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DIGITAL FRONTIERS IN LOGISTICS: A SCALABLE APPROACH TO WIDE-AREA TRANSPORTATION NETWORK OPTIMIZATION

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Abstract. This paper delves into the academic significance of addressing both the Traveling Salesman Problem (TSP) and the Vehicle Routing Problem (VRP). It conducts a comparative analysis between a source-driven method and the Nearest Neighbor algorithm, both falling under the category of greedy algorithms, in the context of TSP resolution. Focused on a national-scale transportation network with five logistic centers and sixty-two retail stores, the study illuminates the computational challenges in optimizing wide-area logistics.

Implementing state-of-the-art technologies, including Docker for containerization and PHP Symfony with Doctrine ORM for backend development, the study introduces a highly scalable application. The system utilizes a MySQL database to store actual road distances between nodes, enabling the determination of the minimum-cost route from logistic centers to multiple stores and back, emphasizing the utilization of real road distances.

This research offers valuable insights into addressing real-world computational challenges in Logistics through a practical and scalable application. Emphasizing the scalability and processing power of the implemented solution, along with the utilization of cutting-edge tools and frameworks widely adopted in the IT industry, adds depth to its technological significance.

Keywords: Transportation Network Optimization, Traveling Salesman Problem (TSP), Greedy Algorithms, Nearest Neighbor Method, Scalable Application, Logistic Centers, Cutting-Edge Technologies.

1. INTRODUCTION

In the ever-evolving landscape of Logistics and Transportation, the optimization of networks plays a pivotal role in enhancing efficiency, reducing costs, and improving overall performance. This paper explores the extensive and highly consequential domain of optimizing transportation networks, with a specific emphasis on the renowned Traveling Salesman Problem (TSP **[1]**). Simultaneously, the study equally concentrates on the Vehicle Routing Problem (VRP **[2]**), a generalization of the TSP (**Figure 1**). The motivation behind this research stems from the escalating importance of addressing the challenges posed by large-scale transportation networks, where the need for optimized routes between logistic centers and multiple stores is of paramount importance.

Transportation optimization has been a subject of extensive research, with the Traveling Salesman Problem standing out as a complex and widely studied computational challenge. The urgency of finding optimal routes between logistic centers and stores has only increased with the growing demands of modern supply chains. In this context, earlier results in the industry have laid the groundwork for understanding and tackling these challenges. This paper builds upon and extends these earlier findings, introducing new results that contribute to the ongoing discourse in the field.

One of the key innovations presented in this study is the computational implementation of a highly scalable application. Leveraging cutting-edge tools and frameworks such as Symfony for PHP and Docker for containerization, the application efficiently processes vast amounts of data. The relational database management, facilitated by Doctrine ORM, stores real-road distances between all nodes, creating a complete graph of considerable dimensions. This comprehensive approach provides a solid foundation for constructing and optimizing large-scale transportation networks, considering the real distances between logistic centers and stores.

This study compares two optimization approaches - one based on a source-driven method and the other employing a nearest neighbor strategy, both falling under the category of greedy algorithms. The research highlights the motivations for optimizing transportation networks, showcases industry results, introduces novel findings, and evaluates the computational implementation of a scalable application. Insights gained from examining these greedy strategies provide valuable perspectives on their trade-offs, showcasing that the second method consistently delivers visibly superior results compared to the first.

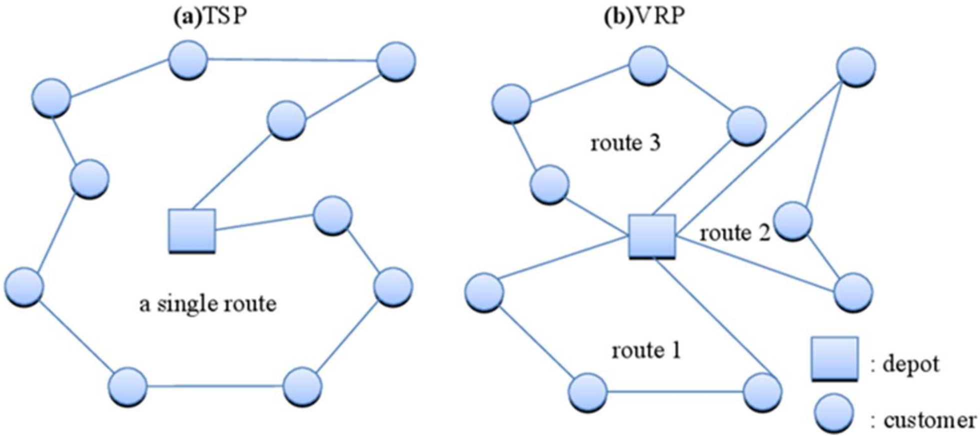


Figure 1 - Illustration of the traveling salesman problem (TSP) and vehicle route problem (VRP) route patterns [3]

2. PRELIMINARIES

2.1 Dynamic Paradigms in Transportation Network Optimization: A Contemporary Overview

Advancements in information technology have significantly enhanced the efficiency of transport logistics, elevating information and computer support to pivotal roles within the logistics framework. In **[4]**, an automated system designed for optimizing freight traffic on transportation networks is introduced. This comprehensive software package seamlessly integrates data input, route computation, and transport scheme optimization.

Furthermore, the exposition delves into the mathematical model that underlies the structure of a transportation network.

