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Sustainable Time-Dependent Cheapest Path Problem with Integrated Collaborative Stakeholders' Perspectives

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Abstract: The Sustainable Time-Dependent Cheapest Path Problem (STDCPP) entails locating a Hamiltonian path that covers all of the graph's vertices at the lowest possible total sustainability cost. The issue is inspired by actual city logistics, where it is important to consider the opinions of diverse stakeholders in the light of sustainable urban mobility plans and service viability. To address this issue, this paper suggests a twofold contribution. First, we describe the Sustainable Time-Dependent Cheapest Path Problem and define the complex cost function, which, based on the multi-criteria decision-making approach, integrates the views of different stakeholders and sustainability elements into the route cost calculation. Second, we show that the modified problem satisfies the FIFO (First-In First-Out) property and demonstrate the applicability of the suggested approach on a real-life scenario where route sustainability is extracted from the traffic sign information system available in Flanders, Belgium.

Keywords: sustainable mobility; sustainable routing; time-dependent cheapest path problem; city logistics; smart mobility; urban data analytics; sustainable urban mobility

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Citation: Semanjski, I.; Gautama, S. Sustainable Time-Dependent Cheapest Path Problem with Integrated Collaborative Stakeholders' Perspectives. *Sustainability* **2024**, *16*, 3706. https://doi.org/10.3390/su16093706

Academic Editor: Aoife Ahern

Received: 5 March 2024
Revised: 24 April 2024
Accepted: 26 April 2024
Published: 28 April 2024

1. Introduction

The improvement of urban mobility has the most relevant impact that the advancement of mobility can have on the overall population's quality of life. This statement can be deducted from the facts that, since some fifteen years ago, the global urban population has surpassed the rural population, with projections indicating that nearly 5 billion individuals will reside in urban areas by 2030 [1], and highlighting the role that mobility plays in the overall quality of life, either directly or indirectly, through externalities such as emissions or noise [2–4]. This synergy between the growth of urban areas and the role of mobility puts significant pressure on city logistics which faces the challenge of supplying the city with sufficient (and increasing) resources for daily life and operations, while trying to balance and reduce the impact that it has on the environment, thus making its operations more sustainable. Recent scholarly works [5–9] underscore the imperative of explicitly considering varied stakeholder perspectives in facing this challenge, while Taniguchi and Thompson [10] identify logistic service providers, shippers, residents and city services administrators as pivotal stakeholders in this regard. Nonetheless, current route planning approaches often treat these views separately, limiting the integration of conflicting stakeholder perspectives [9]. In this paper, we introduce the Sustainable Time-Dependent Cheapest Path Problem (STDCPP) with integrated collaborative stakeholders' perspectives. The STDCPP extends existing time-dependent route planning concepts by considering the sustainability of the route option as an integral part of the arc's traversal cost that varies over time. This integration of route sustainability is facilitated through the adoption of a multi-criteria decision-making approach, allowing for the inclusion of various stakeholders' perspectives and the assessment of sustainability costs relative to the route's spatial and temporal context. We show that the modified problem satisfies the First-In First-Out (FIFO) property and implement an adjusted Dijkstra algorithm to demonstrate the applicability of the proposed approach in a real-life city logistics example. Hence, the contribution of this manuscript can be delineated as follows: (i) we break away from the literature on time-adaptive routing by using a comprehensive cost function which differentiates between fixed and variable costs regarding the spatial and temporal sustainability context of the route; (ii) we extend upon existing routing methodologies by offering the potential for incorporating various stakeholders' viewpoints, rendering it particularly suitable for applications in city logistics; (iii) we show that the modified problem satisfies the FIFO property and thus is solvable by labelling algorithms; (iv) we apply the modified Dijkstra algorithm for the STDCPP; and (v) we demonstrate the applicability of the suggested approach on a real-life example where the spatial and temporal context of the route is derived from a smart mobility traffic sign database.

The subsequent sections of the manuscript are organized as follows: The next section provides a brief literature review on adaptive route planning. Section 3 presents a formal description of the problem, introduces the notation that is used throughout the paper and defines the STDCPP. Section 4 describes the methodology and integration of sustainability into the calculation of time-dependent route costs. The FIFO consistency and adjusted Dijkstra algorithm are presented in Section 5. Section 6 provides a practical computational campaign example for the STDCPP, aiming to illustrate the problem and showcase its applicability. Subsequently, a discussion and concluding remarks are presented in Sections 7 and 8, respectively.

2. Literature Review

The conditions encountered in practice by companies and organizations engaged in the delivery of goods in urban areas exhibit high variability over time. Probably the most illustrative example of this is traffic congestion, where travel times on the road network vary across different hours of the day [11–16]. To meet this challenge, adaptive vehicle route planning takes time-dependent route costs into account. Thus, adaptive route planning, given a graph with time-varying arc-traversal costs, entails determining the least-expensive Hamiltonian path that covers all vertices of the graph. The literature on adaptive route planning is relatively sparse and can be categorized into three general areas: (i) the Time-Dependent Shortest Path (TDSPP) and the Time-Dependent Cheapest Path Problem (TDCPP), (ii) the time-dependent travelling salesman problem (TDTSP) and (iii) the time-dependent vehicle-routing problem (TDVRP), with all of their variants.

To the best of our understanding, the exploration of time-dependent routing was initially conducted by Beasley [17], who examined two distinct periods of the day characterized by varying travel time durations and adjusted the savings algorithm accordingly. Later on, the vertices of a road network graph with time-dependent piecewise constant speeds and derived travel time in an arc from the average speed of the incident vertices were introduced [18,19]. This modelling approach has been incorporated in a commercial courier vehicle scheduling system between 15 offices of a bank. Later on, it was shown that the label-setting and label-correcting algorithms are correct for networks with link times that have a FIFO consistency property [20], and the exact and approximate methods for estimating the fastest vehicular movements in road network graph models, where arc speeds vary over time, were thoroughly examined [21]. The assumptions regarding network conditions acknowledge the inherent link between speed and travel time, implying a First-In First-Out (FIFO) consistency condition that validates the application of Dijkstra's algorithm for pathfinding purposes in this context. Ichoua et al. [22] proposed a travel time modelling approach, based on time-dependent travel speeds, which also satisfies the FIFO property. An experimental evaluation of the proposed model was performed using a parallel tabu search heuristic and it demonstrated that the time-dependent model provides substantial improvements over a model based on fixed travel times. Fleischmann et al. [23] explored the assumptions that piecewise travel speed functions must satisfy to ensure that travel times satisfy the no-passing or FIFO properties. They introduced a comprehensive framework for integrating time-varying travel times into different vehicle routing algorithms. Furthermore, general properties and algorithms for the TDSPP have also been addressed in more detail across the literature [24–27].

