A Multidimensional Approach for Logistics Routing in the Smart Territory

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Abstract. *This work proposes a multidimensional approach for analyzing the routing problem to determine the best routes considering data related to different domains of a city. The proposed strategy defines (i) a quality function for each considered dimension to evaluate the route quality and (ii) a utility function that simultaneously considers the different dimensions by weighting each of them at the decision maker's choice. The approach was implemented on a georeferenced smart city platform that integrates data from several city domains. As proof of concept, the platform is used to combine routing and public safety data and indicates the best routes according to these criteria.*

1. Introduction

Logistics comprises the efficient planning, implementation, and control of delivery collection, storage, and distribution. In this context, *routing* consists of a combinatorial optimization problem for defining exact routes to transport deliveries, resulting in the best solution for the carrier. Defining the best routes goes beyond the task of finding the shortest route since other relevant information should also be considered as means of ensuring effectiveness, efficiency, and safety of transportation [Taniguchi et al. 2001].

In smart cities, a wide range of data collected by sensors, devices, and systems on different aspects of the city are integrated to allow for combined data analysis about the territory. This leads to the concretization of the concept of *smart territory*, which refers to the ability to analyze, diagnose, and make decisions considering geographical, social, economic, and cultural features of the territory [Giovanella 2014]. When applied to logistics, such a multidimensional view enables routing based on the analysis of several city variables that might influence the choice of a route. For instance, crime occurrences in a particular city region (i.e., information related to public safety) may be decisive for carriers in the design of delivery routes, which is information about the logistics domain.

For a logistics company, delivery routes are determined considering various criteria. Information about routes for each delivery can be combined with several other information from the smart territory, such as public safety problems in the city, traffic data, problems on streets, etc. This kind of information is typically available at smart city platforms [Santana et al. 2017]. The combined analysis of route information with additional data about the city can indicate the best routes considering smart territory data as criteria.

This work proposes and implements a multidimensional approach for routing that considers smart territory information. In this approach, route data such as total distance are correlated to data from other city domains that may impact choosing routes, e.g., information related to safety occurrences. Information regarding routes and safety occurrences are organized as layers in *Smart Geo Layers* – SGeoL [Pereira et al. 2022], a smart city georeferenced platform that organizes and manages information about a city representing it as layers, each one with a set of elements (entities) having geospatial attributes. The platform allows combining diverse city domains that may impact the routing decision, such as data about safety problems (aiming at delivery integrity), problems on streets, etc.

The remainder of this paper is structured as follows. Section 2 briefly discusses related work. Section 3 presents the proposed approach for the multidimensional assessment of routes. Section 4 describes the implementation of the proposed approach and its integration with the SGeoL platform. Section 5 brings some final remarks.

2. Related Work

[Korczak and Kijewska 2019] surveyed the literature on smart logistics in the context of smart cities. The authors highlight that data gathered from several sources must be detailed, measurable, and collected in real-time, besides aggregating them for a joint analysis. Their work confirms the relevance of handling logistics issues with information from other smart city domains.

[Kubek and Więcek 2019] proposed a multi-layered decision-making strategy on logistics problems. The proposed strategy was conceived to foster integration and cooperation among the city's logistics entities, focusing on data integration and environmental and economic intelligence to enhance cargo transportation in cities and reduce environmental impact. Logistics issues are handled from a multi-layered perspective in their work, specifically aiming at transportation with environmental sustainability. This work envisions a multidimensional integrated data analysis, but it focuses on defining the best routes considering information from diverse city domains that may impact routing.

[Abella et al. 2017] highlight that smart cities are essential to deal with some of the significant challenges faced by society, such as overpopulation, transportation, pollution, sustainability, safety, and health, and smart city portals offer a large amount of data that can be used by private and public bodies to create services. Their work presents a model that demonstrates how smart city data can generate value for citizens and society. The model includes several dimensions that make data attractive to reuse, besides analyzing mechanisms to create innovative products and services. Such a vision corroborates the proposal of this work in using data from different city domains in a joint analysis to determine the best routes in the logistics context.