- For m starting points ($A_1, A_2, ..., A_m$),
- there are, respectively, $a_1, a_2, ..., a_m$ units of homogeneous cargo,
- that need to be delivered to n destination points ($B_1, B_2, ..., B_n$) in the required quantities of $b_1, b_2, ..., b_n$ units.
- a_i represents the merchandise stocks at the i-th starting point of transportation A_i,
- while b_j represents the required merchandise at the j-th destination point B_j,
- x_{ij} represents the number of units of merchandise transported from point A_i to point B_j
- c_{ij} - the tariffs (cost) of transporting one unit of merchandise from the i-th starting point to the j-th destination point.

The objective function Z achieves the optimal solution when it has a minimum value. The graphical representation for this mathematical model can be found in **Figure 2.**

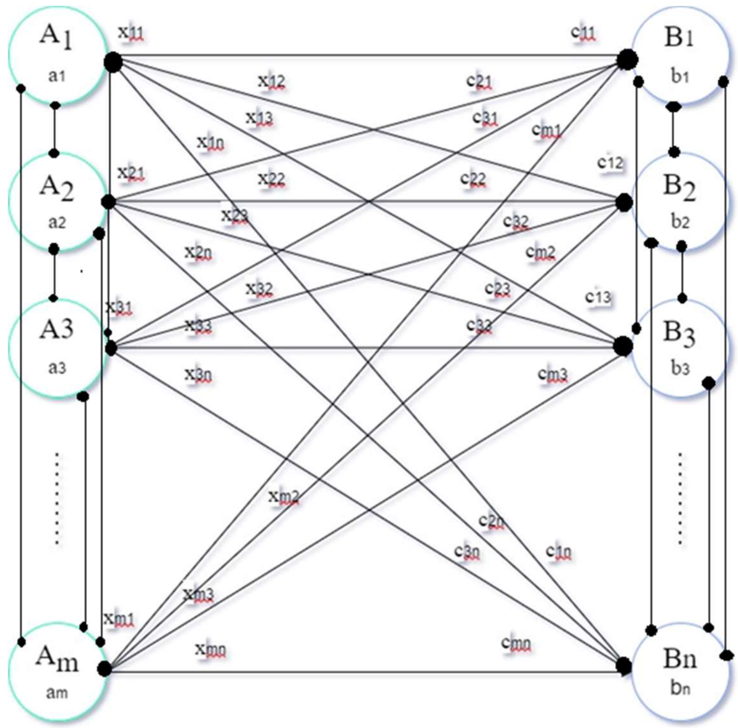


Figure 2 - Mathematical Graphic Representation of a Transportation Network

$$Z = \sum_{j=1}^{n} \sum_{i=1}^{m} c_{ij} x_{ij} \rightarrow \min$$

, where

$$\sum_{i=1}^{n} x_{ij} = a_i \quad (i = \overline{1,m})$$

$$\sum_{i=1}^{m} x_{ij} = b_j \quad (j = \overline{1,n})$$

and $x_{ij} \geq 0$

The analyzed work **[5]** delves into the utilization of Dijkstra's algorithm **[6]** in optimizing extensive road transportation networks. A specific emphasis is placed on the intricacies of home delivery optimization within these large transportation networks, addressing challenges like congested traffic and dynamic changes in road infrastructure. The authors propose a hybrid meta-heuristic approach, integrating Ant Colony Optimization (ACO) **[7]** with Dijkstra's algorithm **[6]** and real-time traffic maps from Japan. This integration aims to identify optimal routes considering both time and distance metrics. The study introduces theoretical concepts such as heuristics and meta-heuristics, providing an abstract framework for designing heuristic algorithms. Notably, meta-heuristics play a crucial role in tackling combinatorial optimization problems, including those associated with Traveling Salesman Problems (TSP) and Vehicle Routing Problems (VRP).

As discussed in **[8]**, Combinatorial Optimization focuses on determining optimal solutions within a finite set of discrete possibilities. In contrast to continuous variables, dealing with an infinite range of values, combinatorial optimization addresses finite or countable options, alternatives, or distinct states that a variable or problem can take. The paper sheds light on Ant Colony Optimization (ACO), a stochastic search algorithm inspired by the foraging behavior of ants, as discussed in **[9]**. Utilizing indirect communication through pheromone trails, ACO falls under the category of stochastic search heuristics, exploring the search space through random movements and accepting new solutions based on probabilistic criteria to find satisfactory solutions to optimization problems, aiming to avoid local minima.

In alignment with these principles, the present work focuses on the Traveling Salesman Problem (TSP), demonstrating its relevance and applicability. The study involves a database comprising 5 logistic centers and 62 stores, forming a complete graph where the real road distances between each node connection are known.

In the subsequent article **[10]**, the Nearest Neighbor Method **[11]** takes center stage for optimizing logistics transport. This study is rooted in real-world scenarios within the private sector, emphasizing the practical application of optimization strategies in managing transportation networks.

The article conducts a detailed comparative analysis, highlighting the complexities of greedy approaches. While known for their relative ease of implementation, these methods make decisions solely at the current step without a comprehensive evaluation of the overall solution. Nevertheless, in specific contexts, they demonstrate an ability to provide quick and sometimes more satisfactory solutions than dynamically programmed methods, albeit with increased implementation simplicity.

It is crucial to clarify the essence of greedy algorithms. These algorithms prioritize immediate benefits without considering the broader picture of the optimal path. They are simpler to implement but may overlook global optimality, making their effectiveness context-dependent.

Regarding the specific analysis conducted within **[10]**, the focus is on optimizing logistic processes within a private sector context. The study centers on a company managing a transportation network, aiming to minimize travel distances and enhance overall logistics efficiency.

