated and then a set covering problem can be solved. The idea is the following. Let the index set be the set of all routes and let each route have a cost associated with it. At that time, the problems that could be solved were rather small.

In the set-covering formulation of the VRP with time windows (VRPTW), the objective is to select a minimum-cost set of feasible routes such that every customer is included in some route. It can also be formulated as an integer programming problem. It has been used to develop heuristics for some routing problems [33]. However, the set of all feasible routes is extremely large and it is difficult to generate them completely. Even if this set is given, the set covering problem becomes a large-scale integer program.

The set of routes is smaller in routing problems than in full-truck routing problems due to the simplicity of a single load. The instances in this study have 50 pickup and 50 delivery customers. This means that 2500 pickup and delivery combinations are possible without considering time windows and an additional 100 trips can be realised by including only one pickup or one delivery in the trip. By taking time windows into account, the number of feasible combinations and individual pick-up/delivery trips is significantly smaller. These orders of magnitude can be handled perfectly by today's optimization software. Even the case with two container sizes (20-foot and 40-foot containers) can be formulated as a set covering problem and solved efficiently [34]. However, the solution resulting from such a covering problem does not provide a solution for our studied problem. It has been learned from the experiments that trucks make four to six pickup and delivery trips per day, so the assignment of each trip to a vehicle is much more complex than the set covering problem. The solution to the set covering problem can only be the optimal solution under two conditions: (1) the number of available vehicles is infinite, and (2) the fixed cost of deploying a vehicle for an entire day is zero. These conditions are far from realistic and cannot be applied in this study. The problems, similar to the one under study, are called multi-trip problems or vehicle routing problems with multiple trips [35].

CONCLUSION

In this study, the deterministic annealing (DA) algorithm has been chosen to solve the Full-Truck Vehicle Routing Problem with Time Windows (FTVRPTW). To classify the types of time windows, two concepts named *specialization* and *concentration* have been introduced. The findings indicate that while *specialization* was anticipated to be a significant factor, the experimental results revealed inconsistent outcomes. This inconsistency warrants further investigation, and potentially, the development of improved or alternative descriptors. On the other hand, the *concentration* leads to a higher number of routes in the final solution and also to higher costs in larger areas. Additionally, the interaction effect between *concentration* and *specialization* leads to a higher final number of routes and higher costs when *concentration* is not accompanied by *specialization*. For practitioners, this study has demonstrated that higher levels of *concentration* in time windows lead to an increase in the number of trucks required and in overall costs. Thus, cost savings may be achievable by reducing such *concentration*. When data reveal high *concentration*, it may be worthwhile to negotiate with certain customers to shift their pick-up or delivery times to other parts of the day. Alternatively—and universally beneficial—relaxing customer time windows can consistently improve routing efficiency.

It is important for the reader to recognize that this is a novel approach and that other, yet-to-be-defined characteristics may also prove relevant—posing an open question for future research. While we are confident in the effectiveness of the metaheuristic employed in this study, alternative approaches may also perform well. Readers are

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encouraged to select a metaheuristic that has shown success in similar problems and to invest time in tuning its parameters to suit their specific operational context. Future research could also explore the impact of clustered customer locations, such as those situated within the same industrial zone or city center.

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CONFLICT OF INTEREST

The authors declare that there is no conflict of interest regarding the publication of this paper.

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Appendix: Detailed Description of The Algorithm

The algorithm aims to minimize a cost function, which consists of two parts: a fixed part and a variable part. The fixed part represents the cost of using a vehicle for a day, independent of the distance that the truck is driving or the time it has to wait. The fixed cost per vehicle can be different for different vehicle types. In our experiments, the cost is the same for all vehicles. The variable part represents the cost of all trips, including the times to leave from and return to the terminal. The algorithm consists of three phases: (1) construction of an initial solution using an insertion heuristic; (2) improvement of the initial solution using a local search heuristic; and (3) improvement of the result obtained in step 2 using a Deterministic Annealing heuristic. In this appendix, the three phases are described in detail.

Insertion Heuristic

A two-phase insertion heuristic is described here to create initial solutions. Consider the case in which a truck needs to serve two customers. They can both be of the type 'pick-up customer' or 'delivery customer', or they can be one of each type. Only when a pick-up customer is served after a delivery customer, a truck can drive from one customer location to the other. In this case, savings can be made in terms of time and cost. In the other customer combinations, the truck first has to return to the terminal before serving the second customer.