3. A Multidimensional Approach for Route Assessment

The multidimensional approach proposed in this work aims to determine the best routes considering data related to different city domains. It seeks to answer the following question: *How to quantitatively assess a route considering multiple dimensions, e.g., total distance, safety aspects, etc.?*

The proposed approach relies on a methodology composed of three elements. The first element concerns *characterizing* the different dimensions according to the layers and possible overlays among them. The second element is defining a *quality function* to assess a route considering each dimension. The third element is related to defining a *utility function* to assess a route by freely weighting each dimension.

Table 1. Example of dimension characterization

Layer	Variable of interest	Value	Qualification
Routes	Route – sequence of lines, each one defined by a pair of points (p_x, p_y)	Total distance	Negative
Occurrences	Occurrence – located in the space by a pair of coordinates (o_x, o_y)	Distance of an occurrence from the points defining a route	Positive

This section presents the proposed approach through a simple illustrative example considering the combination of data regarding the route's total distance and information about safety occurrences on the territory. For this work, it is worth emphasizing that the best route is not necessarily the shortest or the safest one; instead, it can be defined according to the decision maker's parametrizations. Furthermore, the proposed approach is flexible in that it can incorporate other dimensions of interest.

3.1. Dimension Characterization

The characterization of different dimensions according to layers and possible combinations among them consists in: (i) defining the layer that represents the considered information; (ii) defining the variable of interest to be considered; (iii) identifying the value that quantitatively expresses the variable of interest; and (iv) qualifying the value, whether positively (the greater, the better) or negatively (the smaller, the better). Table 1 presents the characterization of information regarding routes and occurrences, which will be considered in the example.

3.2. Route Quality Assessment

The quality assessment of a route consists in defining a quality function for each considered dimension. For the dimension regarding routes, the quality of a route r, given by $Q(r)$, is equal to the total distance between the route origin and target points (i and j) as defined by Equation 1:

$$Q(r) = d(i, j) \tag{1}$$

For the dimension regarding safety occurrences, the quality of a route r, given by $Q(r)$, is equal to the mean of the sum of the Euclidean distances of occurrences with respect to the n route points as defined by Equation 2:

$$Q(r) = \frac{1}{n} \sum_{o \in O} \sum_{p \in P} \sqrt{(o_x - p_x)^2 + (o_y - p_y)^2} \tag{2}$$

with $O = \{o_1, o_2, \ldots, o_m\}$ being the set of occurrences, each one represented by a point of coordinates (o_x, o_y), and $P = \{p_1, p_2, \ldots, p_n\}$ being the set of route points, each point with coordinates (p_x, p_y).

3.3. Route Utility Assessment

Once the quality of a route is assessed, it is necessary to define a utility function that simultaneously considers the different dimensions, each one being freely weighted at the decision-maker's choice. However, as the variables of interest are expressed in different units, the quality of each route must be normalized according to its respective qualification, whether positive or negative. Normalizing the quality of a route results in an integer value $Q_N(r) \in [0, 1]$.

For a positive qualification (the greater, the better), as it is the case of the distance of occurrences from a route, the normalized quality of a route r, given by $Q_N(r)$, is calculated according to Equation 3:

$$Q_N(r) = \frac{Q(r) - Q_{min}}{Q_{max} - Q_{min}} \qquad (Q_{max} \neq Q_{min}) \tag{3}$$

with $Q(r)$ being the assessment value of route r and Q_{min} and Q_{max} being the smallest and the greatest quality value among all possible routes, respectively.

For a negative qualification (the smaller, the better), as it is the case of the total distance of a route, the normalized quality of a route r, given by $Q_N(r)$, is calculated according to Equation 4:

$$Q_N(r) = \frac{Q_{max} - Q(r)}{Q_{max} - Q_{min}} \qquad (Q_{max} \neq Q_{min}) \tag{4}$$

For both qualifications, if $Q_{min} = Q_{max}$, then $Q_N(r) = 1$.

Finally, the utility function to assess a route r for the multiple dimensions and weights assigned to them considers the normalized quality measures $Q_{Ni}(r)$ for the $k > 1$ dimensions. This utility function $u(r)$ is expressed by Equation 5:

$$u(r) = \sum_{i=1}^{k} Q_{Ni}(r) * w_i \qquad (\sum_{i=1}^{k} w_i = 1) \tag{5}$$

with $W = (w_1, w_2, \ldots, w_k)$ being a vector of weights $w_i \in [0,1]$ to weight each dimension i. Therefore, the route with maximal utility will be considered the best one.