2.2 Mathematical Formulations of Static Distances in Transport Networks: An In-depth Analysis

This section delves into mathematical approaches employed in the context of transportation network optimization, specifically focusing on static distance formulations. The examination focuses on implementations that adopt a static, mathematical perspective to determine distances between nodes in a transport network. These approaches aim to achieve swift and satisfactory solutions, particularly in scenarios where abundant informational and road resources may not be readily available.

One notable mathematical foundation employed in such implementations is the Haversine formula **[12]**, known for its efficiency in rapidly calculating distances between two geographical points on the Earth's surface.

In a related context, the paper **[13]** introduces another approach that involves comparing distances from a store to multiple customer addresses. The objective is to determine the nearest location and optimize the delivery route for a workday. The utilization of the Haversine formula plays a crucial role in making these distance comparisons. This formula, rooted in spherical trigonometry, provides estimations of distances on the Earth's surface. Despite its simplicity, the Haversine formula proves effective for approximating distances on short routes or in situations where precision requirements are moderate.

Drawing a parallel to the paper **[14]** the structural similarities between the optimization of a transportation network and societal partitioning become evident. Both address the strategic positioning of logistic centers or Steiner points to efficiently construct networks that minimize distances and associated costs, showcasing the versatile applications of mathematical optimization techniques in diverse domains.

3. LEVERAGING INDUSTRY TECHNOLOGIES FOR DYNAMIC AND SCALABLE TRANSPORTATION OPTIMIZATION

This section elucidates the intricacies of implementing an application designed for the optimization of transportation networks over extensive areas. The focus centers on a network comprising 5 logistic centers and 62 stores, structured as a complete graph. Each connection, be it between logistic centers, logistic centers and stores, or between stores, is characterized by real road distances expressed in kilometers. These distances were dynamically obtained by querying the Google Maps system, leveraging powerful tools for the efficient processing of massive datasets.

The application employs the PHP Symfony framework for the development of computational logic, organized into services, controllers, and object classes, incorporating relational entities based on foreign keys (such as LogisticToLogisticCost, LogisticStoreCost, StoreToStoreCost) through Doctrine ORM **(Figure 3)**. The process involves populating a MySQL database **(Figure 4)** using object classes of command type, executing either once or scheduled as needed, fetching real road distances in a highly efficient manner from Google Maps. Summing up to a total of 4112 distance links, it covers connections between logistic centers and stores.

The application stands out for its scalability, easily expandable due to cutting-edge industry technologies like Docker containerization **(Figure 5)**. This is manifested using Docker containers for the MySQL database service, the PHP service for processing implementation logic, and the Nginx service for the web server, showcasing the flexibility and portability of the solution.

```php
<?php

namespace App\Entity;

use App\Repository\LogisticStoreCostRepository;
use Doctrine\ORM\Mapping as ORM;

papara.cezar
#[ORM\Entity(repositoryClass: LogisticStoreCostRepository::class)]
class LogisticStoreCost
{
    1 usage
    #[ORM\Id]
    #[ORM\GeneratedValue]
    #[ORM\Column]
    private ?int $id = null;

    2 usages
    #[ORM\ManyToOne(targetEntity: Logistic::class, cascade: ["persist"])]
    #[ORM\JoinColumn(name: "logistic_id", referencedColumnName: "id")]
    private Logistic $logistic;

    2 usages
    #[ORM\ManyToOne(targetEntity: Store::class, cascade: ["persist"])]
    #[ORM\JoinColumn(name: "store_id", referencedColumnName: "id")]
    private Store $store;
```