As far as the time-dependent travelling salesman problem is concerned, Malandraki and Daskin [28] formulated the time-dependent travelling salesman problem and piecewise constant travel times as a mixed-integer linear program. They report test results on small, randomly generated problems and argue that the use of time-varying travel times in more complicated algorithms would require excessive computation time. Next to this, the Asymmetric Traveling Salesman Problem with Time Windows (ATSPTW), which considers time-dependent travel times and costs with a focus on a known exact algorithm for the Mixed General Routing Problem for solving this problem, was also investigated [29] as well as general properties and algorithms for the TDTSP [30–34].

The time-dependent vehicle-routing problem was first addressed in the above mentioned work of Malandraki and Daskin [28]. More recently, researchers explored an integrated framework that incorporates the planning of bus routes and schedules within an iterative solution process. This process addresses stochastic bus travel times by iteratively solving a sequence of planned bus scheduling and real-time schedule adjustment problems to determine appropriate bus routes and schedules [35]. Also, a branch-and-price algorithm for the time-dependent vehicle-routing problem with time windows (TDVRPTW) has been investigated [36]. To our knowledge, Franceschetti et al. [37] first considered the time-dependent pollution routing problem, where the cost function comprises emissions and driver costs, taking into account traffic congestion which, while occurring, results in significant vehicle speed variations and increased emissions. More recently, an arc-based formulation for the pollution-routing problem was also introduced [38]. Here, the authors build two mixed-integer convex optimization models for the pollution-routing problem, by employing tools from disjunctive convex programming and test the proposed formulations on benchmark instances. Among others, the integrated decision of path selection within the time-dependent vehicle-routing problem was also considered, encompassing the selection of routes within the road network [39] together with other aspects of the time-dependent vehicle-routing problem [40–44]. Furthermore, departing from route planning, other approaches have also been considered across the literature on how different measures and strategies can be implemented to manage road use and the various impacts that these strategies might have. Some examples include road pricing and diverse vehicle access regulations [45–47]. However, the above-mentioned research mainly considers time-variable cost as travel time, emissions and/or monetary cost separately, while the potential to involve diverse stakeholders in the assessment of the overarching cost estimation could be of added value. The latter might be particularly relevant in supporting various co-creation aspects, integrating citizen initiative outcomes and potentially enhancing the societal aspects of route sustainability [5,7,48,49]. Hence, in this paper we explore in more detail the possibility of modifying adaptive route planning to integrate route sustainability into an arc-traversal cost that varies over time. The integration of the route sustainability is based on the adoption of multi-criterial decision-making to evaluate sustainability cost in regard to the route's spatial and temporal context. Next to this, we test the performance of the suggested adaptive route planning approach on a road network where the route's spatial context is extracted from a traffic sign database.

3. Framing the Problem

This section defines the basic problem under consideration. Formally, we consider a network $N = (V, A, C, f)$, where (V, A) is a graph G, C is a set of costs and f is a function that assigns costs to arcs $f : A \to C$; thus, $f : (v_i, v_j) \to c_{ij}$. The basic problem we address is computing the point-to-point shortest paths. Suppose that the vertices $o \in V$ and $d \in V$ represent the origin and destination vertices. The path (P_{od}) is a sequence of arcs of which the first one originates in vertex o, each next one starts in the exact vertex where the previous one ended and the last one ends in vertex d. Let x_{ij} be the decision variable regarding the arc–path incidence relationship, as defined by Equation (1):

$$x_{ij} = \begin{cases} 1, & if\ a_{ij} \in P_{od} \\ 0, & otherwise \end{cases}. \tag{1}$$

The path cost, denoted by $cost(P)$, is the sum of the related arc costs:

$$cost(P) = \sum_{a_{ij} \in A} c_{ij} * x_{ij.} \tag{2}$$

Hence, the cheapest path between o and d is the one, among all possible paths, which has the smallest overall cost, $\min(cost(P_{od}))$.

In more detail, our focus is on road networks, where:

- Vertices represent the intersections or Point of Interest (PoI) locations;
- Arcs represent road segments;
- The costs are derived from the characteristics of the road segments (such as travel time or length).

A PoI location p divides an arc into two parts where the costs for each part are considered to be c_{ip} and c_{pj}, where

$$c_{ij} = c_{ip} + c_{pj}. \tag{3}$$

Thus, the PoI location is a new vertex with a degree of two. In road networks, PoI often represents pickup or delivery locations.

This problem has a well-known solution: Dijkstra's algorithm [50]. Dijkstra's algorithm processes vertices in increasing order of cost from o and stops when d is reached, resulting in a worst-case scenario running time on a graph with n vertices and m arcs to be $O(n^2)$. Computing the cheapest paths in road networks is a well-studied problem [51–54]. Intuitively, the cost most often denotes the length of the arc a_{ij} or travel time. However, in our case, we will consider a more complex cost function:

$$c_{ij} = c_{ijF} + c_{ijV} \tag{4}$$

where c_{ijF} is a fixed part of the cost associated with the arc a_{ij} and c_{ijV} is a variable one.

In our case, c_{ijF} represents the length of the arc a_{ij}, but generally, it can represent any other cost that does not change under different conditions, like time of day. Respectively, c_{ijV} represent the part of the cost that changes under different conditions and, in our example, it is a sustainability element of the cost function. The Cheapest Path Problem, where the cost associated with the arc is a sustainability-related cost, is a Sustainable Cheapest Path Problem (SCPP), whereas if the sustainability-related cost changes under different conditions, the observed problem is a Sustainable Time-Dependent Cheapest Path Problem (STDCPP). The routing problem with the cost function, as defined by Equation (4), is in its nature the time-dependent routing problem, where even time-dependence is variable across different arcs (e.g., one arc can have $c_{ijV} = 0$, while another can have $c_{ijV} \neq 0$). The simplified versions of this cost function, in relation to the routing problem and the existing literature, are shown in the example of the Cheapest Path Problem (CPP), but the same analogy is translatable to the Traveling Salesman Problem (TSP) and the vehicle-routing problem (VRP) with all of their variants:

$$c_{ij} = \begin{cases} CPP, & if\ c_{ijV} = 0 \\ TDCPP, & if\ c_{ijF} = 0 \end{cases}. \tag{5}$$

The route sustainability is not a simple indication and varies not only over time but also across the views of different stakeholders in the routing process. For example, to ensure more sustainable routing in urban areas, local authorities can request for all light and heavy goods vehicles to avoid roads with school entrances, during the school year and during the school's start and end hours. In this sense, they aim at ensuring a safer, more socially sustainable, mobility environment for children during periods when they are approaching and leaving school areas. In another example, national park authorities can request that all vehicles carrying dangerous goods should avoid passing in the vicinity of the park, as any incident involving these vehicles can have devastating consequences for the preserved natural culture. The same might be the case for companies that want to distinguish themselves as children- or nature-friendly. However, rather than regarding these as one-sided decisions and "hard constrains", imposed by one stakeholder, we consider the sustainability cost as composition of different elements $\left(c_{ijv1}, c_{ijv2}, \ldots, c_{ijvk}\right)$, where k is the overall number of such elements that vary across different areas (s) and time (t) :

$$c_{ijV} = \left(c_{ijV1},\ c_{ijV2},\ \ldots.\ c_{ijVk}\right)_{s,t}. \tag{6}$$

And we suggest integrating it into the overall cost calculation based on the joint perspective of various stakeholders. Hence, taking into account the different stakeholders' views in the routing process, for example, regarding the acceptability of available routing alternatives or sustainability cost for different spatial and temporal contexts, we suggest the adoption of a decision-making approach when determining the sustainability cost.