3.4. An Example

For illustration purposes, consider the directed graph shown in Figure 1 representing the possible routes between points A (origin) and F (target). In this graph, nodes represent the route points, each one with its respective coordinates (p_x, p_y), and edges represent the route segments, each one labeled with a numeric value expressing the distance between two points. This graph shows four possible routes between points A and F, namely, $R_1 : A \rightarrow B \rightarrow C \rightarrow D \rightarrow F$, $R_2 : A \rightarrow C \rightarrow D \rightarrow F$, $R_3 : A \rightarrow F$, and $R_4 : A \rightarrow E \rightarrow F$. The graph also presents the location of occurrences, each one with coordinates (o_x, o_y).

Considering both dimensions, the shortest route is not necessarily the safest one and vice-versa. As shown in Table 2, using Equation 1 and Equation 2 to assess the quality of each of the four routes, route R_4 has the best quality in terms of distance ($Q(R_4) = 14$), but it is the least safe one ($Q(R_4) = 6.3629$). On the other hand, route R_1 has the best quality in terms of being far from the registered occurrences ($Q(R_1) = 8.1301$) despite being the longest one ($Q(R_1) = 27$). This makes it evident the need for an analysis that simultaneously considers both dimensions, instead of a single dimension in isolation, to decide which is indeed the best route.

According to the proposed approach, the next step is normalizing the quality computed for each route for each dimension. As the dimension regarding occurrences has a positive qualification and the one regarding distance has a negative qualification, Equation 3 and Equation 4 are respectively used to normalize the quality of each route. Table 2

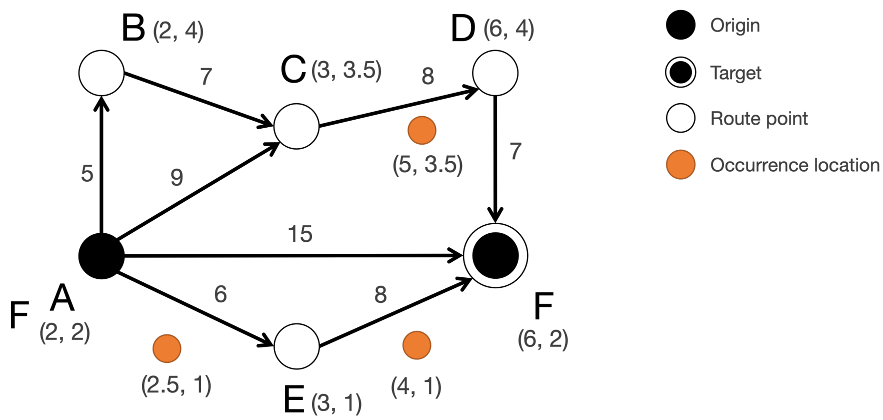

Figure 1. Example of graph representing the possible routes between two points and the location of occurrences.

Table 2. Example of route quality and utility assessment considering both distance and safety dimensions

Route	Quality		Normalized quality		Utility	
	Distance	Safety	Distance	Safety	$W_1 = (0.5, 0.5)$	$W_2 = (0.4, 0.6)$
R_1	27	8,1301	0,0000	1.0000	0.5000	0.7000
R_2	24	7.7406	0.2307	0.7796	0.5052	0.6149
R_3	15	7.1935	0.9230	0.4701	0.6965	0.6059
R_4	14	6.3629	1.0000	0.0000	0.5000	0.3000

shows the normalized quality of each dimension for each assessed route. The best route for a dimension has normalized quality $Q_N(r) = 1$ and the worst route has $Q_N(r) = 0$.

Equation 5 is used to compute the utility of each route according to weights assigned to each dimension. As shown in Table 2, for a vector of weights $W_1 = (0.5, 0.5)$ assigning equal importance to both dimensions, route $R_3 : A \rightarrow F$ is the one of maximal utility, even though it is not necessarily the shortest route (R_4) or the safest one (R_1). When safest routes are preferred using, for example, a vector of weights $W_2 = (0.4, 0.6)$, route $R_1 : A \rightarrow B \rightarrow C \rightarrow D \rightarrow F$ is the one with maximal utility despite being the longest route.