Figure 3 - Example of Doctrine Relation Entity mapping

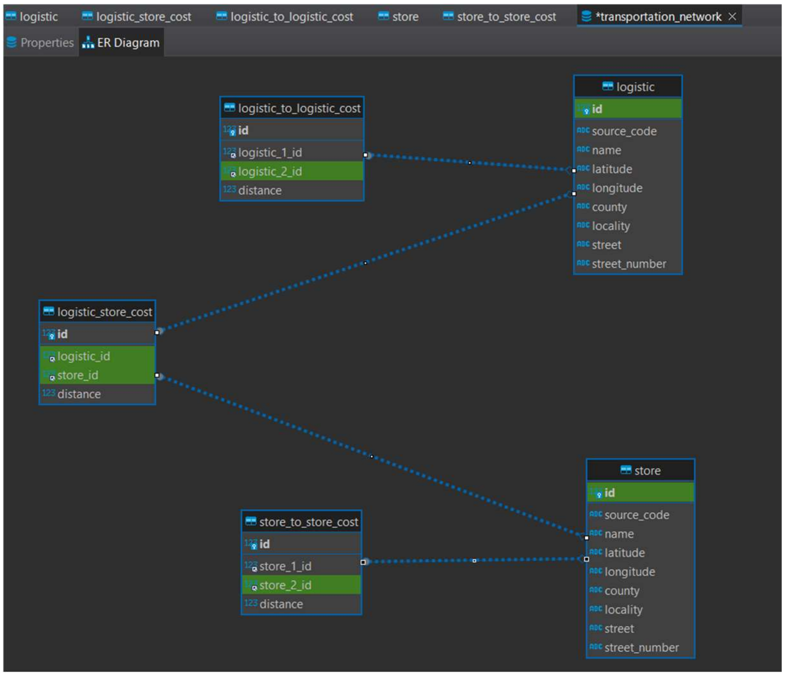


Figure 4 -Database ER Diagram

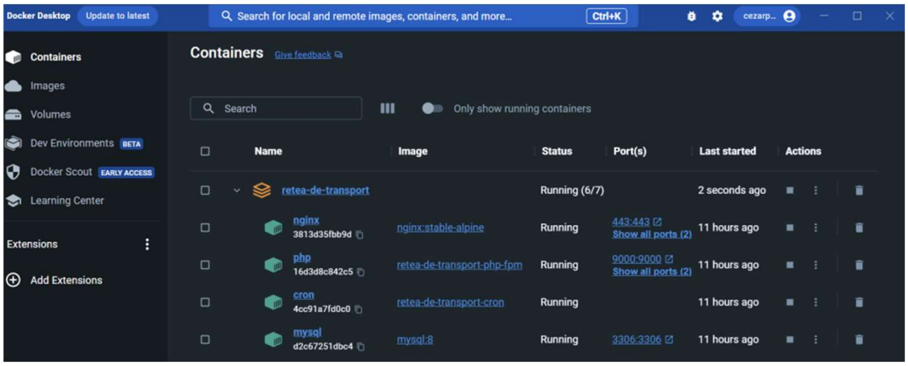


Figure 5 -Docker Application Containers

The application leverages two optimization strategies within the realm of transportation networks. On one hand, it incorporates a Source-Driven approach, and on the other, it employs a Nearest Neighbor method—both falling under the category of greedy algorithms. Both approaches are implemented as services, invoked from controllers for data analysis and presentation to the user interface.

The application **(Figure 6)** is designed to analyze the itinerary of minimum cost starting from an origin point, in this case, a logistic center selected from the network. Traversing multiple stores considered as intermediate points and destinations, the application provides a tabular presentation of the itinerary of minimum cost, detailing additional kilometers to each node at each stage. Additionally, it constructs and displays a visual representation of the route on a map, utilizing Google Maps.

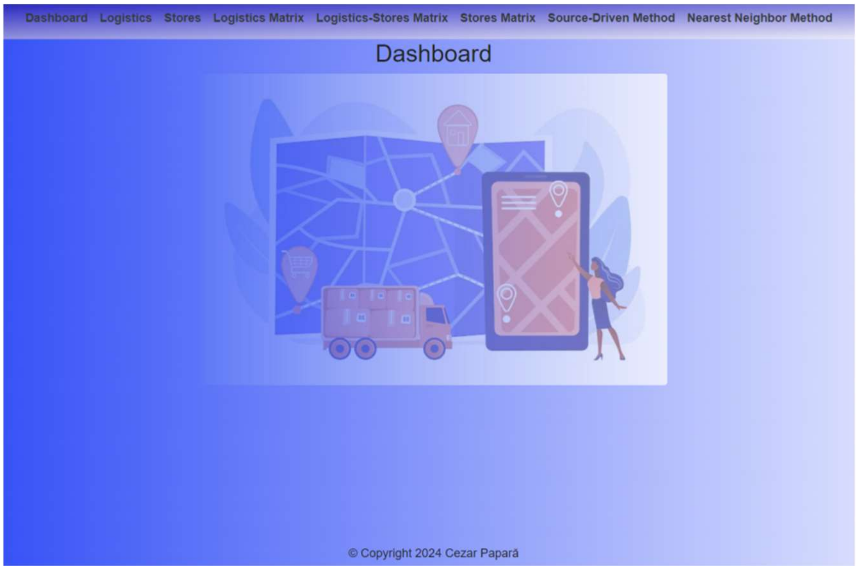
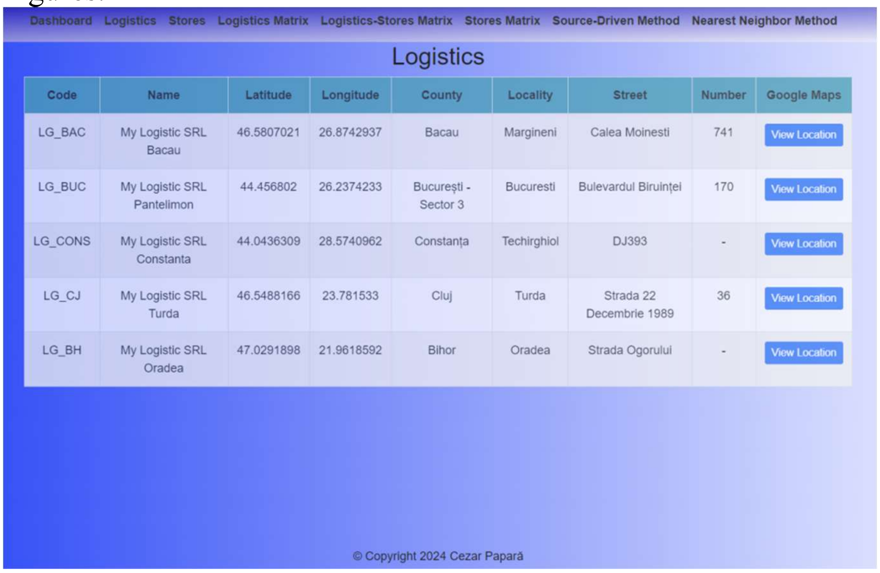


Figure 6 -Homepage of the application

4. IMPLEMENTATION OF OPTIMIZATION METHODS ON A LARGE DATASET AND COMPARATIVE ANALYSIS OF RESULTS

In this section, we incorporated 5 logistics centers into the database **(Figure 7)**, each featuring fields such as id, source_code, name, latitude, longitude, county, locality, street, and street_number. Similar attributes were applied to the 62 stores **(Figure 8)**. Furthermore, connection tables based on id were established, comprising links between logistics centers and other logistics centers (20 connections, **Figure 9**), logistics centers and stores (310 connections, **Figure 10**), as well as stores and other stores (3782 connections, **Figure 11**).