In the first phase, pickup and delivery customers are combined into pairs of customers. Due to the existence of hard time windows, not every pickup customer and delivery customer can be combined into a feasible pair. Also, a limit is imposed on the waiting time between delivery i and pickup j. The pairs of pickup and delivery customers are ranked according to four criteria, including the time window slack between customers i and j (Criterion 1), savings in travel time obtained from serving delivery i and pickup j together (Criterion 2), an opportunity cost for not choosing the best combination for a delivery i or pickup j (Criterion 3), and the opportunity cost related to the time window slack is incorporated in the selection criterion, defined as the difference between the time window slack of the current combination and the smallest time window slack of delivery i or pickup j in any combination (Criterion

4). These four criteria are aggregated by making use of weights. The experiments in this study make use of the following weights: w1 = 20, w2 = 5, w3 = 20 and w4 = 55.

In the second phase, routes are constructed sequentially. Vehicles are used in increasing order of their fixed costs (if relevant). Pairs of customers are eligible to be inserted into routes in increasing order of their latest start time. A pair of customers can be inserted into an existing route k if vehicle k can start later than the time necessary to serve the customers already assigned and on condition that vehicle k can return to the terminal before the terminal closing time.

Local Search Improvement Heuristic

A local search procedure is applied to improve a feasible solution obtained by the insertion heuristic. Three neighborhoods are defined. First, the CROSS operator recombines pairs of customers of different routes. This operator improves the result of the pairing phase in the insertion heuristic. A second operator, COMBINE, joins two routes into one. Finally, customers are removed from a route and inserted into another route by the INSERT operator. The latter two search neighborhoods affect the result of the route construction phase of the insertion heuristic.

These neighborhoods mechanisms form special cases of the general λ-interchange mechanism, described in [24]. The CROSS operator is an example of a 1-interchange mechanism, which involves only a single customer of each route. Due to the CROSS operator, two routes may exchange either pickup customers or delivery customers of two pairs simultaneously. The INSERT operator represents a 2-consecutive-node interchange mechanism. Two consecutive customers, which constitute a pair in a single route are shifted to another route. Similarly, the COMBINE operator may be seen as a n-consecutive node interchange mechanism.

The CROSS operator works as follows. Two pairs of pickup and delivery customers, *(g,h)* and *(i,j)*, are selected from two different routes. These pairs are recombined into new pairs, *(g,j)* and *(i,h)*. The CROSS move is checked for feasibility, taking into account their time windows. Further, it is checked whether the new pairs can be reinserted into the routes. Either *(g,j)* is inserted into the first route and *(I,h)* into the second, or vice versa. The heuristic selects the move with the largest improvement. The COMBINE operator works as follows. It checks whether two routes served by different trucks can be combined into a single route. Two routes can be combined if the last pair of the first route can be served before the latest starting time of the second route. This operator can reduce the number of trucks. The INSERT operator works as follows. It removes pairs of pick-up and delivery customers from their routes and reinserts them into another route. Pairs of customers can be inserted at the beginning of a route, between pairs of customers, or at the end.

Deterministic Annealing Metaheuristic

In a subsequent optimization step, the Deterministic Annealing (DA) algorithm is employed to refine the solutions obtained from the local search improvement heuristic. The three local search operators—CROSS, COMBINE, and INSERT—are integrated into the DA (Deterministic Annealing) framework. Routes are explored in a fixed sequence, with each iteration starting from a randomly selected route. For each pair of routes, at most one move per operator is accepted per iteration. The DA algorithm follows a first-accept strategy, while the local search heuristic selects the best move. The threshold value T is initially set to a maximum *value* T_{max}. In each iteration, the threshold value T is decreased by ΔT units if no improvement in the objective function value is achieved. Once T reaches zero, it is reset to $r^* T_{max}$, where r is a random number between 0 and 1. If no improvement is observed after a predefined number of iterations and T reaches zero again, the algorithm restarts with the currently best solution, S_{best}. The process is repeated for a predefined number of iterations.

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The DA meta-heuristic has several parameters: the maximum threshold value T_{max}, the change in threshold value ΔT, the maximum number of iterations $n_{improve}$, and the predefined number of iterations without improvement n_{wi}. In this study, the following values are used: $T_{max} = 1$, $\Delta T = 0.025$, $n_{improve} = 1000$, and $n_{wi} = 10$.

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