4. Implementation

This section describes the concretization of the approach presented in this work. Activities include: (i) generating delivery points; (ii) generating routes from delivery points; (iii) implementing the multidimensional approach itself; and (iv) integrating with the SGeoL smart city platform considering the routes and safety layers.

Generation of delivery points. The *Loggi Benchmark for Urban Deliveries* (Loggi-BUD)[1] was used to generate delivery points[2]. These points were generated by running the benchmark's pipeline along with the Open Source Routing Machine (OSRM) routing engine [Luxen and Vetter 2011]. Each delivery point is represented in the JSON format and contains geographical information generated from the Brazilian Institute of Geography and Statistics (IBGE) Census microdata and the

[1]Available at https://github.com/loggi/loggibud.

[2]The process to generate delivery points is described at https://bit.ly/loggibud-rn.

Brazilian Institute of Applied Economic Research (IPEA) geodata. The GeoJSON format [Internet Engineering Task Force 2016] is used to properly represent delivery points with georeferenced information. GeoJSON is an open standard proposed as an extension to the JSON format by adding elements that can be located in the geographical space, such as points (including addresses and locations), lines (including streets and roads), and polygons (to delimit areas in the territory), and their properties. A JavaScript program converts the representation of delivery points from JSON to GeoJSON. This conversion also allows plotting delivery points as a layer in the SGeoL platform.

Generation of routes. Delivery points are used to generate routes using the OSRM services. Interaction with OSRM happens through an HTTP GET request to the *route* service, which can determine the fastest route between coordinates. This request returns a *polyline* object that represents a set of segments resulting from the codification of the sequence of coordinates forming the route. Routes are generated by recursively considering multiple vehicles, the delivery size, and the total vehicle's capacity limit.

Implementation of the multidimensional approach for route evaluation. The implementation of the approach proposed in this work initially considered two information sources. The *Delivery Points* layer contained the previously generated delivery points defining possible delivery routes. The *Safety* layer is an existing layer to represent the location of real crime occurrences in the neighborhoods of Natal, a city in Northeastern Brazil. The JavaScript programming language was used to implement the approach[3]. Future work will consider data from other layers for the multidimensional approach.

Integration with SGeoL. The SGeoL platform [Pereira et al. 2022] offers a comprehensive set of functionalities to facilitate the development of smart city applications. It integrates heterogeneous data from different domains and locates them over the territory through geographical information. The *Development Dashboard* is a Web interface to help developers create new applications, layers, and context entities, as well as manage access control to layers and import data. The *Visualization Dashboard* provides users with a Web interface to visualize context entities over the city's urban space, besides correlating information from different layers. To make use of these development and visualization functionalities, the generated and evaluated routes are represented in the GeoJSON format and imported to SGeoL via HTTP POST requests, resulting in a new layer named *Routes*.

Figure 2 shows an overlapping of three layers, two of them related to routing (delivery points and routes) and one related to safety (location of occurrences). This overlapping enables the user to visualize route tracing and the relative distance of routes from the location of safety occurrences. In this example, the selected (preferred) route seems to be longer in the distance than the other available route, but it was evaluated as the safest one. It is worth emphasizing that other possibly existing layers could be overlapped with those three, which could give rise to adding new dimensions to be considered in the process of analyzing routes by following the approach presented in this work.

5. Final Remarks

This work presented a multidimensional approach for logistics routing that considers information provided by the smart territory. Such an approach correlates data about routes with ones from other city domains that may impact choosing the route. The proposed

[3]The implementation is available at https://projetos.imd.ufrn.br/logrouter/algorithmsmartlogrouter.