The two services developed for Source-Driven Method**(Figure 12)** and the Nearest Neighbor method **(Figure 13)** were invoked. At each iteration, the accumulated kilometers were displayed, dynamically generating URLs for each partial route and the overall route. The total number of kilometers from the source to destinations and back to the source was calculated. The results, including the added kilometers per iteration, were dynamically generated and are presented in the subsequent figures.



Code	Name	Latitude	Longitude	County	Locality	Street	Number	Google Maps
LG_BAC	My Logistic SRL Bacau	46.5807021	26.8742937	Bacau	Margineni	Calea Moinesti	741	View Location
LG_BUC	My Logistic SRL Pantelimon	44.456802	26.2374233	București - Sector 3	Bucuresti	Bulevardul Biruinței	170	View Location
LG_CONS	My Logistic SRL Constanta	44.0436309	28.5740962	Constanța	Techirghiol	DJ393	-	View Location
LG_CJ	My Logistic SRL Turda	46.5488166	23.781533	Cluj	Turda	Strada 22 Decembrie 1989	36	View Location
LG_BH	My Logistic SRL Oradea	47.0291898	21.9618592	Bihor	Oradea	Strada Ogorului	-	View Location

Figure 7 - Logistic entity


Dashboard Logistics Stores Logistics Matrix Logistics-Stores Matrix Stores Matrix Source-Driven Method Nearest Neighbor Method

Stores

Code	Name	Latitude	Longitude	County	Locality	Street	Number	Google Maps
AB01	My Store SRL Alba Iulia	46.081172	23.573064	Alba	Alba Iulia	Gheorghe Sincai	4	View Location
AG01	My Store SRL Pitesti	44.87979	24.841384	Argeş	Pitesti	B-dul Nicolae Balcescu	158	View Location
AR01	My Store SRL Arad	46.20131	21.255405	Arad	Arad	Calea Aurel Vlaicu	289C	View Location
BAC1	My Store SRL Bacau 1 - Republicii	46.508976	26.927579	Bacău	Bacau	Republicii	185	View Location
BC02	My Store SRL Bacau 2 - Abatorului	46.573041	26.883496	Bacău	Bacau	Abatorului	5	View Location
BCT1	My Store SRL Bucuresti Giurgiului (Sector 4)	44.371624	26.091193	Bucureşti - Sector 4	Bucuresti	Actiunii	2-4, Sector 4	View Location
BCT2	My Store SRL Bucuresti Valea Cascadelor (Sector 6)	44.424264	25.99674	Bucureşti - Sector 6	Bucuresti	Valea Cascadelor	26, Sector 6	View Location
BCT3	My Store SRL	44.473568	26.161622	Bucureşti -	Bucuresti	Soseaua	426,	View Location

Figure 8 - Store entity


Dashboard Logistics Stores Logistics Matrix Logistics-Stores Matrix Stores Matrix Source-Driven Method Nearest Neighbor Method

Logistics Routing Matrix

Logistic 1 Code	Logistic 1 Name	Logistic 1 Latitude	Logistic 1 Longitude	Logistic 2 Code	Logistic 2 Name	Logistic 2 Latitude	Logistic 2 Longitude	Distance (Km)	Google Maps
LG_BAC	My Logistic SRL Bacau	46.5807021	26.8742937	LG_BUC	My Logistic SRL Pantelimon	44.456802	26.2374233	286 Km	View Route
LG_BAC	My Logistic SRL Bacau	46.5807021	26.8742937	LG_CONS	My Logistic SRL Constanta	44.0436309	28.5740962	390 Km	View Route
LG_BAC	My Logistic SRL Bacau	46.5807021	26.8742937	LG_CJ	My Logistic SRL Turda	46.5488166	23.781533	323 Km	View Route
LG_BAC	My Logistic SRL Bacau	46.5807021	26.8742937	LG_BH	My Logistic SRL Oradea	47.0291898	21.9618592	498 Km	View Route
LG_BUC	My Logistic SRL Pantelimon	44.456802	26.2374233	LG_BAC	My Logistic SRL Bacau	46.5807021	26.8742937	286 Km	View Route
LG_BUC	My Logistic SRL Pantelimon	44.456802	26.2374233	LG_CONS	My Logistic SRL Constanta	44.0436309	28.5740962	221 Km	View Route
LG_BUC	My Logistic SRL	44.456802	26.2374233	LG_CJ	My Logistic SRL Turda	46.5488166	23.781533	439 Km	View Route

Figure 9 - LogisticToLogisticCost entity

Dashboard Logistics Stores Logistics Matrix Logistics-Stores Matrix Stores Matrix Source-Driven Method Nearest Neighbor Method

Logistics-Stores Routing Matrix

Logistic Name	Logistic Latitude	Logistic Longitude	Store Name	Store Latitude	Store Longitude	Distance (Km)	Route On Google Maps
My Logistic SRL Bacau	46.5807021	26.8742937	My Store SRL Alba Iulia	46.081172	23.573064	379 Km	View Route
My Logistic SRL Bacau	46.5807021	26.8742937	My Store SRL Pitesti	44.87979	24.841384	423 Km	View Route
My Logistic SRL Bacau	46.5807021	26.8742937	My Store SRL Arad	46.20131	21.255405	628 Km	View Route
My Logistic SRL Bacau	46.5807021	26.8742937	My Store SRL Bacau 1 - Republicii	46.508976	26.927579	14 Km	View Route
My Logistic SRL Bacau	46.5807021	26.8742937	My Store SRL Bacau 2 - Abatorului	46.573041	26.883496	2.6 Km	View Route
My Logistic SRL Bacau	46.5807021	26.8742937	My Store SRL Bucuresti Giurgiului (Sector 4)	44.371624	26.091193	304 Km	View Route
My Logistic SRL Bacau	46.5807021	26.8742937	My Store SRL Bucuresti Valea Cascadelor (Sector 6)	44.424264	25.99674	309 Km	View Route
My Logistic SRL Bacau	46.5807021	26.8742937	My Store SRL Bucuresti Colentina (Sector 2)	44.473568	26.161622	287 Km	View Route