4. Methods

4.1. Decision-Making Approach

Decision-making involves selecting from multiple options or courses of action. It constitutes a thoroughly examined area within operations research, addressing decision problems considering decision criteria. When there are multiple decision criteria involved, the situation is referred to as a multiple-criteria decision-making (MCDM) problem and it can be regarded as a finite set of both the decision alternatives $D = \{D_i, for\ i = 1, 2, 3, \ldots N\}$ and the criteria by which the desirability of an action is assessed $Cr = \{cr_i, for\ j = 1, 2, 3, \ldots, M\}$. The objective is to ascertain the optimal decision alternative D^* exhibiting the utmost desirability concerning all pertinent criteria cr_i.

In this paper, we employ the Analytic Hierarchy Process (AHP) to assess the sustainability aspect of the routing options. This choice is motivated by its capacity to incorporate both objective and subjective data, and to systematically analyse intricate decision-making issues based on analytical and psychological principles. Additionally, the AHP utilizes a hierarchical structure in decision-making processes, facilitating comprehension among the various stakeholders involved in sustainable route planning. Moreover, it can accommodate decision-making scenarios involving individual or group perspectives. Originally introduced by Saaty [55], the AHP has undergone extensive study and refinement [56–61]. The methodology follows a decompose-before-integrate approach, whereby decision-makers initially break down the problem into a hierarchy or subproblems. The hierarchy typically comprises three fundamental layers: the decision goal, the alternatives to achieve it and the criteria used to assess the alternatives. However, it may involve multiple levels of criteria and subcriteria. Subsequently, decision-makers conduct pairwise comparisons between the elements at each level of the hierarchy relative to the next higher level. These comparisons are conducted utilizing the Saaty scale of importance [55], enabling the conversion of qualitative assessments into quantitative metrics using a numerical scale spanning from 1 to 9. Hence, each of the comparison matrices assumes the following form:

$$D = \left[d_{ij}\right] = \begin{bmatrix} d_{11} & d_{12} & \cdots & d_{1n} \\ d_{21} & d_{22} & \ldots & d_{2n} \\ \vdots & \vdots & \ldots & \vdots \\ d_{n1} & d_{n2} & \ldots & d_{nn} \end{bmatrix} \tag{7}$$

where d_{ij} corresponds to the pairwise comparison, within the same hierarchy level, for elements i and j. This matrix has positive entries everywhere and satisfies the reciprocal property $d_{ij} = \frac{1}{d_{ji.}}$. Hence, given the consistency of the comparison matrix, the reciprocal of the weight value can be obtained by determining the sum of the column, which allows the calculation of the weight vector w in regard to the referent level of the hierarchy. This weight vector w is the principal right eigenvector of the matrix, D, and the normalized weight vector $w = (w_1, w_2, \ldots, w_n)$ can be calculated by solving the following matrix equation:

$$Dw = \lambda_{max} w \tag{8}$$

where λ_{max} is the principal eigenvalue of the matrix, D. Moreover, when implementing the AHP, one has the possibility to follow up on the inconsistency of judgments that tends to occur, particularly in more complex hierarchical structures. This is achieved by following up on the relationship between the principal eigenvalue λ_{max} and the number of rows or columns n of the matrix, D. The closer λ_{max} is to the n value, the more consistent the matrix, D, can be considered and when λ_{max} is equal to n, the consistency index becomes zero, indicating perfect consistency among the judgments. Hence, $\lambda_{max} - n$ quantifies the degree of inconsistency within the $n \times n$ matrix and the divergence from the consistency of the comparison matrix, D, is determined based on the consistency index (CI):

$$CI = \frac{\lambda_{max} - n}{n - 1}. \tag{9}$$

The consistency ratio (CR) quantifies the coherence of the pairwise evaluations and can be calculated as

$$CR = \frac{CI}{RI} \tag{10}$$

where RI represents the average consistency index obtained from the randomly generated judgments (Table 1). For the values of $CR \leq 0.1$, the consistency is considered to be adequate, while for evaluation matrices where this value is higher, it is considered that the desired level of consistency among the judgments is not achieved and that the obtained pairwise comparisons should be revised.

Table 1. Random consistency index (RI).

n	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
RI	0	0	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49

4.2. Incorporating Sustainability into the Computation of Time-Dependent Route Costs

When integrating sustainability-related costs into the STDCPP route cost calculation, we consider the temporal context divided into T non-overlapping periods with c_{ij}^T being the arc a_{ij} cost for the period T, which is (t_{i-1}, t_i). Following the analogy from the literature [17], when considering the time-dependent route cost, then the necessary adjustments to any CPP algorithm, like Dijkstra's, are the following:

- A rule defining the cost c_{ij}^T in terms of the period T;
- A rule for calculating cost when traveling between two vertices falls in two, or more, time periods.

Since only the variable part of the cost is affected by the temporal variability, we will denote it as c_{ijV}^T and hereafter discuss it in more detail. The rule we chose for defining the cost c_{ijV}^T is based on the spatial context of the arc a_{ij} during the period T. We consider that the sustainability element e_i is admissible for the arc a_{ij} only if it is a part of its spatial context during the period T. Thus, only in such cases does its related cost element c_{ijVe} participates in the overall cost c_{ijV}^T. For example, the sustainability cost related to the vicinity of the national park is only relevant for the arcs that pass next to, or across, a national park. For network arcs who, in their vicinity, do not have a national park, the national-park-related sustainability cost will not be a part of their overall cost. Let the S be the sequence of all sustainability elements that appear along the side of arc a_{ij}

$$S = (s_1,\ s_2,\ \ldots,\ s_n) : s_i\ \in a_{ij} \tag{11}$$

and $C(e_i)$ be the count of the unique sustainability element (e_i) appearing along the arc

$$C(e_i) = \left|\left\{i\ \in\ \{1,\ 2,\ \ldots,\ n\} : s_i\ = e_i^{st}\right\}\right|. \tag{12}$$

Thus, the c_{ijVe} can be multiplied by the integer $C(e_i)$ to reflect the quantity of the sustainability element e_i in the overall cost calculation for a given spatial (s) and temporal (t) context. An illustration of this would be an example of the road segment (arc) that passes by two different schools. In this case, its cost contribution related to the school sustainability element would be twice as big as the cost related to the same sustainability element for the arc that passes by only one school. However, not all sustainability elements are equally relevant, and, for example, one could consider national parks to be of higher relevance than a park area. Thus, passing by a national park would yield a higher sustainability cost. For this reason, we adopt the AHP to model weights for each of the sustainability elements.