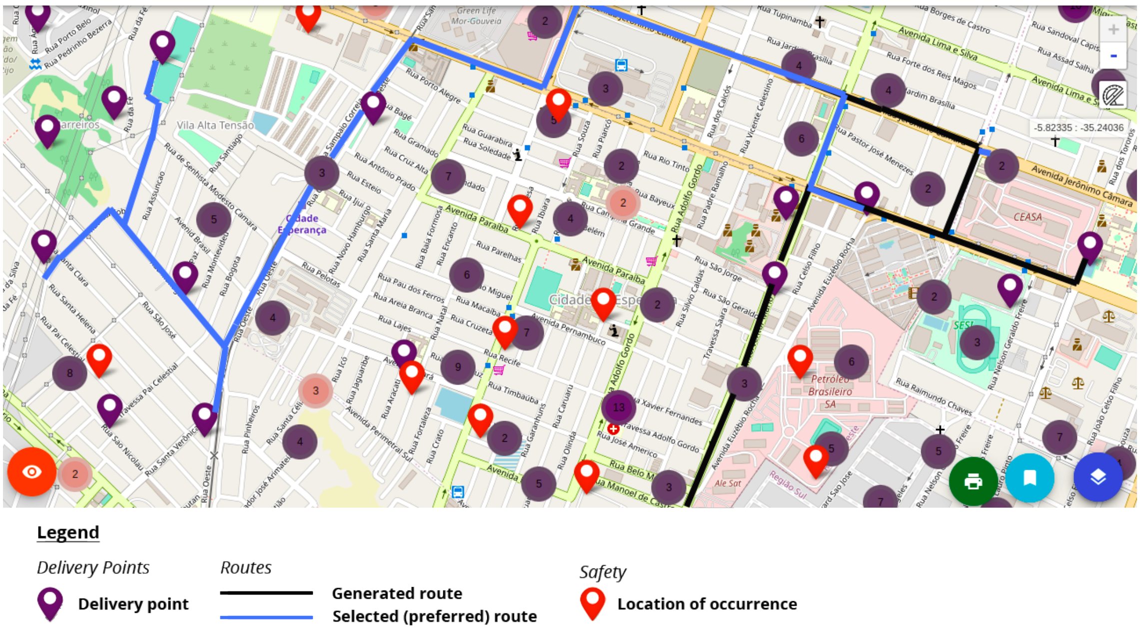

Figure 2. Overlapping routing and safety layers in SGeoL.

approach consists in: (i) characterizing the different dimensions according to the chosen domains, (ii) defining a function to assess the quality of a route considering each dimension; and (iii) defining a utility function to assess each route by freely weighting each dimension. The implementation of the approach was done upon SGeoL, a smart city georeferenced platform. The proof of concept was instantiated in Natal, a city in Northeastern Brazil, and shows the results of correlating routing data with public safety information.

Future work will improve the integration of the multidimensional route assessment approach proposed in this work with the SGeoL platform. SGeoL offers a wide range of resources that enable users to visualize georeferenced information as layers and overlay them while supporting the development of applications with these layers [Pereira et al. 2022]. The integration will develop an application atop SGeoL to enable users to visualize the routes generated and assessed, as well as configure the weights given to the considered dimensions according to their interests. Another line of future work is incorporating other dimensions of the smart territory to assess routes. Due to the flexibility of this work's approach, considering other dimensions of interest requires only (i) characterizing each dimension with information available on the layers and (ii) defining a quality function to quantitatively assess each dimension. Therefore, incorporating new dimensions can enrich route assessment by considering diverse information from the smart territory that may influence logistics routing.

Finally, the approach proposed in this paper can also be expanded towards multi-objective combinatorial optimization while enhancing the realistic conditions of logistics routing. Multiobjective optimization can be defined as the problem of optimizing (minimizing or maximizing) multiple, possibly conflicting objective functions [Ehrgott 2005]. The most classical approach for solving a multiobjective problem relies on scalarization, i.e., transforming the considered criteria into a single function by assigning aprioristic weights to each dimension [Ehrgott and Gandibleux 2003] as done in this work. However, increasing the number of smart territory dimensions and the diverse nature of associated quality functions might make it more difficult to find viable optimal solutions that simultaneously consider all the criteria. Delegating the choice of the solutions to take exclusively for the decision-maker could leave out other possible trade-offs among the dimensions. Future work can be devoted to investigating the use of a multiobjective optimization approach to automatically determining not a single but a set of optimal routes representing a compromise of multiple smart territory dimensions.

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