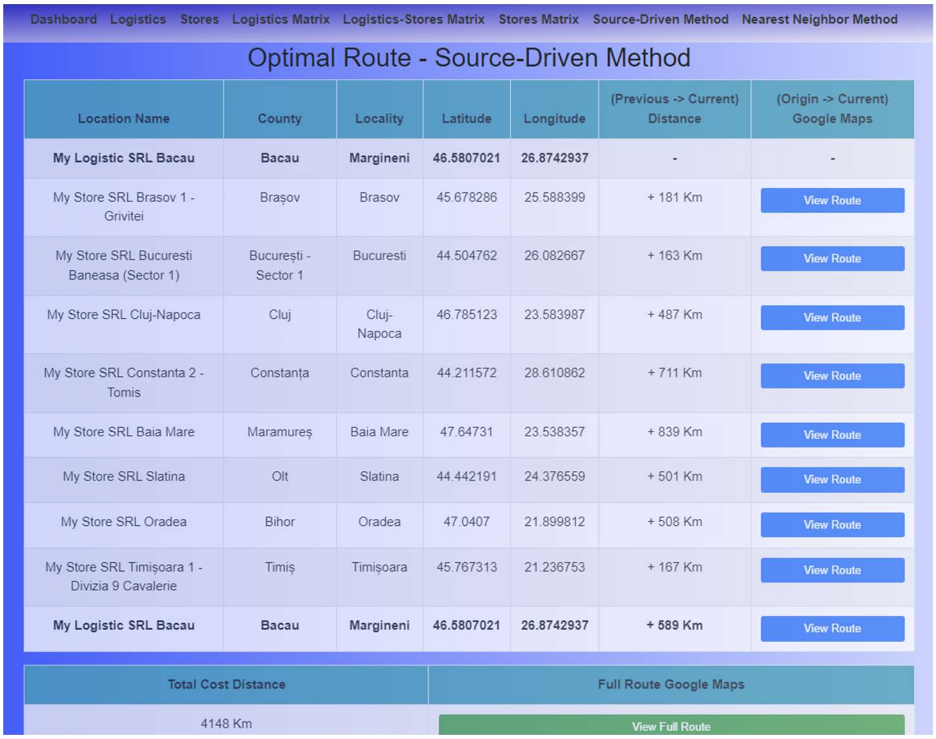
Figure 10 - LogisticStoreCost entity

Dashboard Logistics Stores Logistics Matrix Logistics-Stores Matrix Stores Matrix Source-Driven Method Nearest Neighbor Method

Stores Routing Matrix

Store 1 Code	Store 1 Name	Store 1 Latitude	Store 1 Longitude	Store 2 Code	Store 2 Name	Store 2 Latitude	Store 2 Longitude	Distance (Km)	Google Maps
AB01	My Store SRL Alba Iulia	46.081172	23.573064	AG01	My Store SRL Pitesti	44.87979	24.841384	236 Km	View Route
AB01	My Store SRL Alba Iulia	46.081172	23.573064	AR01	My Store SRL Arad	46.20131	21.255405	257 Km	View Route
AB01	My Store SRL Alba Iulia	46.081172	23.573064	BAC1	My Store SRL Bacau 1 - Republicii	46.508976	26.927579	398 Km	View Route
AB01	My Store SRL Alba Iulia	46.081172	23.573064	BC02	My Store SRL Bacau 2 - Abatorului	46.573041	26.883496	379 Km	View Route
AB01	My Store SRL Alba Iulia	46.081172	23.573064	BCT1	My Store SRL Bucuresti Giurgiului (Sector 4)	44.371624	26.091193	363 Km	View Route
AB01	My Store SRL Alba Iulia	46.081172	23.573064	BCT2	My Store SRL Bucuresti Valea Cascadelor (Sector 6)	44.424264	25.99674	349 Km	View Route

Figure 11 - StoreToStoreCost entity



Dashboard Logistics Stores Logistics Matrix Logistics-Stores Matrix Stores Matrix Source-Driven Method Nearest Neighbor Method

Optimal Route - Source-Driven Method

Location Name	County	Locality	Latitude	Longitude	(Previous -> Current) Distance	(Origin -> Current) Google Maps
My Logistic SRL Bacau	**Bacau**	**Margineni**	**46.5807021**	**26.8742937**	-	-
My Store SRL Brasov 1 - Grivitei	Brașov	Brasov	45.678286	25.588399	+ 181 Km	View Route
My Store SRL Bucuresti Baneasa (Sector 1)	București - Sector 1	Bucuresti	44.504762	26.082667	+ 163 Km	View Route
My Store SRL Cluj-Napoca	Cluj	Cluj-Napoca	46.785123	23.583987	+ 487 Km	View Route
My Store SRL Constanta 2 - Tomis	Constanța	Constanta	44.211572	28.610862	+ 711 Km	View Route
My Store SRL Baia Mare	Maramureș	Baia Mare	47.64731	23.538357	+ 839 Km	View Route
My Store SRL Slatina	Olt	Slatina	44.442191	24.376559	+ 501 Km	View Route
My Store SRL Oradea	Bihor	Oradea	47.0407	21.899812	+ 508 Km	View Route
My Store SRL Timișoara 1 - Divizia 9 Cavalerie	Timiș	Timișoara	45.767313	21.236753	+ 167 Km	View Route
My Logistic SRL Bacau	**Bacau**	**Margineni**	**46.5807021**	**26.8742937**	**+ 589 Km**	View Route