When defining the AHP hierarchy, the decision goal is route sustainability and the criteria for evaluating available alternatives (routes) are the sustainability elements. Hence, c_{ijVe} takes a form based on the corresponding normalized weight vector $w = (w_1, w_2, \ldots, w_n)$ element for the defined AHP problem:

$$c_{ijVe} \propto\ C(e_i)\ *\ w_i \tag{13}$$

and, respectively,

$$c_{ijV} \propto\ \sum_{i=1}^{k} C(e_i)\ *\ w_i \tag{14}$$

$$c_{ijV} = p * \sum_{i=1}^{k} C(e_i)\ *\ w_i \tag{15}$$

where p is the proportionality constant.

If the sustainability is described to the subelement level, then the AHP hierarchy structure is adjusted to include an additional, subcriteria (si) level and the analogy for the defined cost calculation is kept:

$$c_{ijV} = p * \ \textstyle\sum_{i=1}^{k} w_i * C(e_{si})\ *\ w_{si}. \tag{16}$$

Finally, the rule defining the cost c_{ij}^{T} in terms of the period T for arc a_{ij} is then considered to be

$$c_{ij}^{T} = c_{ijF} + p * \ \textstyle\sum_{i=1}^{k} w_i * C(e_{si})\ *\ w_{si}. \tag{17}$$

Figure 1 illustrates a simplified road network graph (a) and a simple shortest path (cheapest, regarding the travelled distance) between two vertices. Part (b) illustrates the graph with the sustainability cost assigned to the relevant arcs. Thus, in this example, the sustainability cost is assigned to the road network arcs that pass next to a school and a park. Also, the arc that has a park only on one side of it has a lower sustainability cost than the one that has two parks (one on each side of the arc). Finally, part (b) illustrates the sustainable route. In the network, as in Figure 1, the sustainable route (b) might be, ideally, of the same length as the shortest path (a), but avoiding arcs with the sustainability elements on it. Networks in real life are not as ‘perfect’ as the one in the given example; thus, practically, STDCPP looks for an alternative route with the lowest cost. However, in reality, the number of possible alternatives and route combinations is high, and it is likely that the route will be somewhat longer.

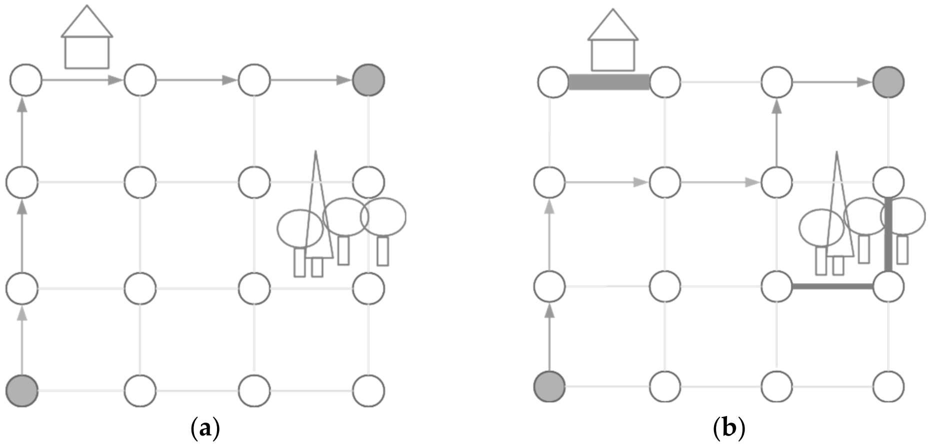

Figure 1. Example of the STDCPP on a simplified road network graph: (**a**) simplified road network graph with a shortest path between two locations; (**b**) simplified road network graph for STDCPP and an STDCPP route.

5. FIFO Consistency and Adjusted Dijkstra's Algorithm

The time-dependency of cost throughout the planning horizon is, in essence, driven by daily changes in the community during different time periods of a day. An example of this is the relevance of school or kindergarten areas that change during different hours. In terms of sustainability, as already stated, this implies that the highest sustainability cost of goods vehicles passing near the school would be during school hours, when children gather around the school (going in or out of the school area), making this area highly sensitive in terms of safety. Another example might be passing near a hospital area where patients need to rest to facilitate their recovery and they might be especially sensitive to noise during night hours; in such periods, noise is likely to cause undesired stress for such patients and prolong their recovery. As already stated, the goal is to find the minimum cost path from the origin vertex to the destination vertex through a network where the costs are time-dependent, meaning that the overall path's cost depends on the departure time. In order to be able to implement Dijkstra's algorithm for this purpose, we need to demonstrate that the FIFO property is satisfied as suggested in [20–23]. The FIFO property guarantees that the cost is not surpassed. In our context, this means that, for any link $a_{ij} \in A$ and any time moment t, if a vehicle departs from a vertex v_i for a vertex v_j at a given time t, any identical vehicle leaving vertex v_i along a link a_{ij} at an earlier time $t - \Delta$ will collect its full cost associated with the arc a_{ij} earlier than vehicle that commenced at time t. Hence, vehicles collect their full cost associated with the arc a_{ij} in the order in which they commenced. It has been shown that the TDCPP in networks that satisfy the FIFO property is polynomially solvable [20], while it is NP-hard in non-FIFO networks. Furthermore, while the computational complexity of the original Dijkstra algorithm is $O(n^2 + m)$, where n indicates the number of vertices and m the number of arcs, for the modified Dijkstra algorithm, where the FIFO property is satisfied, the complexity is $O(n^2 + mK)$, where K represents the maximum number of time intervals considered. Hence, we subject all links to given time period profiles and make use of the time-dependency analogy using a two-level function as in [37,62], developing the travel dynamics under the following assumptions:

1. The cost c_{ij}^T and thus the cost rate cr^T (the rate at which a vehicle collects its cost along the arc a_{ij}) are non-negative real numbers;
2. At any time t on any arc $a_{ij} \in A$, the cost rate cr^T is same on all parts of the arc.

Figure 2 provides an illustration of cost rates (cr) as a function of time and how travel time (TT) varies with the departure time. The left part of the figure depicts a cost rate profile that starts during the non-overlapping time period T until moment m. After moment m, the higher cost rate is associated with the time period T' until moment m_2, after which it returns to the starting cost rate value. In a school-related sustainable routing example, moments m

and m_2 might represent the start and end of the school period. For a given travelled length l and any starting time, the right part of the figure reflects the travel time, illustrating that it takes TT time units to traverse l during the period T (up to $m - TT$). This is a consequence of the uniform cost rate cr along the entire trip, making the FIFO assumption satisfied for such periods. However, starting from $m - TT$ until m, the vehicle will be in the ephemeral zone as its cost rates changes, at the point m, from cr to cr', resulting in a trip performed with two different rates. As such, the travel time exhibits a continuous piecewise linear pattern across different start times. The linearity in the ephemeral zone arises from the stepwise cost rate, leading to variations in cost rates over time. Its slope may be described as $(TT' - TT)/TT$ or $(cr - cr')/cr'$ and the point of intersection with the travel time axis as $\frac{TT-TT'}{TT} * m + TT'$ or $\frac{cr'-cr}{cr'} * m + \frac{l}{cr'}$. Hence, the function $T(t)$ representing the travel time among vertices v_i and v_j depends on the travelled length l and, for any starting time t, we calculate it as shown in Equation (18).