Total Cost Distance	Full Route Google Maps
4148 Km	View Full Route

Figure 12.a –Source-Driven optimization method

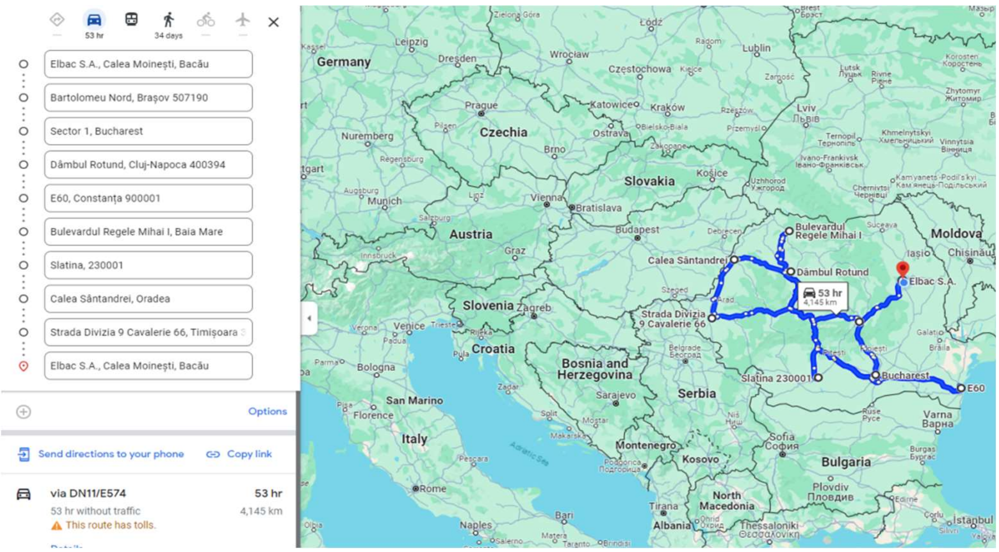
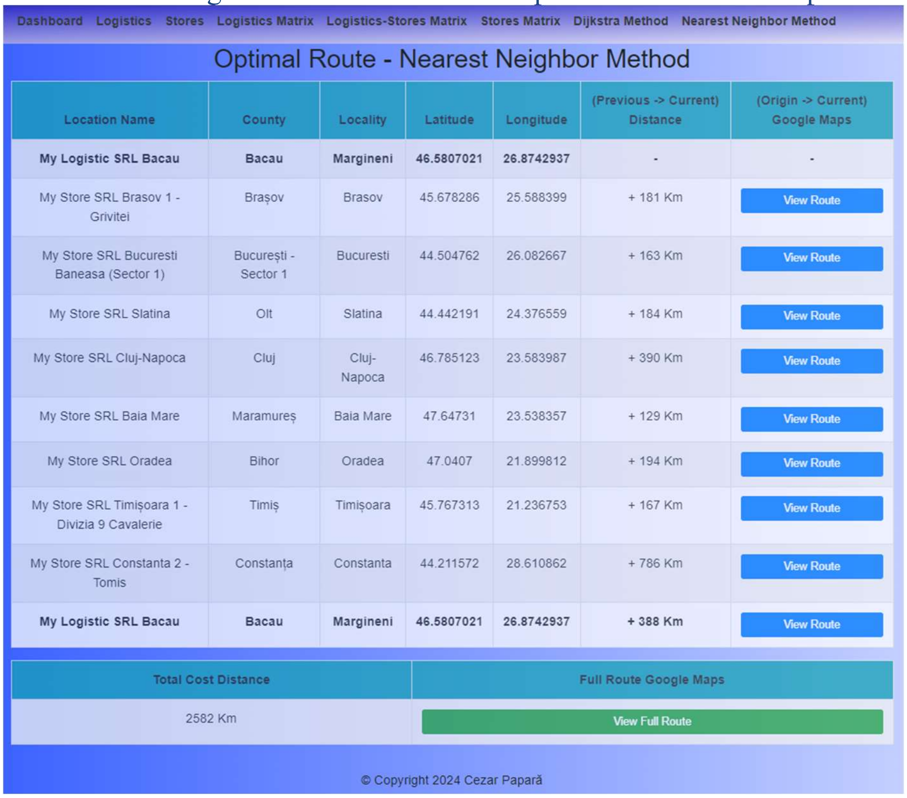


Figure 12.b –Source-Driven optimization method map



Dashboard Logistics Stores Logistics Matrix Logistics-Stores Matrix Stores Matrix Dijkstra Method Nearest Neighbor Method