$$T(t) = \begin{cases} TT & if\ t \leq m - TT \\ \frac{cr'-cr}{cr'} * (m - t) + TT' & if\ m - TT < t < m \\ TT' & if\ t \geq m \end{cases} \quad (18)$$

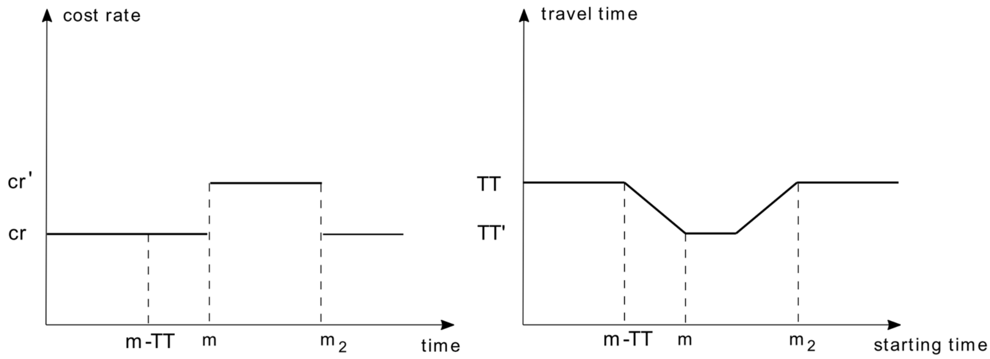

Figure 2. Time-dependent cost rate (**left**) and travel time/cost (**right**).

Given a pair of starting times t and $t + \Delta$, both in the ephemeral area, the moments in which the vehicles would collect their costs are $t + T(t)$ and $t + \Delta + T(t + \Delta)$. Respectively, the disparity between the cost-collecting times of $t + \Delta$ and t is $\Delta + \frac{cr-cr'}{cr'}\Delta > 0$. Hence, the FIFO assumption also holds in the ephemeral area, making the STDCPP solvable with labelling algorithms. The pseudo code for the adjusted Dijkstra algorithm is provided in Figure 3. In short, the algorithm searches for the path with the lowest cost $\min(cost(P_{od}))$ between the origin (o) and destination (d) vertices, by firstly taking a look at the starting time subinterval $T = [t_s, \tau_i]$ and finding the fastest path to each vertex v_i in the graph G, for any starting time in the subinterval. Thus, following Dijkstra's approach, it assigns the earliest arrival time ($e_o(t) := t$) and starting time ($\tau_o := t_o$) to the origin vertex (o), while for all the others the earliest arrival time is set to ∞ (meaning that they are still not visited). Following this step, it forms a priority queue Q based on the ascending order of the earliest arrival times for each vertex, defined by the pair of earliest arrival times and starting times $(\tau_i, e_i(t))$. In each sequential iteration, it refines the starting time subinterval for vertex v_i, and the earliest arrival time, by treating arcs with a variable cost element separately and adding them to the set R. This refinement terminates if Q has no more than one pair or if the arrival time function $e_d(t)$, for the destination vertex is well refined for the whole $T = [t_s, \tau_i]$. When all the arrival times are defined, the STDCPP algorithm looks for the cheapest sustainable path.

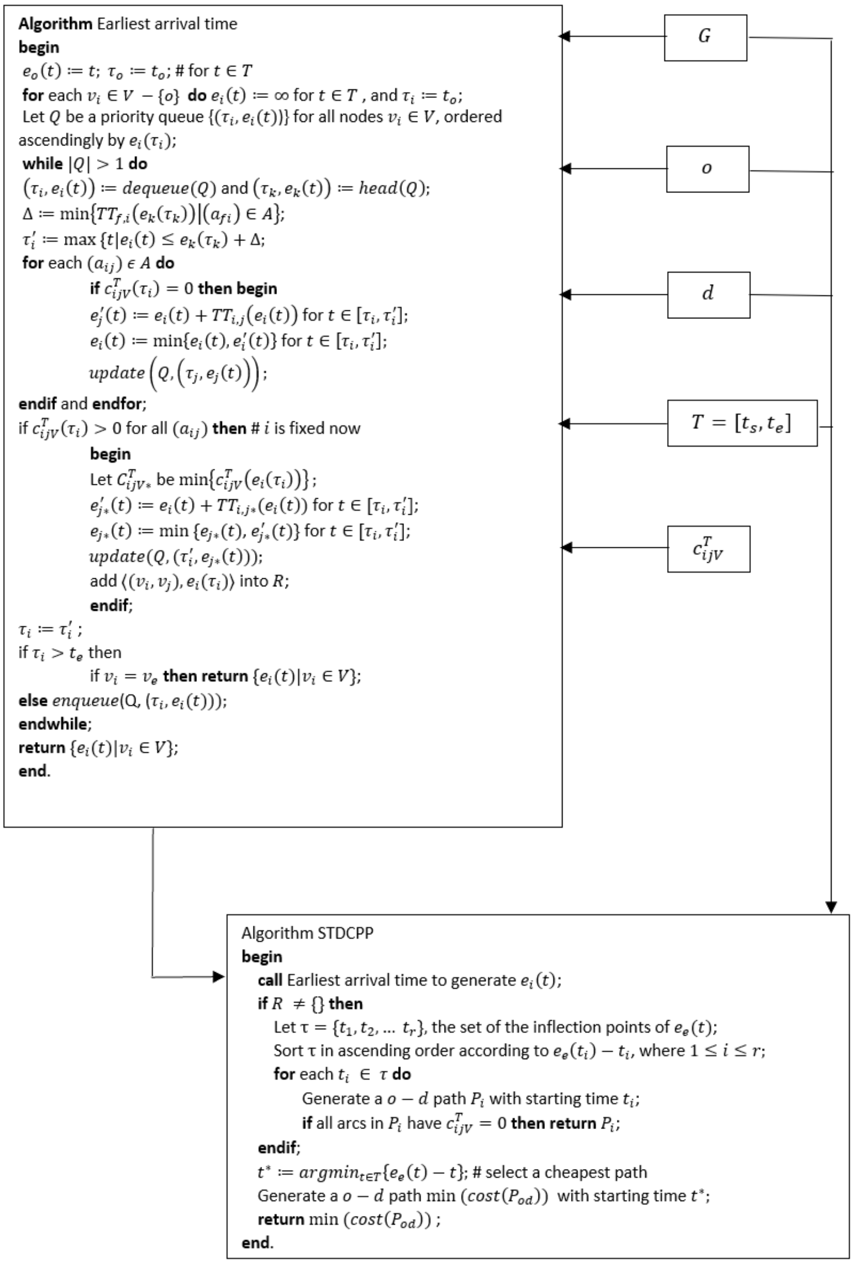

Figure 3. Adjusted Dijkstra's algorithm.