Optimal Route - Nearest Neighbor Method

Location Name	County	Locality	Latitude	Longitude	(Previous -> Current) Distance	(Origin -> Current) Google Maps
My Logistic SRL Bacau	**Bacau**	**Margineni**	**46.5807021**	**26.8742937**	-	-
My Store SRL Brasov 1 - Grivitei	Brașov	Brasov	45.678286	25.588399	+ 181 Km	View Route
My Store SRL Bucuresti Baneasa (Sector 1)	București - Sector 1	Bucuresti	44.504762	26.082667	+ 163 Km	View Route
My Store SRL Slatina	Olt	Slatina	44.442191	24.376559	+ 184 Km	View Route
My Store SRL Cluj-Napoca	Cluj	Cluj-Napoca	46.785123	23.583987	+ 390 Km	View Route
My Store SRL Baia Mare	Maramureș	Baia Mare	47.64731	23.538357	+ 129 Km	View Route
My Store SRL Oradea	Bihor	Oradea	47.0407	21.899812	+ 194 Km	View Route
My Store SRL Timișoara 1 - Divizia 9 Cavalerie	Timiș	Timișoara	45.767313	21.236753	+ 167 Km	View Route
My Store SRL Constanta 2 - Tomis	Constanța	Constanta	44.211572	28.610862	+ 786 Km	View Route
My Logistic SRL Bacau	**Bacau**	**Margineni**	**46.5807021**	**26.8742937**	**+ 388 Km**	View Route

Total Cost Distance	Full Route Google Maps
2582 Km	View Full Route

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Figure 13.a - Nearest Neighbor optimization method

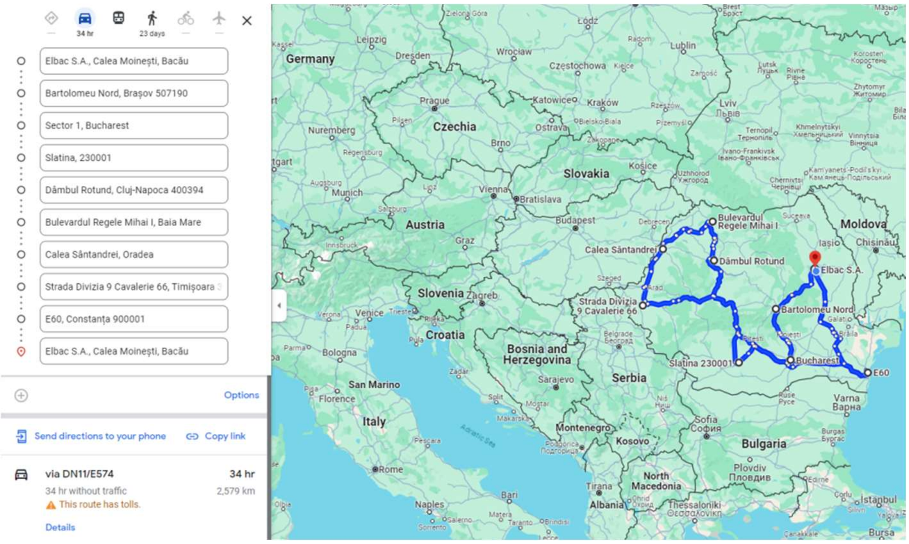

Figure 13.b - Nearest Neighbor optimization method map

Discussion

In this study, we delved into two distinct approaches for optimizing routing in logistics centers: one employing a Source-Driven strategy and the other utilizing greedy algorithms. The Nearest Neighbor algorithmemerged as the superior performer, yielding a more favorable score in our conclusive analysis.

The input parameters included a logistic center (source - Bacău) and eight retail stores (destinations - București, Oradea, Brașov, Cluj, Constanța, Baia-Mare, Slatina, Timișoara), aiming to identify the optimal route from the logistic center, visiting each store, and returning. Despite limiting waypoints to eight for graphical representation on Google Maps, adhering to the platform's constraint of ten, the algorithm implementations executed instantaneously. Notably, the initial population of 4112 distance links in the database, facilitated by the Google Maps Matrix API, was the sole time-intensive process, taking approximately one minute.

Importantly, scalability tests demonstrated the application's robustness. Even with all 62 locations instead of the chosen eight, the program maintained instantaneous execution. This scalability underscores the power of the framework employed, inviting further exploration into its potential in diverse logistics optimization scenarios.

Data Availability and Copyright Notice

The application and dataset are securely stored in a private GitLab repository, accessible upon request for research purposes. Interested parties are encouraged to reach out via email to the copyright holder, ensuring compliance with intellectual property rights.

Requests for access will be considered in adherence to copyright regulations. Users are expected to respect the proprietary nature of the database and code content.

5. CONCLUSIONS

Optimizing transportation networks remains a critical domain, particularly on expansive surfaces. The ever-evolving logistics industry underscores the importance of addressing challenges in optimizing routes, especially concerning the Traveling Salesman Problem (TSP) and Vehicle Routing Problem (VRP).

TSP and VRP persist as contemporary challenges, reflecting the dynamic nature of modern industries. Their relevance is heightened in an environment where efficient resource utilization and strategic planning are paramount.

The role of information technology tools in data processing, information management, and logistical organization cannot be overstated. These tools play a crucial part in refining data processing, enhancing transportation activities, and optimizing overall business operations.

A robust information system forms the cornerstone for scalable implementations tailored to specific business needs. It is pivotal in contributing actively to ongoing research in the transportation optimization domain.

An in-depth analysis of the implemented algorithms Greedy approaches reveals the nuances of their effectiveness. These approachesshowcase remarkable performance, especially on medium-sized datasets.

A meticulous comparison between distances processed in the code and real-time results from Google Maps reveals a negligible difference of less than 0.2%. This attests to the accuracy of our algorithmic calculations and the logical soundness of our code.

The computational implementation, along with the dataset, is housed in a private GitLab repository. Upon request, these resources can be made available, serving as a foundation for further research, development, and benchmarking in the field of transportation network optimization.

In conclusion, this work emphasizes the imperative role of information technology, providing valuable insights into the optimization of large-scale transportation networks. It stands as a starting point for future enhancements, showcasing the potential of robust computational tools in data processing and analysis.

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