6. Practical Example and Motivation for the STDCPP

6.1. Case Study Location

To illustrate the practical viability of the proposed modification to time-adaptive route planning with route sustainability integrated into the arc-traversal costs, we will examine a road network routing scenario in the city of Ghent, Belgium. Ghent is home to approximately 250,000 inhabitants, with a high ratio of studenta and active bike users. The main access to the city is achieved via two major motorways (E40 and E17) and five railway stations, while the inner structure of the city's network features two ringways (R4 and R40), facilitating connectivity between its outskirts and the city centre areas [63]. The focal area selected for illustration of the proposed approach is a neighbourhood located in the southern region of Ghent called Merelbeke. It is reachable through the E40 motorway and connected via the R4 ringway. The practical scenario under consideration pertains to the exploration of a more sustainable routing option for a light goods vehicle concerning the following spatial components:

(i) Nature park spatial components (for instance, national parks or recreational areas where citizens engage in relaxation or sports activities);
(ii) Historical spatial components (including monuments and historic sites sensitive to traffic-related externalities such as emissions or vibrations);
(iii) Care facility spatial components (healthcare facilities utilized for medical treatments and recuperation);
(iv) Construction zone spatial components (locations where traffic may elevate particulate matter levels, such as dust);
(v) Children-related spatial components (zones where children congregate, play or attend school).

Additionally, two distinct time periods are considered: school hours (t_s) and non-school hours (t_{ns}). The spatial sustainable routing context is delineated using data from a regional traffic sign database, which catalogues traffic sign information along Flanders' road network, encompassing approximately 62,000 kilometres of paved roads, with details including geographic coordinates, traffic sign orientation, street names, the date of recording, sign types, dimensions and visual representations (Figure 4).

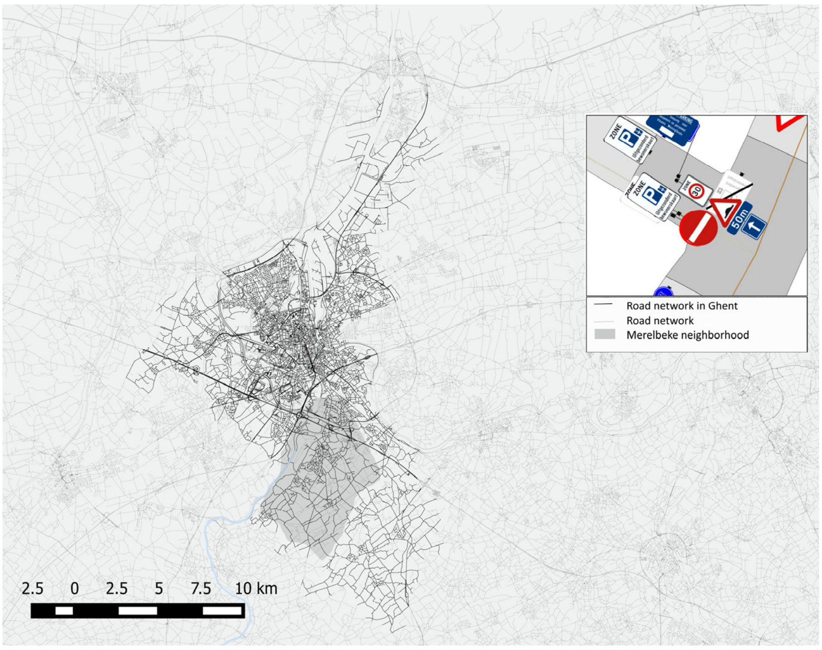

Figure 4. Map of the area with an example record from the traffic sign database.

We refer readers interested in knowing more about the results obtained from the applied AHP-based approach and the pairwise evaluations to a paper that describes this in more detail [9].

The suggested approach is evaluated on a sustainable time-dependent routing example. The problem represents a real-life case study from a logistics company operating in the region and aims to provide an exemplary instance of the possibility of achieving a consensus among stakeholders in the context of sustainable routing. The suggested approach also aimed for a consensus-based proportionality constant, set to be 1000 (p = 1000) for c_{ijF} denoted in meters (path length) for a given example. The main motivation for this was the ease of interpretation when considering a balance between c_{ijF} and the contribution to the overall cost for the defined sustainability components, as determined from the normalized weight vector.

6.2. Computational Campaign

Figure 5 illustrates the spatial context of the routing site within the Merelbeke area, with an indication of the traffic sign types present. The considered routing problem is initiated at the vehicle's starting location (the northeast vertex) and it needs to visit the in-between locations, finishing its route at the southwest vertex. There is no cost for the return trip (it is set to be zero) as the vehicle only passes through the neighbourhood. Another specificity of this example is that the spatial context does not only involve the point-based information, but also the traffic signs that indicate a zone. For instance, the A23 traffic sign indicates a school, and based on the national traffic regulations it is placed, in regard to the vehicle's moving direction, 150 m before reaching the school entrance's location (in exceptional cases it can be placed at another distance from the entrance, but in such cases, it needs to have a Type I underplate that specifies the exact distance to the entrance location). However, the Living Street and 30 km/h zones are areas that are indicated by the F12a and F4a traffic signs and are valid until the end of the area is announced (F12b and F4b). In such cases, the sustainability cost associated with the respective sustainability subelement is assigned to the spatial context of each network's arc in that zone. Figure 6 shows the same area as the previous figure, but for clarity reasons, it indicates only the A23, F4a, F4b, F12a and F12b traffic signs (indicated by the red colour) and the locations (the road network graph vertices) that the delivery vehicle needs to visit (indicated in blue). Figures 7 and 8 illustrate the routing results for this problem for the (t_{ns}) and (t_s) periods.

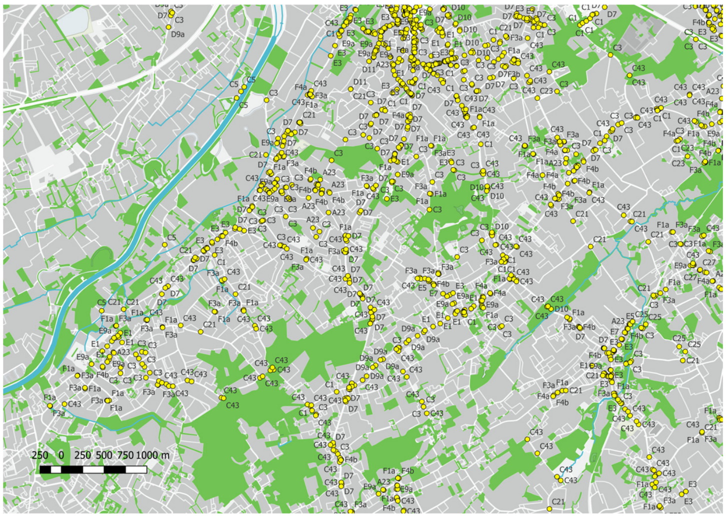

Figure 5. Visualization of the case study area with indication of the present traffic sign codes.

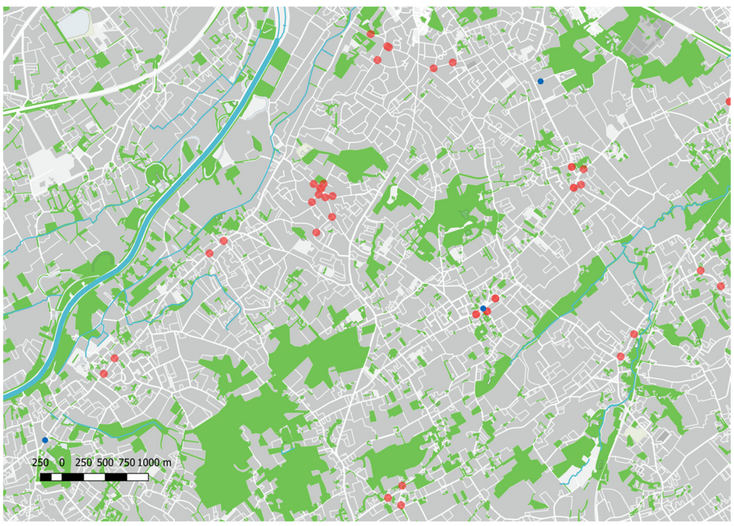

Figure 6. The case study area with indicated sustainability subelements related to traffic sign codes (in red) and road network graph vertices that need to be visited by the vehicle (in blue).

Figure 7. The non-school-hours route for the routing location with indicated sustainability subelements related to traffic sign codes (in red) and road network graph vertices that need to be visited by the vehicle (in blue).

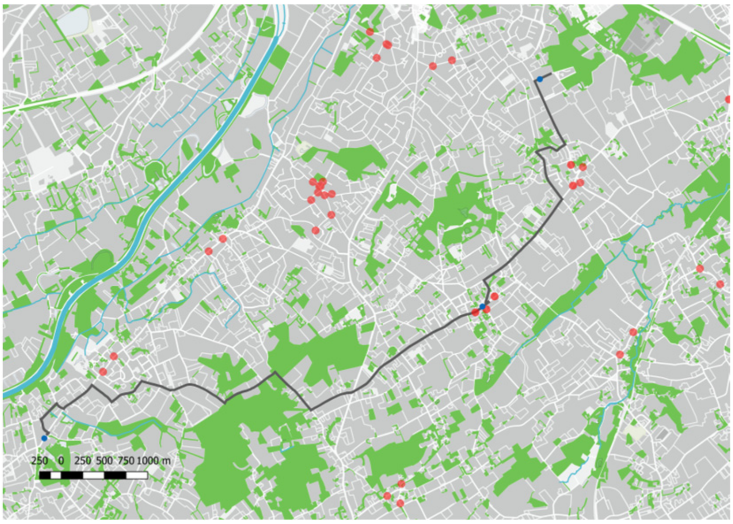

Figure 8. The school-hours route for the routing location with indicated sustainability subelements related to traffic sign codes (in red) and road network graph vertices that need to be visited by the vehicle (in blue).

Table 2 summarizes the results for both time periods, while Figure 9 shows the evolution of the path's cost and distance over t_{ns} and t_s , where they change in moment $t = 30$. Considering the cheapest path results for cases when the cost denotes the length of the arcs, the overall cost during the t_s period and the overall cost during the t_{ns} period, the actual lengths of the paths are in general considered to be comparable, but the route to be made during t_s is altered to avoid the Living Street and zone 30 km/h areas (orange polygons on Figures 7 and 8). However, the suggested route does not avoid one of the schools, as the school itself was the in-between delivery location, but it alters the path approaching the school to avoid the use of the links in the zone 30 km/h area around the school.

Table 2. Sustainable routing results—ASTDTSP.

	t_s			t_{ns}		
	c_{ijF}	c_{ijV}	c_{ij}	c_{ijF}	c_{ijV}	c_{ij}
Cost	9787.17	2317.82	12,104.99	9747.98	139.83	9887.82
Percentage	80.85%	19.15%	100.00%	98.59%	1.41%	100.00%

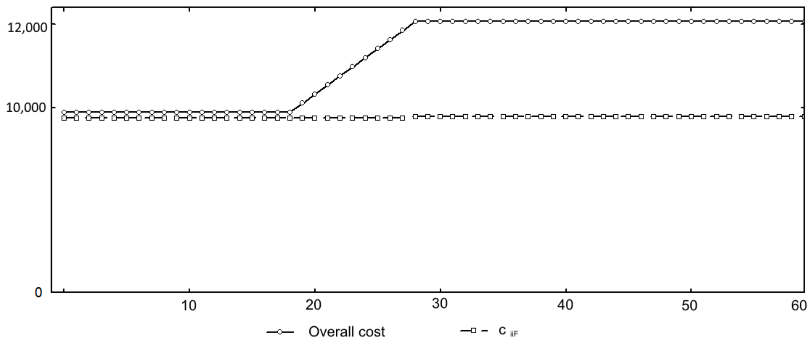

Figure 9. Evolution of overall cost and path length (c_{ijF}) over time.

7. Discussion

Urban centres depend significantly on effective city logistics to maintain their appeal, improve quality of life and foster economic growth. However, the growing presence of light and heavy goods vehicles in city road networks raises concerns regarding safety and environmental impacts [37,64,65]. The recent literature underscores the importance of considering diverse stakeholder perspectives to address these issues effectively [5–7,66–68]. This paper introduces the Sustainable Time-Dependent Cheapest Path Problem, which integrates route sustainability into arc-traversal costs using a multi-criteria decision-making (MCDM) approach. This approach serves three primary purposes. Firstly, it facilitates the integration of stakeholders' views regarding the significance of sustainability elements within routes and their spatial and temporal contexts and enables city administrations to address conflicts between stakeholders, such as shippers, logistics service providers and residents, by involving them in decision-making processes collaboratively. Secondly, it offers additional advantages by enabling sensitivity analysis to explore various scenarios, allowing decision-makers to assess outcomes effectively. Lastly, the adoption of the MCDM approach permits the consideration of both quantitative and qualitative parameters, thereby accommodating subjective factors like safety and quality of life alongside measurable elements such as financial costs. This holistic approach acknowledges the inherent complexity of societal costs, which often transcend straightforward monetary values. Surely, if one has only quantitative parameters, like a community that charges goods vehicles EUR 10 per vehicle for passing through a pedestrian area between 8 and 10 h, and has only one stakeholder, the city administration, then the complete problem is simplified and only the path's length (in our case, the non-time-dependent part of the route's cost) needs to be recalculated in monetary units and the problem can be summarized to obtain the route's cost. Another borderline example is to place traffic signs that forbid goods vehicles from entering specific zones, such as school areas, within the community. Such a solution would require, in the suggested approach, setting the sustainability cost for affected arcs to $+\infty$ or, simply, considering the subgraph of the not affected arcs for the routing problem. However, such measures in real life exhibit a lack of flexibility, whereas the suggested approach looks at both the time of delivery and the possible route alternatives. Hence, it first looks for an option where companies can still perform their activities in a manner that is acceptable for the community (as they do deliver goods to the community) and leaves more extreme conflict resolution measures as a possible, but least considered, solution. Furthermore, the time-dependability of the TDCPP is a consequence of daily changes in the community during different time periods of a day, and more realistically describes real-life urban conditions than traditional CPP approaches.

In order to be able to implement Dijkstra's algorithm for STDCPP finding purposes [20–23], we have demonstrated that the FIFO property is satisfied and have adjusted Dijkstra's algorithm correspondingly. We evaluated the performance of the proposed adaptive route planning approach on an urban road network where the use case spatial context is derived from the traffic sign database and a pairwise comparison of different sustainability elements; the result is a consensus between authorities, research institutions, citizens and city logistics service providers. The results show that routing time-dependency and route sustainability can be successfully modelled using the suggested approach. Furthermore, the obtained alternative route suggestion was rendered an acceptable solution to all stakeholder, highlighting the possibility to integrate conflicting perspectives to navigate jointly towards a solution. This is particularly illustrated in the fact that the suggested solution resulted in a slightly longer route (conflicting with the interests of the logistics service provider) and that it did not completely avoid all locations with high sustainability costs (e.g., one school was visited). Nonetheless, a solution acceptable to all was found (including the school, which was itself a delivery location, where prolonged working hours were avoided and a compromise to receive deliveries during the school hours while avoiding the school start and end times was achieved). Moreover, the suggested approach is adaptable across various domains and/or stakeholders, as the relative importance of the sustainability elements can be reconsidered in light of the organization(s) and specific local context. Additionally, the geographically encoded traffic sign data prove to be a practical and valuable resource for describing the spatial context of road networks. With the anticipated rise in autonomous vehicle usage relying on such databases and additional services, such as ISA (Intelligent Speed Adaptation,), their prevalence is expected to increase. The findings from the real-life use case suggest that the inclusion of sustainability-related costs, participating with up to 20% of the total route cost, is deemed acceptable by all stakeholders. However, the proposed approach exhibits a limitation reflected in the increased complexity of the cost function, leading to increased computational demands for large networks. Moreover, expanding the number of considered non-overlapping time periods would further augment complexity, as each period necessitates determining the variable component of the cost function. In addition, certain dynamic contexts, e.g., changes in the geospatial characteristics (e.g., a new educational facility is opened) or the introduction of a type of sustainability cost that was previously not relevant for a given community (e.g., new urban blue/green areas), might require revisiting the results of the pairwise comparisons among the stakeholders over time. This is a repetitive step that might be good to consider conducting in a circular manner in any case (e.g., every 5 to 10 years) to make sure that the assessment reflects well the attitudes of different stakeholders towards sustainability. Furthermore, while the availability of verified spatial routing context data may pose limitations in certain areas, it is anticipated that the availability of such, and similar, data sources will proliferate in the near future. Next to this, regular updating and verification of these data sources might pose a challenge and preferably an automated approach to this would be valuable to consider. In addition, to draw broader conclusions regarding the acceptability of sustainability-related costs in the total route cost, it would be advantageous to evaluate the proposed approach across a more extensive array of use cases encompassing a diverse set of sustainability elements. Moreover, exploring the applicability of the adaptive routing approach beyond urban settings, or within broader city areas, could potentially be an intriguing avenue for future research.

Overall, the suggested approach was flexible enough to integrate quite diverse views of different stakeholders on route sustainability. Furthermore, the cost function with fixed and spatiotemporal components seems particularly useful as general description of a wider range of time-dependent routing problems, whereas the multi-criteria decision-making adaption performed well in balancing the importance of different variable cost elements.

8. Conclusions

In this paper, we have introduced the sustainable time-dependent shortest cheapest problem that belongs to adaptive route planning approaches with complex cost functions. This way, we have extended the current, mainly travel-time-related, time-adaptive routing problems with a sustainability-related cost that participates as a variable element in the overall route's cost calculation. For this problem, we have presented a modified cost function with an integrated multi-criteria decision-making approach, showed that it exhibits FIFO consistency and demonstrated its applicability based on two real-life examples and the adjusted Dijkstra algorithm. Subsequent research will concentrate on applying the concepts outlined in this paper to analogous issues such as the ATDTSP with time windows, the time-dependent vehicle-routing problem and the testing of the suggested approach on practical examples that include larger networks, more diverse sets of sustainability elements and larger numbers of time intervals.

Author Contributions: Conceptualization, I.S. and S.G.; methodology and validation, S.G. and I.S.; formal analysis, I.S. and S.G.; data curation, I.S.; writing—original draft preparation, I.S. and S.G.; writing—review and editing, I.S.; visualization, S.G.; project administration. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by the Regional and community funding: Special Research Fund's project Robust and Trustworthy Smart Mobility Systems (grant number BOF/STA/202209/004), the Flemish government agency for Innovation by Science and Technology and the Flemish Institute for Mobility.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The datasets presented in this article are not readily available because privacy reasons and technical limitations.

Acknowledgments: The authors thank all the participants of the Vebimobe project for their contributions to the adoption of the regional traffic sign database and the evaluation of sustainability elements' relevance for the practical examples.

Conflicts of Interest: The authors declare no conflicts of interest.

Nomenclature

Notation	**Description**
A	Arcs
a_{ij}	Arc that starts in v_i and ends in v_j
C	Costs
c_{ij}	Cost associated with the arc a_{ij}
c_{ijF}	Fixed part of the cost associated with the arc a_{ij}
c_{ijV}	Variable part of the cost associated with the arc a_{ij}
c_{ijVe}	Variable part of the cost for unique sustainability element e and arc a_{ij}
c_{ij}^T	Cost associated with the arc a_{ij} for the time period t
$C(e_i)$	Count of the unique sustainability element (e_i) appearing along the arc
$cost(P)$	Path cost
Cr_i	Criteria
cr^T	The rate at which a vehicle collects its cost along the arc a_{ij}
CI	Consistency index
CR	Consistency ratio
d	Destination vertex
D_i	Decision alternative
d_{ij}	Pairwise comparison rating for hierarchy elements i and j
e_i	Unique sustainability element

$e_i(t)$	Earliest arrival time
f	Function
G	Graph
k_i	Traffic-sign-related sustainability elements
m	Moment where two time periods switch
N	Network
o	Origin vertex
p	Proportionality constant
P_{od}	Path between vertex o and d
Q	Priority queue
R	Set of arcs with variable cost element
RI	Average consistency index of the randomly generated comparisons
S	Sequence of all sustainability elements along arc a_{ij}
si	Subcriteria
s	Space
t	Time
t_s	School-hours time period
t_{ns}	Non-school-hours time period
TT	Travel time
$T(t)$	Travel time function dependent upon the departure time
V	Vertices
w_i	Weight
x_{ij}	The decision variable regarding the arc–path incidence relationship
λ_{max}	Principal eigenvalue of the matrix D

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